Métricas de Avaliação dos Modelos de Circulação Geral

Disciplina: PNTC

https://subsazonal.cptec.inpe.br/

http://funceme.br/dashboard/subsaz_forecast

https://www.wmolc.org/seasonPmmeUI/plot_PMME

Qual é a Finalidade do Modelo?

- Previsão
 - Previsão em tempo real;
 - Previsão retrospectiva.

- Simulação
 - AMIP (Model Intercomparison Project)
 - Pesquisa

Previsão em Tempo Real

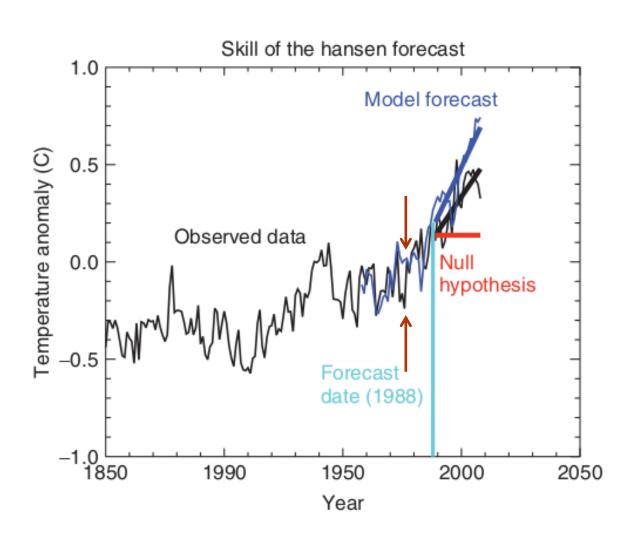
Previsão de Tempo Previsão climática sazonal **Future** Present Weather -Weather forecast hours Nowcasting days Medium-range weeks Sub-seasonal Climate Climate forecast months seasonal predictions decades decadal predictions centuries secular projections Near-normal rainfall Precipitable Water (mm) and CAPE (J/kg 4Hr GFS Issued: 12716JUL2023 Valid: 127 Mon 17 JUL 2023

Previsão Retrospectiva

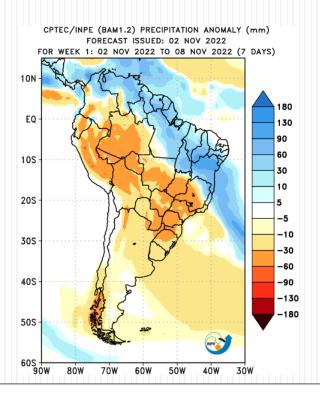
 Mesmo que a previsão em tempo real. Porém, inicializadas no presente com datas do passado

Projeção

Hargreaves (2010)

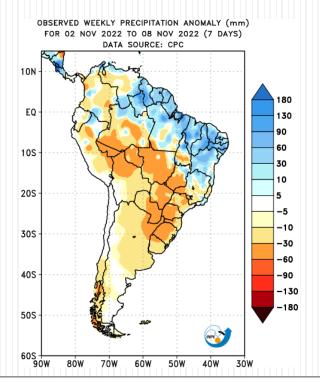


Previsão

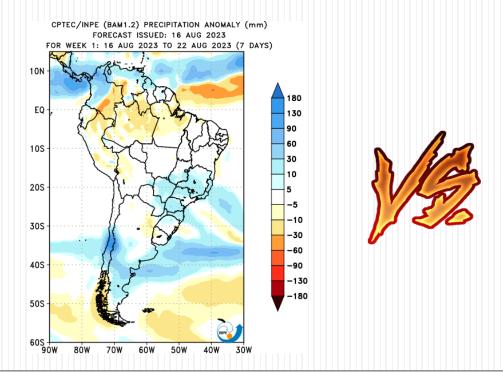




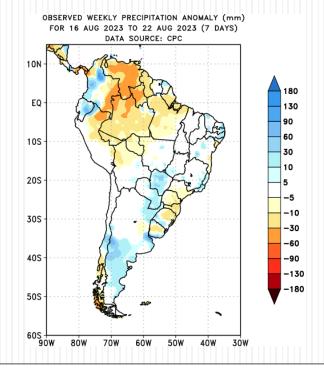
Dado de Referência (observação)



Previsão



Dado de Referência (observação)



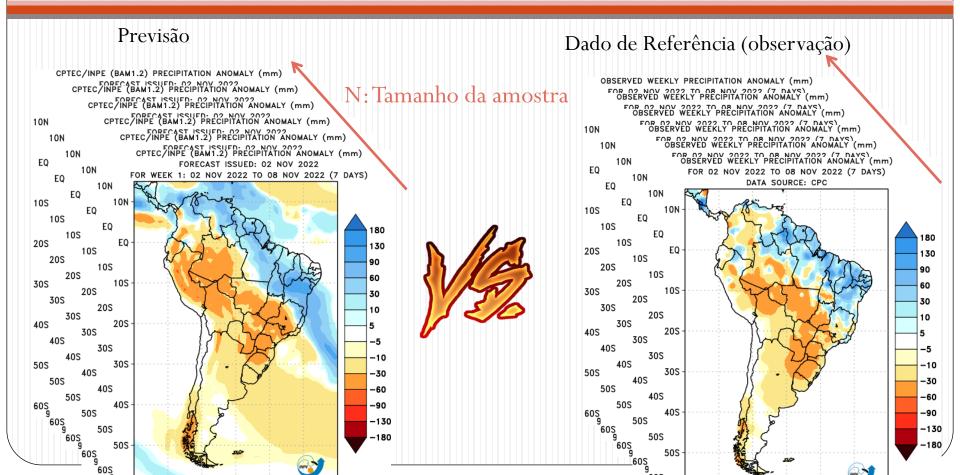
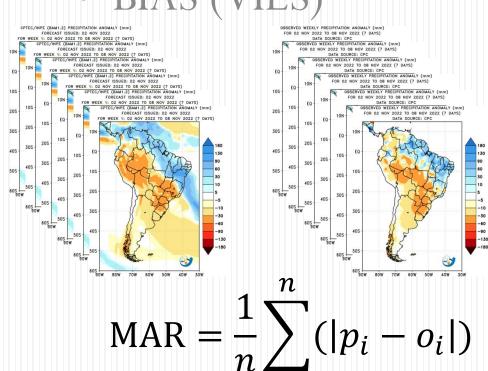


TABLE 1 Common Metrics (or Scores) for Verifying Continuous Deterministic Forecasts (F_i) Against the Observations (O_i)

Metric	Equation	Attribute Measured	Characteristics
Bias (linear bias, B)	$B = \frac{1}{N} \left[\sum_{i=1}^{N} (F_i - O_i) \right]$	Accuracy (average error)	Estimates the persistent or average error based on a specific data set; negative orientation (best when $B = 0$)
MAE	$MAE = \frac{1}{N} \left[\sum_{i=1}^{N} F_i - O_i \right]$	Accuracy	Average error magnitude, negative orientation (best when $MAE = 0$)
RMSE	RMSE = $\left[\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2\right]^{1/2}$	Accuracy	Average error magnitude weighted to larger errors; Negative orientation (best when RMSE $= 0$)
SS (Skill Score)	$SS = \frac{S_{y} - S_{y}}{S_{p} - S_{y}} = \frac{S_{y} - S_{y}}{S_{y}} = 1 - \frac{S_{y}}{S_{y}}$	Skill (general format)	Fractional improvement of the forecast over an unskilled reference.
,		For negatively oriented scores, perfect score $S_p = 0$)	Range: $-\infty$ to 1.
Pearson correlation coefficient (r)	$r = \frac{\sum_{i=1}^{N} (F_i - \overline{F}) (O_i - \overline{O})}{\sqrt{\sum_{i=1}^{N} (F_i - \overline{F})^2} \sqrt{\sum_{i=1}^{N} (O_i - \overline{O})^2}}$	Association	Strength of the linear relationship between forecasts and observations Range: -1 to 1.

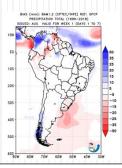
Note: Subscripts i refer to the ith case of the verification sample; the sample of forecast and observation pairs is of size N; the overbar indicates sample averaging. S_f (usually) refers to either the MAE or RMSE scores computed for the N pairs of F_i and O_i according to the equations in the table; S_r refers to the same score computed using a unskilled reference forecast such as the variable mean (climatology) or the latest observed value of the variable (persistence); S_p refers to the score for the perfect forecast. For perfect forecasts where $F_i = O_i$ for all N pairs, both MAE and RMSE equal zero (i.e., $S_p = 0$).

• BIAS (VIÉS)

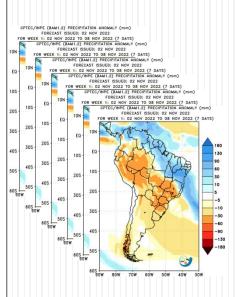


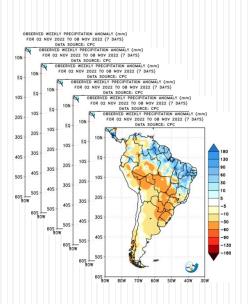
$$v = \frac{1}{n} \sum_{i=1}^{n} (P_i - o_i)$$

$$v = \bar{p} - \bar{o}$$



RMSE | MSE

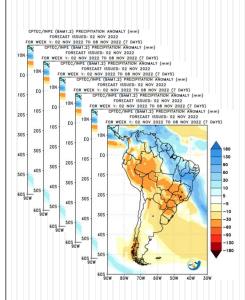


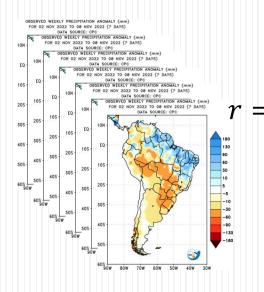


RMSE =
$$\sqrt[2]{\frac{1}{n}} \sum_{i=1}^{n} (p_i - o_i)^2$$

MSE =
$$\frac{1}{n} \sum_{i=1}^{n} (p_i - o_i)^2$$

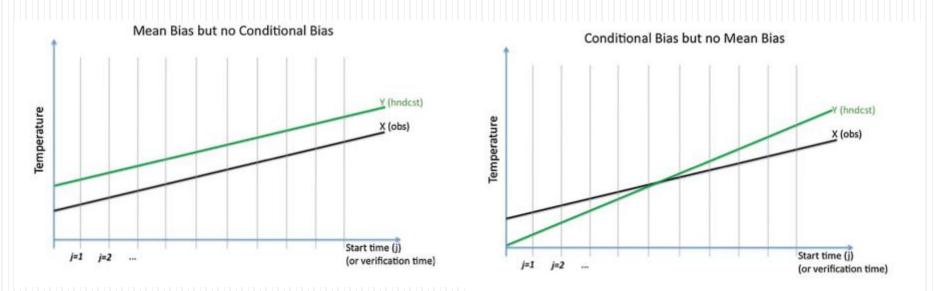
Correlação





$$\frac{\sum_{i=1}^{n} (p_i - \bar{p})(o_i - \bar{o})}{\sqrt[2]{\sum_{i=1}^{n} (p_i - \bar{p})^2} \sqrt[2]{\sum_{i=1}^{n} (o_i - \bar{o})^2}}$$

• Correlação não é skill. Ela é um potencial skill.



Goddard et al. (2012)

• Skill Score (índice de destreza do MSE)

$$SS = 2\left(\frac{s_p}{s_o}\right)r - \left(\frac{s_p}{s_o}\right)^2 - \left[\frac{(\bar{p} - \bar{o})}{s_o}\right]^2$$

$$SS = 1 - \left(\frac{MSE}{MSE_R}\right) \frac{\text{Se Ref. for a climatologia}}{\text{climatologia}}$$

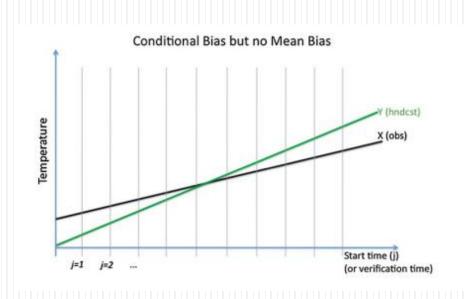
$$SS = r^2 - \left[r - \left(\frac{s_p}{s_o}\right)\right]^2 - \left[\frac{(\bar{p} - \bar{o})}{s_o}\right]^2$$

$$s_p = \frac{1}{n} \int_{i=1}^{n} (p_i - \bar{p})^2$$

$$s_o = \frac{1}{n} \int_{i=1}^{n} (o_i - \bar{o})^2$$

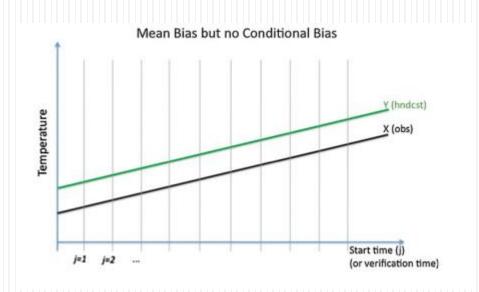
• BIAS (viés) condicional

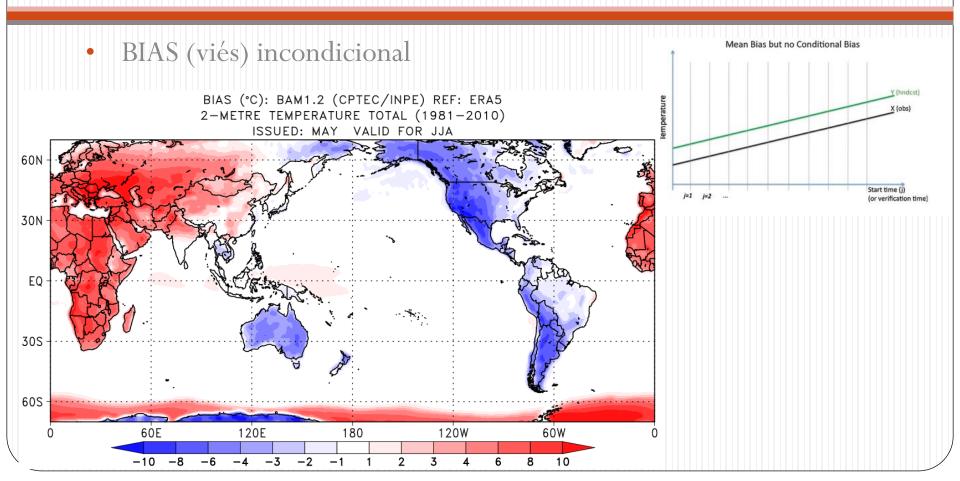
$$BC = \left[r - \left(\frac{S_p}{S_o}\right)\right]^2$$



• BIAS (viés) incondicional

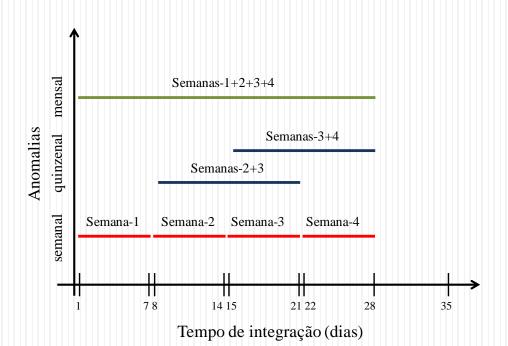
$$BI = \left[\frac{(\bar{p} - \bar{o})}{s_o}\right]^2$$





Interpretação das Métricas Determinísticas

Ver scripts



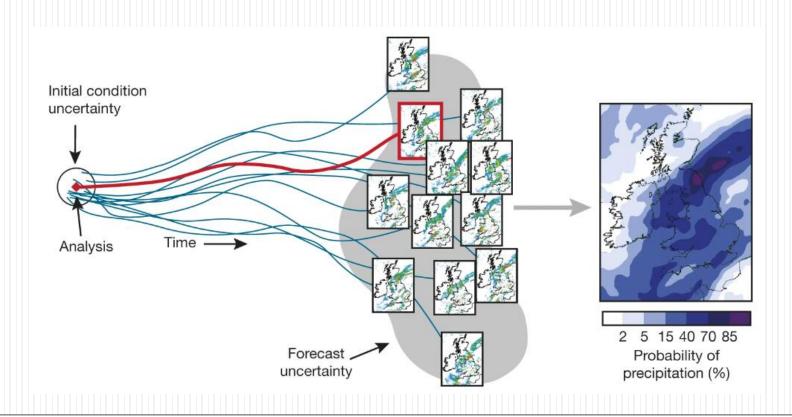
Datas das inicializações das previsões retrospectivas do BAM-1.2

DIAS	MESES	PERÍODO
03 e 14	NOVEMBRO	1999 a 2010
01 e 15	DEZEMBRO	1999 a 2010
04 e 14	JANEIRO	2000 a 2011
01 e 15	FEVEREIRO	2000 a 2011
03 e 14	MARÇO	2000 a 2011

Interpretação das Métricas Determinísticas

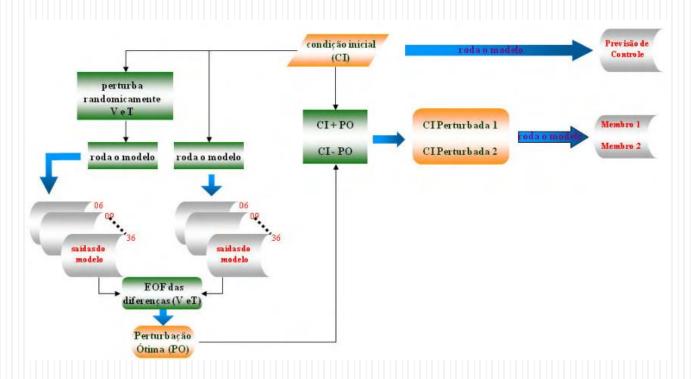
• Ver site subsazonal

Ensemble



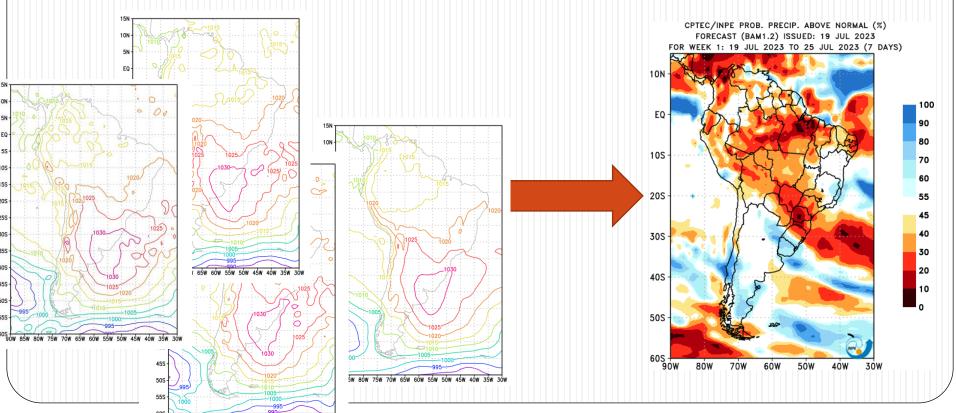
Ensemble

Mudança na condição inicial



Ensemble

• Perturbações na condição inicial



- Definição do evento
 - Precipitação acima de um limiar (e.g., 50 mm/dia)
 - Ciclone tropical
 - Anomalia positiva de precipitação
 - Temperatura do ar no tercil superior

TABLE 2 Contingency Table Format and Associated Scores

Measure	Equatio	n/Format				Range-Orientation	Characteristics
Contingency				oserved		Normally, as shown,	Equivalent to a scatterplot for
table	F o r	Yes	Yes a (Hits)	No b (False alarms)	Total fcst a+b (total events forecast)	columns are conditional observation totals, and rows are	categorized variable; 2 × 2 table most common—two categories, one threshold.
	e c a s	No	c (Missed events)	d (Correct negatives)	c+d (total non- events forecast)	conditional forecast totals.	
	avente (Control	b+d (total non- events obs)	N=a+b+c+d (sample size)				
FB	Ratiobe	$FB = \frac{a+b}{a+c}; \frac{c+d}{b+d}$ Ratio between the total number of events forecast (or not forecast) and the total number of events observed).			0 to ∞	Best score = 1. Simple comparison of forecast frequency to observed frequency.	
H (Probability of detection)	$H = \frac{a}{a+a}$	Ē				0 to 1	Best = 1. Incomplete score— does not account for false alarms.
F (probability of false detection)	$F = \frac{b}{b+d}$	ī				1 to 0	Best = 0. Can be improved by forecasting the event less often to reduce false alarms.
FAR	$FAR = \frac{1}{a}$	$\frac{b}{b+b}$				1 to 0	Best = 0. Sensitive to false alarms but ignores misses. Use with H.
TS (critical success index)	$TS = \frac{1}{a+1}$	$\frac{a}{b+c}$				0 to 1	Best = 1. Sensitive to both false alarms and misses; ignores correct negatives.

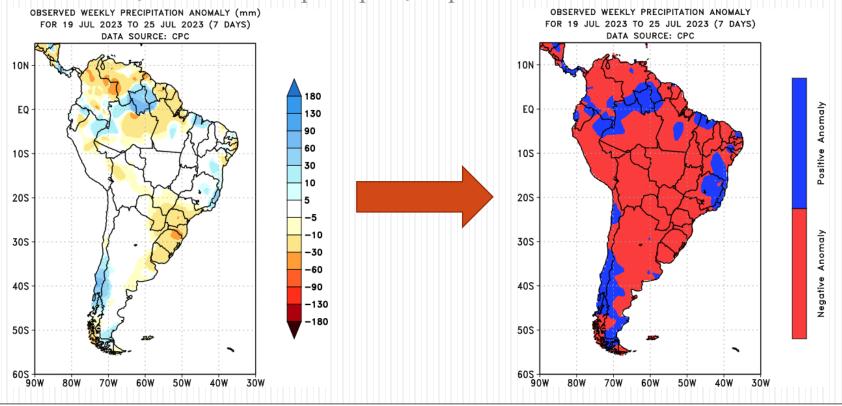
Continued

TABLE 2 Contingency Table Format and Associated Scores—cont'd

Measure	Equation/Format	Range-Orientation	Characteristics
ETS (Gilbert skill score)	ETS = $\frac{a - a_r}{a + b + c - a_r}$ where $a_r = \frac{(a + b)(a + c)}{N}$	-1/3to1;0 indicates no skill over chance.	Best = 1. TS adjusted for the number correct by chance (guessing), a form of SS. Always <ts.< td=""></ts.<>
KSS (also true skill statistic TSS or Pierce skill score	$KSS = \frac{a}{a+c} - \frac{b}{b+d} = H - F$	-1 to 1; 0 indicates no discriminant ability	Best = 1. Related to the ROC area and EDI/SEDI scores. Indicates the ability of the forecast to discriminate between events and nonevents, as a basis for decision-making.
HSS	$HSS = \frac{(a+d) - E_r}{N - E_r}$ where $E_r = \frac{1}{N}[(a+c)(a+b) + (c+d)(b+d)]$	−∞ to 1	Best = 1. SS in the general format, with "chance" as the reference forecast.
EDI	$EDI = \frac{\ln F - \ln H}{\ln F + \ln H}$	-1 to 1; 0 indicates no accuracy.	Best = 1. Designed to avoid convergence to 0 or 1 for low frequency (rare) events. Most often used for verifying extreme event forecasts.
SEDI	SEDI = $\frac{\ln F - \ln H + \ln(1 - H) - \ln(1 - F)}{\ln F + \ln H + \ln(1 - H) + \ln(1 - F)}$	-1 to 1; 0 indicates no accuracy.	Best = 1. Similar to EDI, but approaches 1 only for unbiased forecasts.

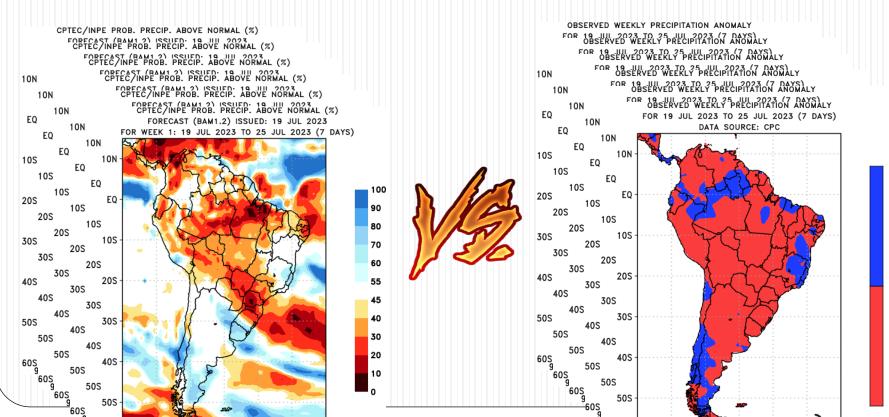
Note: The letters a, b, c, and d refer to total counts of cases with the corresponding pairing of forecast and observation. Sample size is denoted as N.

Definição do evento precipitação positiva



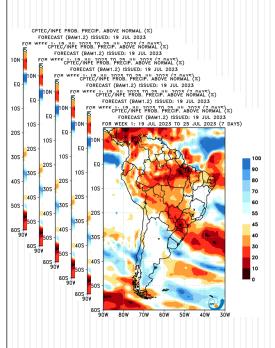


Ocorrência ou não do evento(observação)

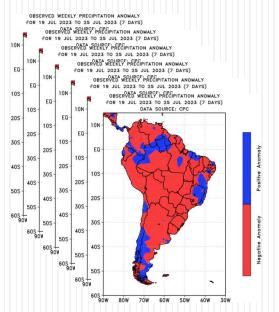


Previsão Probabilística

Ocorrência ou não do evento(observação)







• Brier Score

$$BS = \frac{1}{n} \sum_{i=1}^{n} (p_i - o_i)^2$$

$$0 \le BS \le 1$$

• Decomposição do Brier Score

$$BS = \frac{1}{n} \sum_{\substack{i=1 \\ \text{Confiabilidade}}}^{n} (p_i - o_i)^2 \qquad 0 \le BS \le 1$$

$$BS = \frac{1}{N} \sum_{k=1}^{j} I_k (p_k - \bar{o}_k)^2 - \frac{1}{N} \sum_{k=1}^{j} I_k (\bar{o}_k - \bar{o})^2 + \bar{o}(1 - \bar{o})$$

$$\bar{o}_k = p(o_k | p_k) = \frac{1}{N_k} \sum_{t \in N_k} o_t \quad \bar{o} = \frac{1}{n} \sum_{i=1}^{n} o_i$$

$$k = 1, ..., j = 11: p_1 = 0, p_2 = 0, 1... p_{11} = 1$$

$$BSS = Con - Res + Inc$$

$$BSS = 1 - \left(\frac{BS}{BS_R}\right)$$

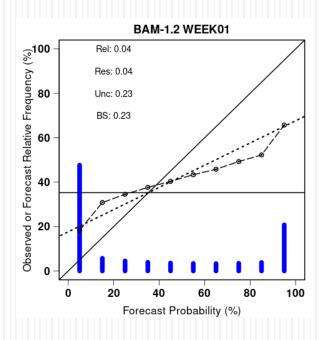
$$Se Ref for a climatologia$$

$$BS_R = 0 - 0 + Inc$$

$$BSS = 1 - \left(\frac{Con - Res + Inc}{Inc}\right)$$

$$BSS = \frac{(Res - Con)}{Inc}$$

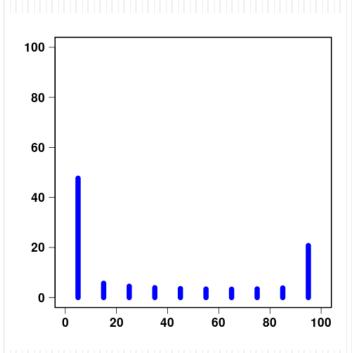
• Diagrama de Confiabilidade (Reliability Diagram)

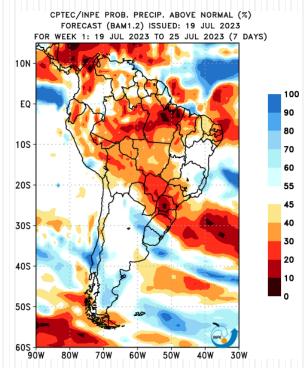


Atributos do diagrama de confiabilidade:

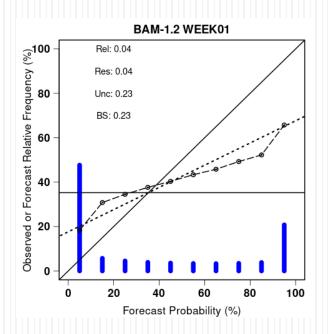
- Confiabilidade;
- Resolução;
- Nitidez.

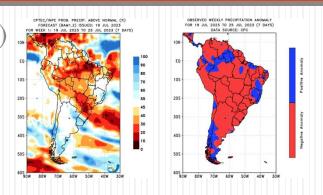
• Diagrama de Confiabilidade (Reliability Diagram)





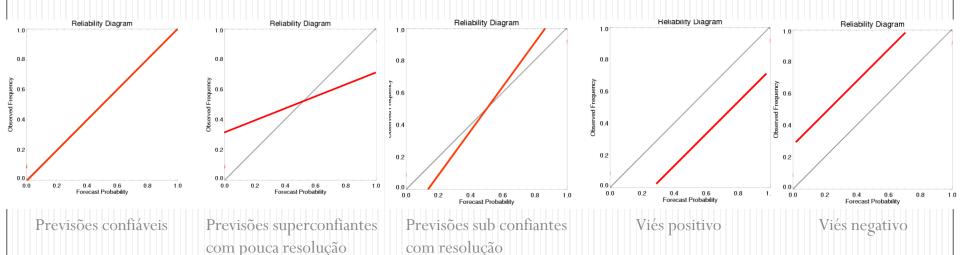
• Diagrama de Confiabilidade (Reliability Diagram)





Probabilidades previstas	Nº Previsões	Previsão perfeita	Previsão real
100%	8000	8000 (100%)	7200 (90%)
90%	5000	4500 (90%)	4000 (80%)
80%	4500	3600 (80%)	3000 (66%)
10%	5500	550 (10%)	800 (15%)
0%	7000	0 (0%)	700 (10%)

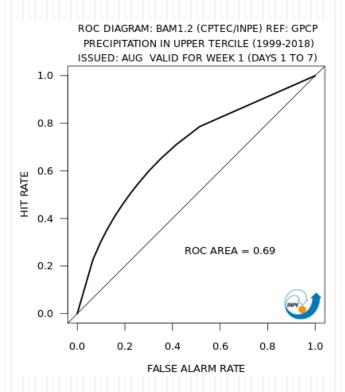
• Diagrama de Confiabilidade (Reliability Diagram)



• Área sob a curva ROC (Relative operating characteristics)

			Obs		
			Yes	No	Total fcst
	F	Yes	a	b	a+b
1	0		(Hits)	(False	(total events
1	r			alarms)	forecast)
1	е	No	С	d	c+d
1	С		(Missed	(Correct	(total non-
1	а		events)	negatives)	events
1	s				forecast)
ı	t				
		Total	a+c	b+d	N=a+b+c+d
		obs	(total events obs)	(total non- events obs)	(sample size)

Área sob a curva ROC é uma medida de discriminação



Interpretação das Métricas Probabilísticas

Ver scripts

Interpretação das Métricas Probabilísticas

• Ver site subsazonal

• Simulações com modelos de circulação geral são realizadas para diversos fins. Dessa forma, não existe um protocolo de avaliação definido para todos os tipos de avaliação (assim como mostrado no caso das previsões).

MJO Simulation Diagnostics

CLIVAR MADDEN-JULIAN OSCILLATION WORKING GROUP:

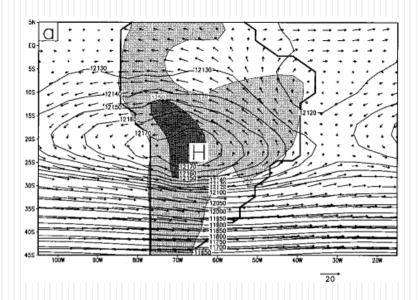
D. Walering, Jet Propulsion Laboratory, Pasadena, California; K. Sperrer, Lawrence Livermore National Laboratory, PCMDI, Livermore, California; H. Hendon, Centre for Australian Weather and Climate Research, Melbourne, Australia D. Kra, Scoul National University, Seoul, South Korea; E. Malloren, Colorado State University, Fort Collins, Colorado; M. Wheeler, Centre for Australian Weather and Climate Research, Melbourne, Australia; K. Weickmann, NOAA/Earth System Research Laboratory, Boulder, Colorado; C. Zaung, Rosenstel School of Marine and Atmospheric Science, Miami, Florida; L. Doneur, NOAA/Earth, Princeton, New Jersey; J. Gottschaler, W. Hrogens, NOAA/Earth, Princeton, New Jersey; J. Gottschaler, W. Hrogens, NOAA/CEP, Camp Springs, Maryland; L.-S. Kang, Seoul National University, Seoul, South Korea; D. Ligeler, U.S. Celivar Office, Washington, D. C.; M. McNecrer, NOAR, Boulder, Colorado; S. Schubert, NASAGSFC, Greenbelt, Maryland; W. Steren, NOAA/GFDL, Princeton, New Jersey; F. Velar, European Centre for Medium-Range Weather Forecasts, Reading, United Kingdom; B. Wang, IPRC, University of Hawaii at Manoa, Honolulu, Hawaii; W. Wang, NOAA/NCEP, Camp Springs, Maryland; S. Wocksoucai, University of Reading, Reading, United Kingdom

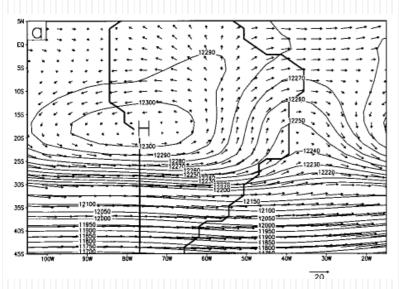
(Manuscript received 17 July 2008, in final form 13 November 2008)

ABSTRACT

The Madden-Julian oscillation (MJO) interacts with and influences a wide range of weather and climate phenomena (e.g., monsoons, ENSO, tropical storms, midlatitude weather), and represents an important, and as yet unexploited, source of predictability at the subseasonal time scale. Despite the important role of the MJO in climate and weather systems, current global circulation models (GCMs) exhibit considerable shortcomings in representing this phenomenon. These shortcomings have been documented in a number of multimodel comparison studies over the last decade. However, diagnosis of model performance has been challenging, and model progress has been difficult to track, because of the lack of a coherent and standardized set of MJO diagnostics. One of the chief objectives of the U.S. Climate Variability and Predictability (CLIVAR) MJO Working Group is the development of observation-based diagnostics for objectively evaluating global model simulations of the MJO in a consistent framework. Motivation for this activity is reviewed, and the intent and justification for a set of diagnostics is provided, along with specification for their calculation, and illustrations of their application. The diagnostics range from relatively simple analyses of variance and correlation to more sophisticated space-time spectral and empirical orthogonal function analyses. These diagnostic techniques are used to detect MJO signals, to construct composite life cycles, to identify associations of MJO activity with the mean state, and to describe interannual variability of the MJO.

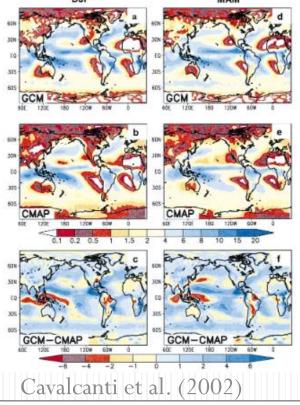
• Influência dos Andes na formação da Alta da Bolívia

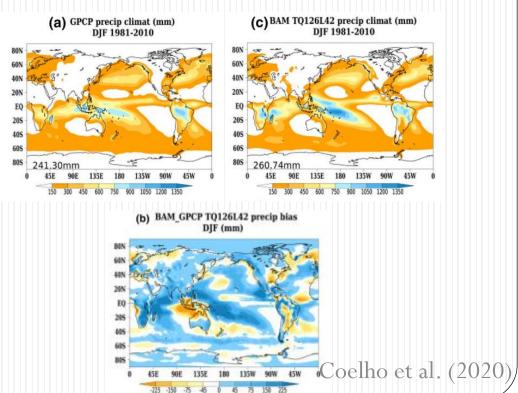




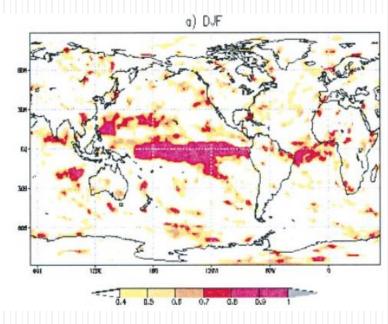
Lenters e Cook (1997)

• Simulação climática com os modelos globais do CPTEC

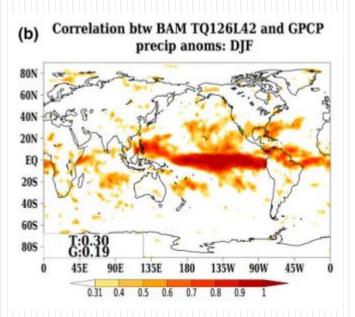




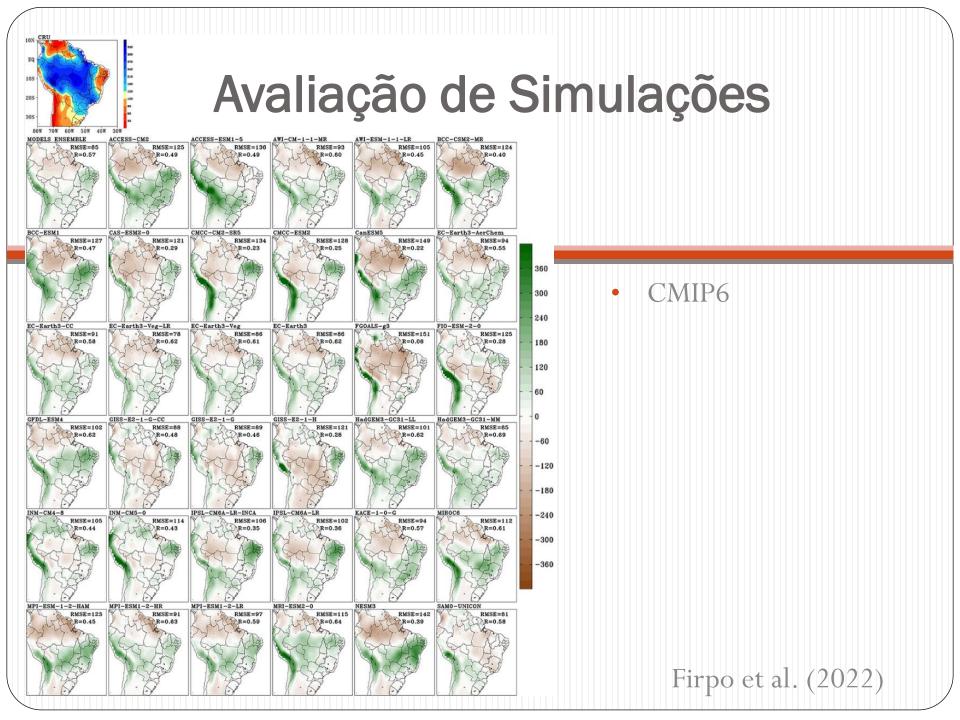
• Simulações climáticas com os modelos globais do CPTEC



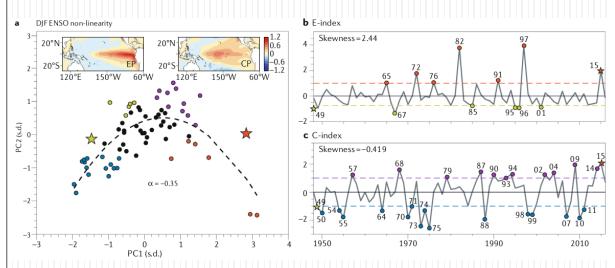
Cavalcanti et al. (2002)

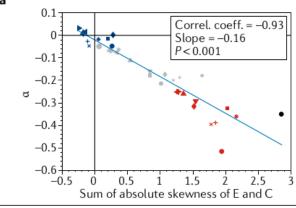


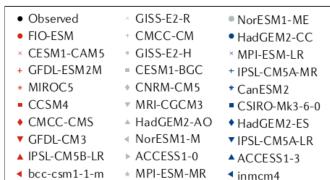
Coelho et al. (2020)



CMIP e ENOS







* bcc-csm1-1

► GDFL-ESM2G

▶ CMCC-CESM

FGOALS-s2

Cai et al. (2020)

Diagrama de Taylor

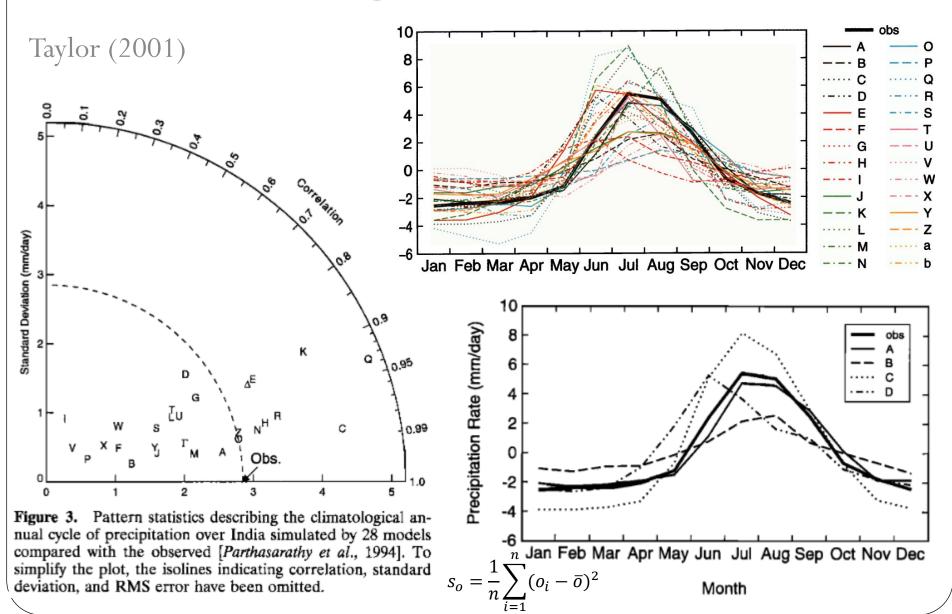


Diagrama de Taylor

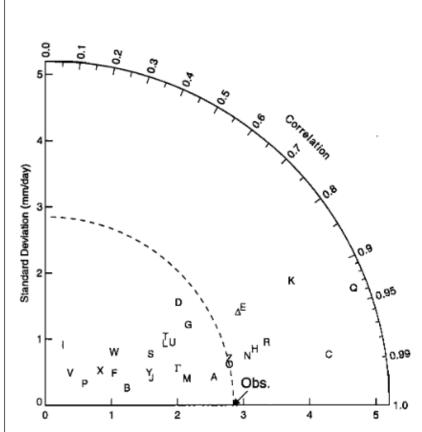
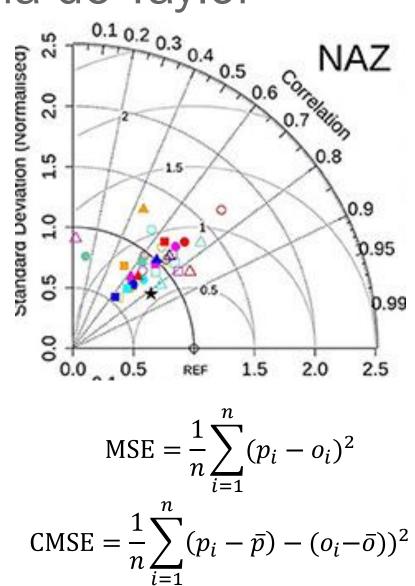


Figure 3. Pattern statistics describing the climatological annual cycle of precipitation over India simulated by 28 models compared with the observed [Parthasarathy et al., 1994]. To simplify the plot, the isolines indicating correlation, standard deviation, and RMS error have been omitted.



Pontos destacados

- Definição das principais métricas estatísticas de verificação;
- Atributos de cada métrica;
- Diferenças entre previsão e simulação;
- Aplicação das métricas estatísticas na avaliação de previsão e simulação;
- Prática.

Referências

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- MURPHY, Allan H. A new vector partition of the probability score. **Journal** of Applied Meteorology and Climatology, v. 12, n. 4, p. 595-600, 1973.
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