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II SIMPÓSIO DA BACIA HIDROGRÁFICA DO RIO SÃO FRANCISCO

Desafios da Ciência para um novo Velho Chico

Evaluation of the rainfall estimation for different global climate models (GCMs) in the São Francisco River Basin, Brazil

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Abstract. The effects of climate change on water resources can be assessed by the results of simulations from Global Climate Models (GCMs). The Intergovernmental Panel on Climate Change (IPCC) has periodically published reports pointing to several model results for the prediction of current and future climate scenarios based on historical information. The evaluation of the performance of GCMs prediction and its intra-annual variation is an important step for the application of downscaling techniques, that allow to produce future projections with a lower degree of uncertainty. In this sense, the present study aims to evaluate the performance of 44 IPCC GCMs to predict the monthly precipitation distributed over the São Francisco River basin (SFRB), and to do so, a new skill indicator (*Im*) was proposed. *Im* index is composed by a relativized combination of Pearson correlation coefficient (*r*), the Root Mean Square Error (*RMSE*), the Precision percent of the cell in the grid (*PCell*) and the Seasonality Bias (*SB*). The proposed index was effective in evaluating the performance of global climate change models in the prediction of rainfall in the São Francisco River Basin. A loss in GCMs performance to predict rainfall was detected as the assessment approached the coast, ie to the mouth of the basin. The EC-EARTH GCM shows the best values to the index in three regions of the São Francisco River Basin.

Key words – IPCC AR5, downscaling, skill index.

INTRODUCTION

The effects of climate change on water resources can be assessed by the results of simulations from Global Climate Models (GCMs). These models are the main tools that project future climate change information, however these models currently do not provide reliable information on scales below about 200 km for most hydrological-relevant variables (Maraun et al., 2010), leading to outcomes for individual regions can vary significantly among the various GCMs (Cai et al., 2009).

The Intergovernmental Panel on Climate Change (IPCC) has periodically published reports pointing to several model results for the prediction of current and future climate scenarios based on historical information (IPCC, 2013). In the Fifth Report of the IPCC (AR5), it was considered the fifth phase models of the Coupled Model Intercomparison Project Phase 5 (CMIP5). In this AR5, the scenarios were denominated RCP (Representative Concentration Pathways), with values related to the levels of radiative forcing at the end of the 21st century, being used as input for climate modeling. Four IPCC-AR5 scenarios were defined as: RCP8.5, RCP6, RCP4.5 and RCP2.6.

The quantification of climatic changes in hydrological modeling responses, for example, presupposes an adequate representation of the interrelation between variables, such as precipitation and temperature, as well as their seasonal behavior in a basin (Piani et al., 2010). In this sense, the size of the study area, considering the low resolution of most of the GCMs, becomes a limiting factor for an adequate performance of these models in the representation of the climate. Downscaling techniques can help to overcome this limitation, considering empirical or statistical models (Chen et al., 2013).

The evaluation of the performance of GCMs prediction considering a specific climatic variable such as precipitation and its intra-annual variation is an important step for the application of downscaling techniques, that allow to produce future projections with a lower degree of uncertainty. Several studies present techniques for evaluating the skill of climate models, with applications in several parts of the world (Watanabe et al., 2012; Catto et al., 2013).

Precipitation is a critical variable of hydrologic studies and it is much more difficult to be simulated by climate models than temperature (Chen et al., 2013). In the Northeast region of Brazil, precipitation is erratic, concentrated in four or five months of the year (rainy season) and it is characterized uncertainty related to occurrence and spatial distribution. Among the basin of this region, São Francisco river basin is the most important since it covers a large area, drains several states of this region, and due to the long drought period started in 2012, this river became the main water resource for a huge population. In this context, this study aims to evaluate the performance of AR5 GCMs to predict the monthly precipitation distribution in the São Francisco River basin (SFRB) based on a new skill indicator index.

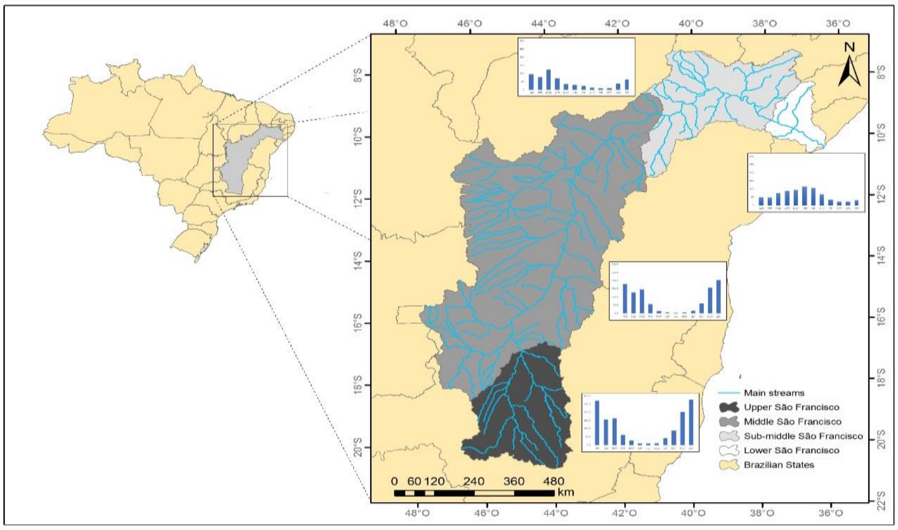
MATERIALS AND METHODS

Study Area

The São Francisco River basin is the most important in the Northeast region of Brazil, because it is the longest river in this region and cross the semiarid area in whole being the main water resource available, as well as due to its hydropower potential. The basin area is around 640,000 km^2, representing 8% of Brazilian territory (Figure 1). This basin comprises 521 municipalities with areas into six Brazilian States: Bahia, Minas Gerais, Pernambuco, Alagoas, Sergipe and Goiás, besides the Federal District (ANA, 2017). More than 14.2 million people, equivalent to 7.5% of the Brazilian population, lived in this basin in 2010. Agriculture is one of the most important economic activities, but the region has strong socioeconomic contrasts, with areas of marked richness and high population density and areas of critical poverty and dispersed population (ANA, 2017).

Because of its large area, and for the water resources management purpose the São Francisco basin was divided in four different regions: 1 – Upper São Francisco: beginning in the mountainous area where headwater locates, in the Serra da Canastra, extending to the city of Pirapora, in the north-central part of Minas Gerais, the region cover an area of 111,804 km^2; 2 – Middle São Francisco: crosses all the west of Bahia State until lake of Sobradinho, in the municipality of Remanso. It is the largest of the four divisions, with 339,763 km^2 in area; 3 – Sub-middle São Francisco: after the city of Remanso, the river changes its course to the east, constituting the natural border between the states of Bahia and Pernambuco, until reaching the border with Alagoas. This is the second largest portion of the main basin area, with 155,637 km^2; 4 – Lower São Francisco: contain the region where the river is the natural border, between the states of Alagoas and Sergipe, with an area of 32,013 km^2, and from there, the São Francisco River flows toward the Atlantic Ocean (CBHSF, 2017).

FIGURE 1. Location of the São Francisco River Basin and its four regions considering the intra-annual distribution of rainfall



The climate in the lower river basin usually is hot and dry, the average maximum and minimum temperature for the region is 33° C and 19° C, respectively. Rainfall is erratic over the basin area, and drought is frequent mainly in the Semiarid portion of the basin. Mean annual rainfall varies from 510 to 1,020 mm in most of the middle basin and from 1,000 to 2,000 mm in the region downstream Paulo Afonso Falls which is along the main São Francisco river. In most of the falls area mean annual precipitation is last than 510 mm and also areas with a mean annual precipitation of 250 mm is found. Rainy season occurs during the summer time (December to March) and the rest of the year the weather is quite dry (Britannica, 2017).

Data Set used

- Estimated Data (*ED*): monthly precipitation series of 44 GCMs (Table 1) from the Coupled Model Intercomparison Project Phase 5 - CMIP5 (WCRP, 2016) obtained from the link https://pcmdi.llnl.gov/projects/esgf-llnl/. It was considered time series of precipitation from 1980 to 2005, coinciding with the data used to evaluate the performance of the models;

- Reference Data (*RD*): Monthly precipitation series from the Brazil Gridded Meteorological Data base within the period 1980-2015 (Xavier et al., 2015). The grid has a spatial resolution of 0.25° and cover the Brazilian territory (https:///utexas.app.box.com/v/xavier-etal-ijoc-data); Such interpolated data has shown satisfactory correlations with field data in similar regions of Northeastern Brazil (Cruz et al., 2017);

TABLE 1. IPCC/AR5 Global Climate Model evaluated (WCRP, 2016)

	MODELO	**INSTITUIÇÃO**
1	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology, Australia
2	ACCESS1.3	Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology, Australia
3	BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration
4	BCC-CSM1.1(m)	Beijing Climate Center, China Meteorological Administration
5	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University
6	CanCM4	Canadian Centre for Climate Modelling and Analysis
7	CanESM2	Canadian Centre for Climate Modelling and Analysis
8	CCSM4	National Center for Atmospheric Research
9	CESM1(BGC)	National Science Foundation, Department of Energy, National Center for Atmospheric Research
10	CESM1(CAM5)	National Science Foundation, Department of Energy, National Center for Atmospheric Research
11	CESM1(FASTCHE	National Science Foundation, Department of Energy, National Center for Atmospheric Research
12	CESM1(WACCM)	National Science Foundation, Department of Energy, National Center for Atmospheric Research
13	CMCC-CESM	Centro Euro-Mediterraneo per I Cambiamenti Climatici
14	CMCC-CM	Centro Euro-Mediterraneo per I Cambiamenti Climatici
15	CMCC-CMS	Centro Euro-Mediterraneo per I Cambiamenti Climatici
16	CNRM-CM5	Centre National de Recher Meteorologiques / Europeen de Recher et Form Avancees en Calcul
17	CNRM-CM5-2	Centre National de Recher Meteorologiques / Europeen de Recher et Form Avancees en Calcul
18	CSIRO-Mk3.6.0	Commonwealth Scientific and Ind Res Organisation with the Climate Change Centre of Excellence
19	EC-EARTH	EC-EARTH consortium
20	FIO-ESM	The First Institute of Oceanography, SOA, China
21	GFDL-CM3	Geophysical Fluid Dynamics Laboratory
22	GISS-E2-H	NASA Goddard Institute for Space Studies
23	GISS-E2-H-CC	NASA Goddard Institute for Space Studies
24	GISS-E2-R	NASA Goddard Institute for Space Studies
25	GISS-E2-R-CC	NASA Goddard Institute for Space Studies
26	HadCM3	Met Office Hadley Centre
27	HadGEM2-AO	Met Office Hadley Centre
28	HadGEM2-CC	Met Office Hadley Centre
29	HadGEM2-ES	Met Office Hadley Centre (HadGEM2-ES realizations contributed by INPE)
30	INM-CM4	Institute for Numerical Mathematics
31	IPSL-CM5A-LR	Institut Pierre-Simon Laplace
32	IPSL-CM5A-MR	Institut Pierre-Simon Laplace
33	IPSL-CM5B-LR	Institut Pierre-Simon Laplace
34	MIROC-ESM	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan
35	MIROC-ESM-	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan
36	MIROC4h	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan
37	MIROC5	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan
38	MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M)
39	MPI-ESM-MR	Max Planck Institute for Meteorology (MPI-M)
40	MPI-ESM-P	Max Planck Institute for Meteorology (MPI-M)
41	MRI-CGCM3	Meteorological Research Institute
42	MRI-ESM1	Meteorological Research Institute
43	NorESM1-M	Norwegian Climate Centre
44	NorESM1-ME	Norwegian Climate Centre

All routines for interpolation, extraction and processing of information were constructed as scripts in the R x64 v 3.2.2 software, using the *ncdf4*, *ncdf*, *maptools*, *raster* and *utils* packages.

The GCMs performance evaluation index (*Im*)

The performance of GCMs is assessed according to their ‘‘skill scores’’ (Cai et al., 2009). The skill scores were calculated through a proposed index (*Im*) using four indicators: Pearson correlation coefficient (*r*), Root Mean Square Error (*RMSE*), Precision percent (*PCell*) and Seasonality Bias (*SB*).

The Pearson Correlation Coefficient (*r*) is obtained by the equation 1:

$$r = \frac{\sum_{i=1}^{n}\left(ED_i - \overline{ED}\right)\left(RD_i - \overline{RD}\right)}{\sqrt{\sum_{i=1}^{n}\left(ED_i - \overline{ED}\right)^2} \cdot \sqrt{\sum_{i=1}^{n}\left(RD_i - \overline{RD}\right)^2}} \quad (1)$$

The Root Mean Square Error (*RMSE*) is calculated by the equation 2:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(ED_i - RD_i\right)^2}{n}} \quad (2)$$

RD and *ED* represent values of reference and estimated monthly precipitation, respectively and *n* is the number of observations for each cell in the grid;

Later, for each region and for each GCM, the average *r* and *RMSE* values considering all cells of the grid are calculated.

The Precision percent (*PCell*) is related to the percent of the grid cells in a region that average *ED* is placed inside the acceptable range around the average *RD* value. In this study, the limits for this range was considered ± 25%. It is not expected that all GCMs *ED* had high precision, because their coarse scale, however, this indicator can be useful to compare this skill among all GCMs evaluated. The higher the *PCell*, the best is the estimation performance of the evaluated GCM. *PCell* can be calculated by the Equation 3:

$$\left.\begin{array}{l} 0.75 \cdot \overline{RD} \le \overline{ED} \le 1.25 \cdot \overline{RD} \rightarrow K_j = 1 \\ \\ 0.75 \cdot \overline{RD} \ge \overline{ED} \ge 1.25 \cdot \overline{RD} \rightarrow K_j = 0 \end{array}\right\} \quad PCell = \frac{\sum_j^Z K_j}{Z} \times 100 \quad (3)$$

K is the counter of the number of grid cells placed into the range for each GCM; *j* is the number of a specific cell in the grid; *Z* is the total number of cells in the grid for the evaluated region.

The last indicator is Seasonality Bias (*SB*), which is related to the ability of a GCM in representing intra-annual distribution of precipitation in a region. It is not evaluated how far is the difference between mean *ED* and mean *RD* in each month, but only if the relation between each average monthly precipitation and annual total precipitation is similar for $\overline{ED}$ and $\overline{RD}$. Then, the difference among monthly/year precipitations relations for $\overline{ED}$ and $\overline{RD}$, is calculated or evaluated. After, *SB* is obtained through of the sum of these differences in absolute values: the lower value of *SB* indicates the best seasonality representation. The *SB* indicator can be calculated by the equation 4:

$$SB = \sum_{m=1}^{12} \left| \frac{\overline{ED}_m}{\sum_{m=1}^{12} \overline{ED}_m} - \frac{\overline{RD}_m}{\sum_{m=1}^{12} \overline{RD}_m} \right| \tag{4}$$

m is the number related to the month (January is 1, February is 2, etc.).

Once all indicators were calculated, all of them are relativized in relation to its best value obtained, which receives the value 1.0. This way, the *Im* index (Equation 5) is calculated by the sum of the four relativized indicators then, 4.0 is the maximum possible value to the index, and, how bigger is *Im*, better is the general performance of the GCM for the region evaluated.

$$\mathrm{Im} = r_{rel} + RMSE_{rel} + PCell_{rel} + SB_{rel} \tag{5}$$

r_{rel} is the Pearson Correlation Coefficient relativized, $RMSE_{rel}$ is the Root Mean Square Error relativized, $PCell_{rel}$ is the Percent precision indicator relativized and SB_{rel} is the Seasonality Bias indicator relativized.

RESULTS AND DISCUSSION

It can be observed in Table 2 that, in general, the GCMs performance decay from Upper to Lower São Francisco River basin area. The Person Correlation Coefficient (*r*) shows best values in Upper São Francisco River Basin, with average of 0.62 and the best value of 0.73. In this region, 50% of the correlations between GCMs data (*ED*) and *RD* are situated above r =0.63. In the Lower SFRB, this indicator shows the worst values: average of 0.10 and maximum value equal to 0.28. This behavior can be associated to the difficulties of the GCMs in representing the rainfall in regions near to the ocean, being the same behavior observed in other studies for the same region (Cruz et al., 2017). Similar behavior was observed considering *RMSE*, excepting in the Middle SFRB, where this indicator was a little better than in the Upper region. It should be noted that the highest values are in the Lower SFRB, where the maximum value it was *RMSE*= 441.39, with an average *RMSE* of 132.79.

As for the *PCell* indicator, in the Upper SFRB the median was 56.0 %, which means that the most part of the GCMs data had his monthly bias situated into the 25% of tolerance in this region. It is interesting to note that the maximum value for this indicator in Upper SFRB and in the Middle SFRB were 99.5% and 93.6%, respectively, showing a very high precision for a coarse scale model. Otherwise, the minimum value to *PCell* was 0.0% and 0.2% for Upper and Middle SFRB, indicating that at least one GCM has its time series outside the tolerance limit for the monthly bias.

TABLE 2. Statistical summary from indicators for the 44 AR5 GCMs evaluated in the four regions of São Francisco River basin (SFRB)

Region	Statistics	r	RMSE	PCell	SB
Upper SFRB	Average	0.62	109.81	47.4%	0.21
	Median	0.63	105.23	56.0%	0.18
	Max	0.73	163.32	99.5%	0.43
	Min	0.44	84.75	0.0%	0.08
	Std.Dev.	0.07	18.56	34.8%	0.07
Middle SFRB	Average	0.53	105.93	41.0%	0.28
	Median	0.55	103.22	42.5%	0.26
	Max	0.65	174.96	93.6%	0.64
	Min	0.35	79.79	0.2%	0.11
	Std.Dev.	0.07	17.18	23.1%	0.11
Sub-middle SFRB	Average	0.41	111.51	17.3%	0.35
	Median	0.42	99.71	7.4%	0.33
	Max	0.49	222.10	76.5%	0.59
	Min	0.26	63.18	0.0%	0.17
	Std.Dev.	0.05	42.68	22.1%	0.12
Lower SFRB	Average	0.10	132.79	20.3%	0.69
	Median	0.12	111.29	13.9%	0.61
	Max	0.28	441.39	66.7%	1.18
	Min	-0.09	66.92	0.0%	0.30
	Std.Dev.	0.09	86.99	20.4%	0.23

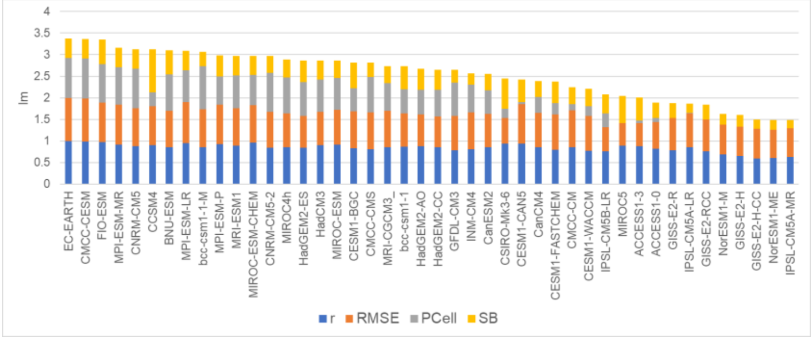
The assessment of monthly seasonality it was made by the *SB* indicator. The closer *SB* is to zero, the better is the indicator. The best values were obtained in the Upper SFRB, with average *SB* equal to 0.20, and above 50% of the GCMs with *SB* < 0.18. It must be noted that the worst minimum value of *SB* for all GCMs was obtained in the Lower SFRB (*SB* = 0.30).

The four indicators were standardized in relation to the best value of all GCMs and the maximum value became 1.0 for all indicators. After, the indicators were summed to obtain de *Im* index value and identify the best GCMs skills.

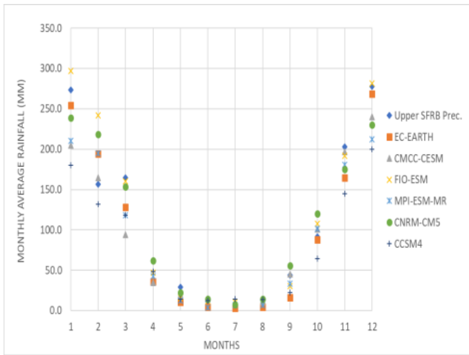
Upper SFRB: The sum of the four indicators compounded the index Im for Upper SFRB and these values can be observed in the Figure 2. Three GCMs shows the highest values to Im: EC-EARTH (Im = 3.374), CMCC-CESM (Im = 3.367) and FIO-ESM (Im = 3.356). The maximum possible value to Im is 4.0, however, others six GCMs have Im superior to 3.0: MPI-ESM-MR (Im = 3.159), CNRM-CM5 (Im = 3.130), CCSM4 (Im = 3.128), BNU-ESM (Im = 3.101), MPI-ESM-LR (Im = 3.093) and BCC-CSM1-1-M (Im = 3.064). All selected GCMs showed satisfactory representation of the monthly precipitation distribution by year (Figure 2a and 2b).

Middle SFRB: The index *Im* for Middle SFRB and the values of indicators can be observed in the Figure 3 (a). Only three GCMs shows values to *Im* above 3.0: EC-EARTH (*Im* = 3.587), HadGEM2-CC (*Im* = 3.224) and CMCC-CESM (*Im* = 3.074). Near to this value the GCMs were: CESM1-CAN5 (*Im* = 2.816), ACCESS1-3 (*Im* = 2.807) and HadGEM2-AO (*Im* = 2.803). It was observed a decrease in the GCMs accuracy when the evaluation is assessed near to the Atlantic Ocean. In the Figure 3(b) is possible to see that all selected models showed satisfactory seasonality representation, with an exception to CESM1-CAN5 model response for December, because this GCM underestimated the total rainfall. It should be noted that in February all selected models show values above the observed rainfall.

FIGURE 2. Index *Im* and its indicators obtained for 44 GCMs (a) and monthly average rainfall for the six best GCMs skills (b) in the Upper São Francisco River Basin

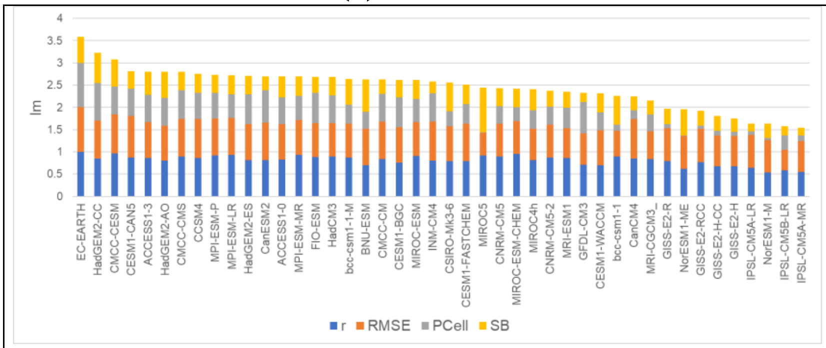


(a)

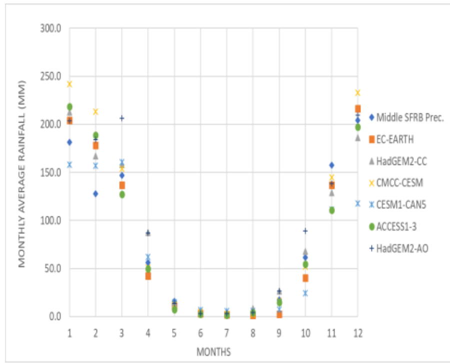


(b)

FIGURE 3. Index *Im* and its indicators obtained for 44 GCMs (a) and monthly average rainfall for the six best GCMs skills (b) in the Middle São Francisco River Basin



(a)

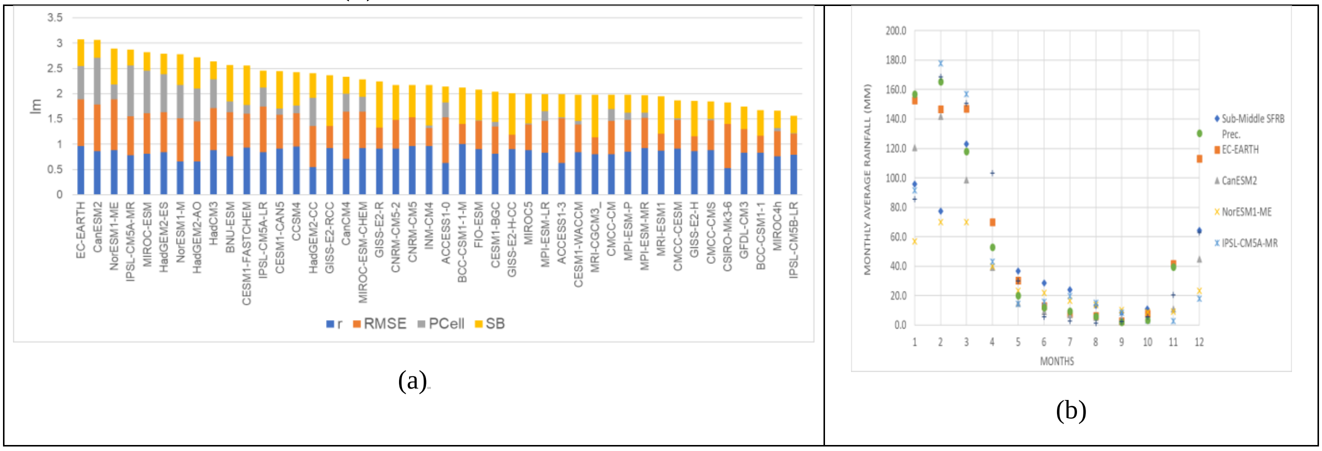


(b)

Sub-Middle SFRB: Considering the index *Im* and its composition for Sub-Middle SFRB the values can be observed in the Figure 4 (a). Only two GCMs shows values to *Im* above 3.0: EC-EARTH (*Im* = 3.073) and CanESM2 (*Im* = 3.065). Other four models have a good performance near to this value: NorESM1-ME (*Im* = 2.897), IPSL-CM5A-MR (*Im* = 2.877), MIROC-ESM (*Im* = 2.818) and HadGEM2-ES (*Im* = 2.796). The accuracy of all models was significantly reduced, mainly in the rainy months (Figure 4 (b)).

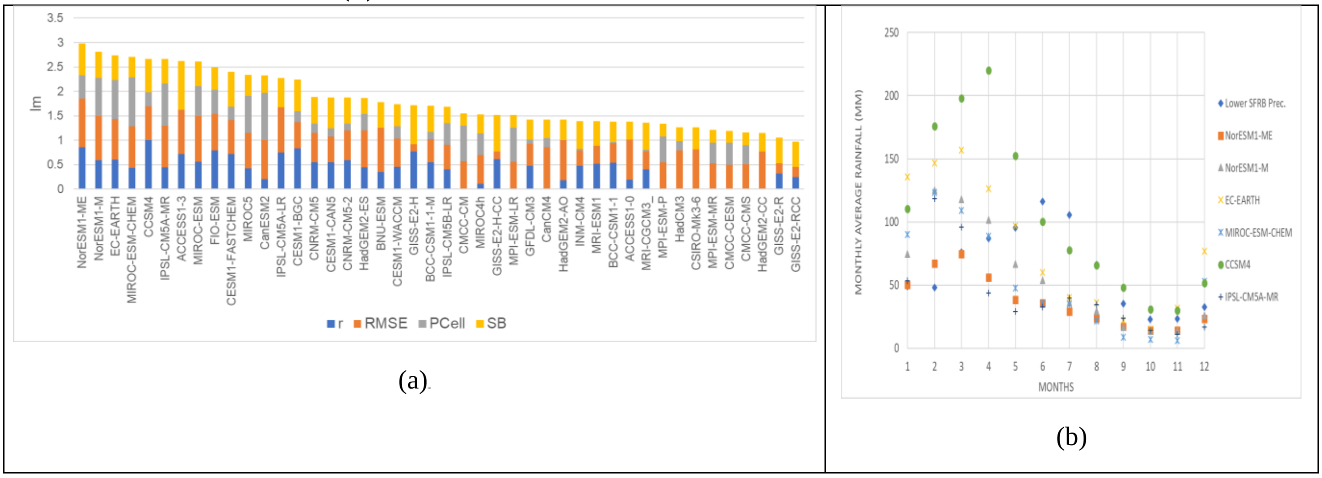
Lower SFRB: The worst performance was observed in the Lower SFRB, the region nearest to the Atlantic Ocean. The index *Im* and its composition for Lower SFRB can be observed in the Figure 5 (a). The Norwegian GCM´s show the best *Im* values, however these values were below 3.0: NorESM1-ME (*Im* = 2.978) and NorESM1-M (*Im* = 2.808). Other models with reasonable values to *Im* were EC-EARTH (*Im* = 2.736), MIROC-ESM-CHEM (*Im* = 2.705) and CCSM4 (*Im* = 2.664). All models have shown a decreasing in performance with respect to the representation of the intra-annual seasonality, as can be observed in Figure 5 (b). It is also observed that there was a trend in all models to locate rainfall peaks between March and April, unlike what occurs in this coastal region, where the highest rainfall occurs near the middle of the year, June and July (Cruz et al., 2017).

FIGURE 4. Index *Im* and its indicators obtained for 44 GCMs (a) and monthly average rainfall for the six best GCMs skills (b) in the Sub-Middle São Francisco River Basin



(a) (b)

FIGURE 5. Index *Im* and its indicators obtained for 44 GCMs (a) and monthly average rainfall for the six best GCMs skills (b) in the Lower São Francisco River Basin



(a) (b)

Based on the model evaluations for the different regions of the São Francisco river basin, there is a significant drop in the index values in the direction of the coast, mainly in relation to indicators related to intra-annual seasonality. However, it can be said that some of the GCMs have proved to be more efficient in more than one region, such as EC-EARTH, that appears among the five first models in all regions, or CMCC-CESM, to Upper and Middle regions of São Francisco Basin and CCSM4 to Sub-Middle and Lower regions.

CONCLUSIONS

- The proposed index was effective in evaluating the performance of global climate change models in the prediction of rainfall in the São Francisco River Basin.
- A loss in GCMs performance to predict rainfall was detected as the assessment approached the coast, ie to the mouth of the basin.
- The EC-EARTH GCM shows the best values to the index in three regions of the São Francisco River Basin.

REFERENCES

ANA. **Portal da Agência Nacional de Águas**. Disponível em: http://www.ana.gov.br. Acesso em Mai. 2017.

CAI, W., A. SULLIVAN, AND T. COWAN. Climate change contributes to more frequent consecutive positive Indian Ocean Dipole events, **Geophys. Res. Lett.**, 36, L23704, 2009.

CATTO, J. L., JAKOB, C., NICHOLLS, N. A global evaluation of fronts and precipitation in the ACCESS model, **Aust. Meteorol. Oceanogr. Soc. J**., 63, 191–203, 2013.

CBHSF. Comitê da Bacia Hidrográfica do Rio São Francisco**. Plano de Recursos Hídricos da Bacia Hidrográfica do rio São Francisco 2016-2025**. Resumo Executivo. 2016, 300p. Disponível em: http://cbhsaofrancisco.org.br/planoderecursoshidricos/relatorios/. Acesso em Set. 2017.

CHEN, J., F. P. BRISSETTE, D. CHAUMONT, M., BRAUN. Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America, **Water Resour. Res.**, 49, 4187–4205, 2013.

CRUZ, M.A.S., MOTA, P.V.M., ARAGÃO, R., ROCHA, R.O.F. Avaliação das precipitações geradas pelo modelo climático regional ETA-HadGEM2-ES para o Estado de Sergipe. **Scientia Plena**, v.13, n.10, p.1-9, 2017.

IPCC. **Climate Change 2013: The physical science basis**. Working Group I Contribution to the Fifth Assessment Report of the IPCC, Stockholm, September, 2013. 2216p.

MARAUN, D., WETTERHALL, F., IRESON, A.M., et al. Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user**. Rev. Geophys**. 48, 2010.

PIANI, C., WEEDON, M., BEST, S. M., GOMES, P. et al. Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. **J. Hydrol.**, 395, 199–215, 2010.

WATANABE, S., KANAE, S., SETO, S., HIRABAYASHI, Y., et al. Intercomparison of bias-correction methods for monthly temperature and precipitation simulated by multiple climate models**. J. Geophys. Res.** 117: D23114, 2012.

WCRP. **Coupled Model Intercomparison Project 5 (CMIP5).** World Climate Program Research. Disponível em: https://pcmdi.llnl.gov/projects/cmip5/. Acesso em mai.2016.

XAVIER, A.C., KINGB, C.W., SCANLONC, B.R. Daily gridded meteorological variables in Brazil (1980–2013). **Int. J. Climatol**. Wiley Online Library, 2015.