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Towards an objective assessment of climate multi-model ensembles. A case study : the Senegalo-Mauritanian upwelling region

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Abstract. Climate simulations require very complex numerical models. Unfortunately, they typically present biases due to parameterizations, choices of numerical schemes, and the complexity of many physical processes. Beyond improving the models themselves, a way to improve the performance of the modeled climate is to consider multi-model combinations. In the present study, we propose a method to select the models that yield a multi-model ensemble combination that efficiently reproduces target features of the observations. We used a neural classifier (Self-Organizing Maps), associated with a multi-correspondence analysis to identify the models that best represent some target climate property. We can thereby determine an efficient multi-model ensemble. We illustrated the methodology with results focusing on the mean sea surface temperature seasonal cycle on the Senegalo-Mauritanian region. We compared 47 CMIP5 model configurations to available observations. The method allows us to identify a subset of CMIP5 models able to form an efficient multi-model ensemble. The future decrease of the Senegalo-Mauritanian upwelling proposed in recent studies is then revisited using this multi-model selection.

1- Introduction

28   In this study, we present a methodology aimed at selecting a coherent sub-ensemble of the

29   models involved in the Climate Model Intercomparison Project, Phase 5 (CMIP5) that best

30   represents specific observed characteristics. While the future evolution of the global climate is

31   subject to great changes and great uncertainty (Collins et al., 2014), the most common way to

32   predict the evolution of the climate is to run climate models that include fully coupled

33   atmosphere-ocean-cryosphere-biosphere modules. Due to their low resolution, and the fact that

34   they use different parameterizations of the physics, numerical schemes and sometimes include or

35   neglect different processes, these models have some marked biases in specific regions. They also

36   have different responses to an imposed increase of atmospheric greenhouse gases, which partly

37   explain their mean climate biases. This variety of models allows us to assess the uncertainty of

38   present climate representation when compared to observations and, by studying their dispersion,

39   to roughly estimate the uncertainty of the response to future climate change.

40   For several generations of climate models, it has been shown that for a large variety of

41   variables the multi-model average generally agrees better with observations of present day

42   climate than any single model (Lambert and Boer, 2001; Phillips and Gleckler, 2006; Reichler

43   and Kim, 2008; Santer et al., 2009; Tebaldi and Knutti, 2007). Several studies also suggest that

44   the most reliable climate projection is given by a multi-model averaging (Knutti et al., 2010),

45   rather than, for example, averaging different projections performed with a single model run with

46   different initial conditions. This result relies on the assumption that if choices of

47   parameterizations or specific numerical schemes are made independently for each model, then the

48   errors might at least partly compensate, resulting in a multi-model average that is more skillful

49   than its constitutive terms(Tebaldi and Knutti, 2007). The significant gain in accuracy can be

50   explained by the fact that the errors specific to each model compensate each other in the

51   averaging procedure used to build the multi-model mean. However, the number of GCMs

52   available for climate change projections is increasing rapidly. For example, the CMIP5 archive

53   (Taylor et al., 2012), which was used for the fifth IPCC Assessment Report (Stocker et al., 2013),

54   contains outputs from 61 different GCMs and 70 contributions are expected for CMIP6. It thus

55   becomes possible - and probably needed - to select and/or weight the models constituting such an

56   average. Recent work has suggested that weighting the multi-model averaging procedure could

57   help to reduce the spread and thus uncertainty of future projections. Such an approach has been

58   applied extensively to the issue of climate sensitivity (Fasullo and Trenberth, 2012; Gordon et al.,

59 2013; Huber and Knutti, 2012; Tan et al., 2016). Valuable improvement of model selection has

60 also been found in studies of the carbon cycle (Cox et al., 2013; Wenzel et al., 2014), the

61 hydrological cycle (Deangelis et al., 2015; O'Gorman et al., 2012), the Antarctic atmospheric

62 circulation (Son et al., 2010; Wenzel et al., 2016), extratropical atmospheric rivers (Gao et al.,

63 2016), atmospheric and ocean heat transports (Loeb et al., 2015), European temperature

64 variability (Stegehuis et al., 2013) and temperature extremes (Borodina et al., 2017).

65   The present paper is dedicated to the elaboration of an objective method to select models

66 according to their performance for a specific phenomenon. Here, we use the Senegalo-

67 Mauritanian upwelling area as a case study to construct an efficient climate multi-model

68 combination together with its related confidence interval in order to anticipate the effect of

69 climate warming by the end of the century in this region. The Senegalo-Mauritanian upwelling

70 has been the focus of increasing attention over recent years. The very productive waters

71 associated with the upwelling have a strong economic impact on fisheries in Senegal and

72 Mauritania, and a crucial societal importance for local populations. It is therefore important to

73 predict the evolution of the dynamics and the physics of the upwelling in the forthcoming

74 decades, due to the effect of climate warming and its consequences on biological productivity,

75 which may impact the fisheries. The Senegalo-Mauritanian upwelling lies at the southern end of

76 the Canarian upwelling system, which has ~~itself~~ a relatively weak seasonality and is maximum in

77 summer. On the contrary, the Senegalo-Mauritanian upwelling presents on the contrary a well-

78 marked seasonal variability. Its intensity is stronger in boreal winter and it disappears in summer

79 with the northward progression of the ITCZ. Due to the enrichment of the sea surface layers with

80 nutrients upwelled from deep layers, it drives an important phytoplankton bloom that is observed

81 on ocean color satellite images (Demarcq and Faure, 2000; Farikou et al., 2015). The maximum

82 intensity of this bloom occurs in March-April (Farikou et al., 2015; Faye et al., 2015; Ndoye et

83 al., 2014). Its important seasonal cycle is also associated with mesoscale patterns whose

84 variability has been recently studied by several oceanographic campaigns (Capet et al., 2017;

85 Faye et al., 2015; Ndoye et al., 2014) and theoretical work (Sirven et al., 2019). Sylla et al., 2019

86 have recently shown that the intensity of the SST seasonal cycle along the coast of Senegal and

87 Mauritania was a good marker of the upwelling in this specific region in climate models. They

88 have used this index together with other more dynamical indices to predict that the upwelling will

89 decrease by about 10% of its present-day amplitude by the end of the 21st century. Nevertheless,

90   their study also highlighted a large uncertainty due to model biases in this region. The method we

91   have developed selects a subset of the CMIP5 ensemble based on the capability of the climate

92   models to reproduce the SST seasonal cycle observed during the historical period in key sub-

93   regions. These sub-regions are identified by a neural classifier. The method leads us to rank the

94   different models and to determine an efficient multi-model combination for the analysis of the

95   Senegalo-Mauritanian upwelling and projections of its behavior in global warming conditions.

96   The paper is structured as follows: section 2 presents the different climate models and the

97   climatological observations used in the study, together with the region of interest. The

98   classification method is described in section 3 and applied to the extended region. Section 4

99   presents a qualitative analysis able to group the different climate models in clusters presenting

100   similar performances. Section 5 investigates the results of the method applied over a smaller area,

101   more focused over the upwelling region. Section 6 uses the two multi-model clusters defined in

102   sections 4 and 5 respectively to tentatively predict the representation of the Senegalo-Mauritanian

103   upwelling changes under global warming. Conclusions are given in section 7.

104

2- Climate Models and region of interest

2.1 Data

107   This study is based on the CMIP5 (Coupled Model Inter-comparison Project Phase 5) database.

108   We use the output of 47 simulations listed in Table 1. The models are evaluated over the

109   historical period defined as [1975-2005] by comparing their output to observations. The mean

110   seasonal cycle of SST anomalies over this period is constructed for each model grid point as the

111   difference between the monthly mean temperature and the mean annual temperature. When

112   several members of historical simulations are available for a specific model configuration, they

113   are averaged together. However, this has practically no impact on the estimated mean seasonal

114   cycle (not shown). The mean climatological cycle of the CMIP5 models under study is evaluated

115   against the Extended Reconstructed Sea Surface Temperature data set (ERSST- v3b, Smith et al.,

116   2008), averaged over the same time period. This data set was produced by NOAA at 2° spatial

117   resolution. It is derived from the International Comprehensive Ocean–Atmosphere Dataset with

118   missing data filled in by statistical methods. This dataset is used as the target to be reproduced

119 and is denoted "observation field" hereafter. In order to deal with data at the same resolution, all

120 model outputs as well the observation fields were regridded on a 1-degree resolution regular grid

121 prior to analysis. A previous study (Sylla et al., 2019) has compared the performance of this

122 dataset as compared to the gridded SST data set from the Met Office Hadley Centre HadISST

123 (Rayner, 2003). The main results regarding the future of the upwelling were shown to be

124 independent of the validation dataset primarily because the models' biases and the inter-model

125 differences were much larger than the differences between the validation datasets. The

126 methodological and oceanographic results presented in this study are thus expected to depend

127 only very weakly on the target dataset.

128 In section 6, the model selections are used to characterize the response of the upwelling to

129 climate change. This response is characterized in terms of SST anomalies as well as wind

130 intensity. For wind intensity, the simulated wind stress is compared to the TropFlux reanalysis.

131 This data set combines the ERA-Interim reanalysis for turbulent and long-wave fluxes, and

132 ISCCP (International Satellite Cloud Climatology Project) surface radiation data for shortwave

133 fluxes. This wind stress product is described and evaluated in (Praveen Kumar et al., 2011).

134

2.2 The Senegalo-Mauritanian upwelling region

136 In this study, we evaluate the ability of the different climate models to represent the Senegalo-

137 Mauritanian upwelling. Following (Sylla et al., 2019), we consider the intensity of the seasonal

138 cycle of the SST anomaly as a marker of the upwelling variability and localization. This variable

139 is shown in Fig. 1 for the eastern tropical Atlantic. This figure confirms that the Senegalo-

140 Mauritanian coast stands out with a very strong seasonal SST cycle as compared to similar

141 latitudes in the open ocean. This results from the cold SST generated by the strong winds

142 occurring in winter. The Senegalo-Mauritanian upwelling is confined in a small region of the

143 order of 100km off the western coast of Africa. It is part of a complex and fine-scale regional

144 circulation system recently revisited by Kounta et al., 2018. Since the grid mesh of most of the

145 climate models is of the order of 1° (~100km), this regional circulation is poorly resolved, which

146 favors a relatively large-scale analysis of the upwelling representation in climate models. The

147 Senegalo-Mauritanian upwelling is also embedded in a large scale oceanic circulation pattern,

148 encompassing the North Equatorial Counter Current flowing eastward in the southern part of the

149 region and the return branch of the subtropical gyre in the northwestern part. Therefore, we firstly

150 study the representation of the SST seasonal cycle intensity in the different climate models over a

151 relatively large region that includes part of the Canary current in the north and the Guinea dome

152 in the south. The so-called "extended region" is defined by a rectangular box extending from

153 9°W to 45°W and from 5°N to 30°N (Fig. 1). In a second step, we will proceed to the same

154 analysis and classification of the models within a much more focused (hereafter zoomed) region,

155 namely [16°W-28°W and 10°N-23°N] (Fig. 1). All the results below will be first shown for the

156 extended region. Comparison with the focused region will be done in section 4.

157 **3 - Comparing observations and models: a methodological approach**

158 The methodology we have developed is based on the ability of the climate models to adequately

159 reproduce the climatology of the seasonal cycle of the SST anomalies as observed during the last

160 three decades in key sub-regions of the studied domain. These key sub-regions are determined

161 from the similarity of their physical and statistical characteristics through an unsupervised

162 classification, which clusters pixels having similar observed seasonal SST climatology. We chose

163 to deal with a neural classifier, the so-called self-organizing map (SOM hereafter) developed by

164 Kohonen, 2013 followed by a Hierarchical Ascendant Clustering (HAC, Jain and Dubes, 1998).

165 This method leads to a dynamically interpretable classification. The SOM determines a vector

166 quantization of the dataset, which compresses the initial dataset into a relatively small number of

167 reference vectors. Doing so allows us to take the non-linearities of the dataset into account and to

168 filter the noise, which can make the classification spurious. This reduced number of dataset

169 vectors enables an HAC to determine the highly non-linear borders between the different SOM

170 clusters. This procedure has been used with success in several studies (Farikou et al., 2015; Jouini

171 et al., 2016; Niang et al., 2003, 2006; Sawadogo et al., 2009). Note that the use of an HAC

172 directly on the initial dataset would not be efficient in the present study because the number of

173 degrees of freedom (here the grid points of the initial domain) is too large for this method to work

174 efficiently. In the present section, we describe the methodology we developed to score the

175 different climate models with respect to the observations. In section 4, we will tentatively group

176 the different climate models into blocks having the same behavior by using a Multiple

177 Correspondence Analysis (MCA).

178

179   **3.1 The unsupervised classification method**

180   The first step of the methodology was to decompose the selected region in different classes (the

181   key sub-regions mentioned above) by using a neural network classifier, the so-called SOM

182   (Kohonen, 2013). This algorithm constitutes a powerful nonlinear unsupervised classification

183   method. It has been commonly used to solve environmental problems (Hewitson and Crane,

184   2002; Jouini et al., 2013, 2016; Liu et al., 2006; Reusch et al., 2007; Richardson et al., 2003). The

185   SOM aims at clustering vectors (here the 12 SST seasonal anomalies) of a multidimensional

186   database (D) (here the grid points of the studied domain) into classes represented by a fixed

187   network of neurons (the SOM map). The self-organizing map (SOM-map) is defined as an

188   undirected graph, usually a 2D rectangular grid. This graphical structure is used to define a

189   discrete distance (denoted by δ) between the neurons of the map and thereby identify the shortest

190   path between two neurons. Moreover, SOM enables the partition of D in which each cluster is

191   associated with a neuron of the map and is represented by a prototype that is a synthetic

192   multidimensional vector (the referent vector w). Each vector z of D is assigned to the neuron

193   whose referent w is the closest, in the sense of the Euclidean Norm (EN), and is called the

194   projection of the vector z on the map. A fundamental property of a SOM is the topological

195   ordering provided at the end of the clustering phase: two neurons that are close on the map

196   represent data that are close in the data space. In other words, the neurons are gathered in such a

197   way that if two vectors of D are projected on two "relatively" close neurons (with respect to δ) on

198   the map, they are similar and share the same properties. The estimation of the referent vectors w

199   of a SOM and the topological order is achieved through a minimization process using a learning

200   data set base, here from the observations. The cost function to be minimized is of the form:

$$J_{SOM}^{T}(\chi, W) = \sum_{zi \in D} \sum_{c \in SOM} K^{T}(\delta(c, \chi(z_i))) \|z_i - w_c\|^2$$

201   where $c \in SOM$ indices the neurons of the SOM map, χ is the allocation function that assigns

202   each element z_i of D to its referent vector $w_{\chi(z_i)}$ and $\delta(c, \chi(z_i))$ is the discrete distance on the

203   SOM-map between a neuron c and the neuron allocated to observation z_i. K^{T} a kernel function

204   parameterized by T (where T stands for "temperature" in the scientific literature dedicated to

205   SOM) that weights the discrete distance on the map and decreases during the minimization

206   process. At the end of the learning process, the classification can be visualized onto the SOM-
207   map and interpreted in term of geophysics.

208   **3.2 - Classification of the observations**

209   In the present problem we chose to classify the annual cycles of the SST seasonal anomalies
210   observed in the Senegalo-Mauritanian upwelling. The study was made on the "extended region"
211   constituted of 25 x 36 = 900 pixels, but this enlarged region covers a part of the African continent
212   and 157 pixels are in fact over land. That means that we have truly 743 ocean pixels to deal with.
213   We consider a time-period of 30 years [1975 to 2005] extracted from the ERSST-V3b database.
214   For a given grid point and a given year and month, the monthly anomaly is the SST of the pixel
215   for which we have subtracted the mean of the considered year. The climatological mean of the
216   anomaly is then computed for each grid point by averaging each climatological month over the
217   30 years. Thus, the learning data set D is a set of 743 twelve-component vectors z, each
218   component being the mean monthly anomaly computed as above. We denote "SST seasonal
219   cycle" the vector z in the following.

220   We used a SOM-map to summarize the different SST seasonal cycles present in the "extended
221   region". We found that 120 prototypes (or neurons) can accurately represent the 743 vectors of D.
222   This reduction (or vector quantization) is made by using a rectangular SOM-map of 30 x 4
223   neurons.

224   We then reduced the number of neurons in order to facilitate their interpretation in terms of
225   geophysical processes. For this, we applied a HAC using the Ward dissimilarity (Jain and Dubes,
226   1988). We grouped the 120 neurons of the SOM into a hierarchy that can contain between 1 and
227   120 clusters. Then the different classifications proposed by the HAC were applied to the
228   geographical region: each SST seasonal cycle of each grid point of the region is assigned to a
229   neuron and consequently to a cluster (assignment process), thereby defining the so-called region-
230   clusters. The problem is then to choose a number of clusters that adequately synthesizes the
231   geophysical phenomena over the region. This was done by looking at the different possible
232   classifications and choosing one representing the major characteristics of the upwelling region.
233   In Fig. 2a, we observe that when we partition the SOM in 7 clusters, the associated 7 region-
234   clusters are constituted of contiguous pixels in the geographic map, and that two clusters (6, 7)
235   are within the upwelling region and present a well-marked seasonal cycle. For each region-

236 cluster, we estimated the monthly mean of the SST seasonal cycle and the associated spread
237 captured by the neurons constituting this region-cluster.

238   The typical SST climatological cycles for each region-cluster are presented in Fig. 2b
239 together with their related error bars. We note that the region-clusters are well identified, their
240 typical climatological annual cycles of SST being well separated. Furthermore, the 7 region-
241 clusters are spatially coherent and have a definite geophysical significance.

242   For the extended region under study, 7 therefore appears to be an adequate cluster
243 number, since this number balances a clear partition of the clusters on the HAC decision tree with
244 a clear physical significance to each region-cluster. The Senegalo-Mauritanian coastal upwelling
245 is associated with clusters 7 and 6. Cluster 2 corresponds to deep tropical waters associated with
246 the equatorial Countercurrent. Cluster 1 corresponds to surface waters of the Gulf of Guinea.
247 Cluster 3 corresponds to the offshore tropical Atlantic, and cluster 5 has extratropical
248 characteristics. Cluster 4 is transition between 3 and 5. As expected, the equatorial regions
249 (clusters 1 and 2) have a very weak seasonal cycle, which increases towards the extratropics
250 (clusters 3 to 5). The upwelling regions (clusters 6 and 7) are characterized by an exceptionally
251 strong seasonal variability.

252

253 **3.3 – Classification of the climate models on the extended upwelling region**

254   The aim is now to find the model(s) that best fit the "observation field". A heuristic
255 manner is to compare the pattern of the different region-clusters of the CMIP5 models with
256 respect to those of the "observation field" through a sight evaluating process. This kind of
257 approach has been proposed in Sylla et al., 2019, and we indeed immediately see that some
258 models better fit the "observation field" than others. Nonetheless, this method remains very
259 subjective.

260   In the following, we present a more objective approach. We use the previous
261 classification to objectively estimate how each CMIP5 model fits the "observation field" and its
262 seven region-clusters. For this, we projected the SST annual cycle of each CMIP5 model grid
263 point of the extended region onto the SOM learned with the observations (section 3.2) using the
264 assignment procedure described in this section. Each grid point thus corresponds to a cluster of

the SOM and is represented on the geographical map by its corresponding color. Doing so, we can represent each CMIP5 model by the geographical pattern of the 7 clusters partitioning the SST seasonal cycle of its grid points. The geographical maps representing the 47 models and their associated clusters are plotted in Fig. 3. This graphical visualization is easier to compare than the original characteristics (amplitude and phase) of the annual cycle at each grid point of a model since each grid point can only take one discrete value among seven. This representation immediately allows identification of the model biases and the models that best reproduce the cluster-regions identified in the observations. A huge amount of information could in principle be extracted from these maps, both from individual modelling groups, to understand the representation of this region by the models and the origins of possible biases, and from experts of the area, to understand the difficulties of the climate models in representing the SST seasonal cycle in this region.

For a more quantitative assessment, we counted the number of grid points of a region-cluster for a given CMIP5 model matching the same region-cluster of the "observation field". We then computed the ratio between that matching number and the number of pixels of the region-cluster of the considered model. That number is noted in the color-bar for each region-cluster in Fig. 3. We denote Rm_i the ratio for the region-cluster i and the model m, where $i = 1, …, 7$ is the number of the region-cluster and m $= 1, …, 47$ is the number of the model (see table 1). We note that $Rmi \leq 1$. Doing so, each model m is represented by a 7-dimensional vector Rm, each component being the ratio of a region-cluster. We estimated the total skill of a model by averaging the 7 ratios. Note that this procedure gives the same weight to each region-cluster whatever its number of grid points and its proximity with the upwelling region. In the following, the skill is presented as a percentage: the higher the skill, the better the fit. In Fig. 3, the 47 CMIP5 models are ranked by their total skill, which is indicated above each panel beside the model name. The model skills are very diverse, ranging from 79% to 28%. This figure also shows that the models presenting the best total skill are also those representing thoroughly the upwelling region. Some models represent the large-scale structure in the eastern tropical Atlantic (region-clusters 3, 4, 5) very well but not the upwelling (33-GISS-E2-R and 34-GISS-E2-R-CC for example). Others represent pretty well the upwelling region-clusters (region-clusters 6 and 7), but not the large-scale structures of the SST seasonality (13-CSIRO-Mk-3-6-0, 6-CMCC-CESM for example). None of these models is ranked among the best models, with a score greater than

296   60%. As indicated above, this representation gives a very synthetic view of the structure of the

297   seasonality of the SST cycle in each of the models, potentially a very useful guide for climate

298   modelers to identify rapidly major biases.

299

4 – Qualitative analysis of the climate models

301   In order to further progress in the selection of the models, the 47 climate models and the

302   observation field were then analyzed by using a Multiple Correspondence Analysis (MCA in the

303   following). MCA is a multivariate statistical technique that is conceptually similar to principal

304   component analysis (PCA), but applies to categorical rather than continuous data. Similarly as

305   PCA, it provides a way of displaying a set of data in a two-dimensional graphical form.

306   In the following, we apply a MCA analysis to the (47,7) matrix $\mathbf{R}$ = [R$m i$] whose

307   elements represent the skills of the clusters of the models shown in front of the color bars in Fig.

308   3: the rows m represent the 47 different models, the columns i the 7 region-clusters. The MCA,

309   as the PCA, projects the initial matrix on a new basis in such a way that the new axes are the

310   matrix eigenvectors (PC), the inertia of each axis being the corresponding eigenvalues.

311   According to the theory, the MCA matrix analysis of R gives i-1 = 6 independent PCs. Each

312   model is thus now associated with a 6-dimensional vector on which it has a specific weight. The

313   MCA uses for this analysis the χ^2 distance. In figure 4, we present the projection of the models

314   and the "region clusters" in the plane formed by the two first axes (x=PC1 and y= PC2) of the

315   MCA. These two axes represent 70 % of the total inertia. Each model is represented by a small

316   circle and each region-cluster by a purple square. We also projected the observation field (green

317   diamond) on that plane. To have a more precise view of the topology, it would be necessary to

318   consider the projection on the 5 other PCs, which represent 30% of the inertia.

319   In the (PC1, PC2) plane, the shorter the distance between two models, the more similar

320   the distribution of their region-cluster skills. Proximity between a model and a region-cluster

321   leads us to affirm that this region-cluster is well represented by that model. Clearly, some models

322   adequately represent the southern part of the extended region (region-clusters 1, 2 or 3), where

323   the SST seasonal cycle is weak, and are very distant from the upwelling regions (region-cluster 6

and region-cluster 7) whose large SST cycle is poorly reproduced. In this group of models, one recognizes the model 16-IPSL-CM5A-MR, at the extreme bottom of Fig. 4, close to region-clusters 4 and 5, consistently with Fig. 3. At the other end of this group of models, the model 23-HadCM3 for example is located very close to the region-cluster 1. Fig. 3 indeed shows that most of its grid points over the region of interest have a seasonal cycle resembling the one found in the offshore tropical ocean. Another group of models is located in the center of this plan, thus at an optimal distance of each of the observed regions-clusters, and not far from the overall position of the observations (diamond). We recognize in this group of models those that have a high skill in Fig. 3. The positioning of the observations (green diamond in Fig. 4) with respect to the models indeed allows selecting those that best represent the observations field. The representation given in Fig. 4 allows understanding the drawback of the different models with respect to the 7 Modes of SST-cycles.

As indicated in the introduction, the main objective of the methodology is to select an ensemble of models that represents at best the upwelling behavior with respect to the observations and to use this ensemble to predict the impact of climate change in the Senegalo-Mauritanian upwelling with some confidence. The problem is now to determine a subset of models which has a better skill than Model-All, in other words minimize the distance to the observations. As the number of models is small enough, we chose to cluster them by an HAC according to their projections onto the six axes provided by the MCA, and select the optimal jump in the hierarchical tree (Jain and Dubes, 1988). We recall that the HAC (hierarchical ascending clustering) is a bottom-up algorithm for dataset clustering. The key operation in hierarchical bottom-up clustering is to repeatedly combine the two nearest (according to a certain distance) clusters into a larger cluster. The HAC starts from individuals and combines them according to their similarity (with respect to the chosen distance) to obtain new clusters. The process is repeated up to get one cluster only (the full dataset). This algorithm is visualized through a tree-like diagram, the so-called connection tree or dendrogram: the branches of the connection tree represent the connections between the clusters (Fig. 5). From Fig. 5, we obtain four homogeneous groups which are well separated (group 1, 2, 3, 4). They are plotted with different colors in Fig. 4. We denote Model-group 1, Model-group 2, Model-group 3, Model-group 4 these multi-model ensembles hereafter. Note that Fig. 4 shows the projection of the individual models on the first two axes of the MCA. The fact that only two axes are shown here

can introduce some bias in the visualization and this figure must be considered with some caution.

Through MCA+HAC, we thus grouped the models into clusters, using the χ^2 distance, according to their proximity to the observations and their internal similarity. For each group, we computed a multi-model average whose outputs are the mean of the outputs of its different members and we analyzed it according to the same procedure (projection of the SST-seasonal cycle and assignment to a region-cluster) used for each individual model. In addition, we introduced the full multi-model average (Model-All in the following), which is the multi-model ensemble, which averages the 47 CMIP5 model outputs. Model-All was also projected in the MCA plane and it is represented by a red star in Fig. 4. Comparison of the four model-groups with Model-All and the observations are presented in Fig. 6. This figure visually highlights the dominance of Model-group 4 for the reconstruction of the SST seasonal cycles of the different region-clusters for the extended region. This is particularly clear for region-clusters 6 and 7, which are those located in the upwelling region (Fig. 2). Model-group 3 seems to group models characterized by an equatorward shift of the main structures, since the region-cluster 1 of tropical waters is not reproduced and Region-clusters 4 and 5 of extratropical waters are overestimated. Fig. 4 indeed shows that this Model-group is very close to the Regions-clusters 4 and 5, which correspond to the extratropical and the transition geographical regions. Model-group 2 misrepresents the region of the Canary upwelling. Model-group 1 overestimates the SST seasonal cycle in all the tropical open Atlantic. These two last model-groups overestimate the region-Cluster 1, again consistently with their position in Fig. 4. A detailed physical interpretation of the Model-groups is nevertheless beyond the scope of this paper. Clearly Model-All represents the SST seasonal cycle of the off-shore ocean, but it proposes a very poor representation of the upwelling region.

Two models (models 7 and 25) have a better skill than Model-group 4 and Model-All. These two models are very close to the observations on the first two axes of the MCA (Fig 4). It is easily seen that Model-group 4 and the projection of Model-All on this plane is farther than that of model 7 and model 25 from the observation projection. This explains the lower performance of these two multi-models as compared to models 7 and 25. In the present case, the method permits to determine the best models (model 7 and model 25) and to outline the best

385   multi-model (Model-group 4) whose skill is better than any model with a probability of 95%

386   (number of models whose skill is smaller than the skill of Model-group 4 with respect to the total

387   number of models). Projection of the models on the other planes of the MCA analysis should

388   confirm this interpretation. One could then question the use of Model-group 4 rather than model

389   7 or model 25 individually. Furthermore, we argue that multi-model averages are in general more

390   robust for climate studies than the use of a single model that can have good performance for a

391   very specific set of constraints but not for neighboring ones. The following section will partly

392   justify this point.

393

394   **5 - Analysis of the climate models over a zoomed upwelling region**

395   The classification presented above relies largely on the ability of the models to represent

396   the offshore seasonal cycle of the SST. In the following, we propose to test the classification over

397   a much more reduced area in order to focus the analysis on the upwelling area. This "zoomed

398   upwelling region" is shown in Fig. 1.

399   As for the extended region, we partitioned the observations of the zoomed upwelling

400   region with a SOM (ZSOM in the following) followed by a HAC. We then applied a new MCA

401   to regroup the climate models. We did a similar analysis as this performed in section 4. We

402   obtained four new well separated region-clusters denoted ZRegion-clusters. Fig. 7 shows the four

403   ZRegion-clusters obtained from ERSSTv3b observations together with their associated mean

404   SST seasonal cycle. Again, the ZRegion-clusters are spatially coherent. The upwelling area is

405   now decomposed into three ZRegion-clusters (ZRegion-clusters 2, 3, 4). This new decomposition

406   thus refines the study performed for the extended region: ZRegion-cluster 1 represents the

407   offshore ocean, its grid points typically have a SST seasonal cycle amplitude of 4°C, very similar

408   to Region-cluster 4 in the classification performed over the extended region (Fig. 2). ZRegion-

409   cluster-4 identifies the core of the Senegalo-Mauritanian region, with grid points characterized by

410   the greatest amplitude of the SST seasonal cycle of the domain, typically 6.5°C. It is interesting

411   to note that an additional upwelling ZRegion-cluster (ZRegion-cluster 3) appears south of

412   ZRegion–cluster 4. Indeed, several studies have shown that the Cape Verde peninsula, located

413   around 15°N, separates the upwelling region into two distinct areas having a different behavior

414   north and south of this peninsula (Sirven et al., 2019; Sylla et al., 2019). The location of the

separation between ZRegion-cluster 3 and 4 is determined with some uncertainty due to the coarse resolution (1°) of the ocean models. ZRegion-cluster 3 is marked by a time shift of the seasonal cycle: the warmest season seems to occur somewhat one month earlier than in the other regions as clearly seen in Fig. 7 (left panel, yellow curve in June). Due a classification using a much larger region, such a characteristic does not appear in the extended area study. The physical interpretation of the SST seasonal cycle of this ZRegion-cluster is beyond the scope of the present study, but one can suspect a role of the ITCZ seasonal migration covering these grid points earlier than further north. Finally, ZRegion-cluster 2 is a transition between the large scale ocean and the upwelling region.

As for the extended region, we applied a MCA analysis to the (47 x 4) matrix R = [Rmi] whose elements represent the skills of the four clusters (i) of the 47 models. This MCA was followed by a HAC leading the definition of five ZModel-groups. The members of each group are given in appendix. Fig. 8 shows the ZRegion-cluster obtained in the zoomed area by projecting these five ZModel-groups and Model-All model on the ZSOM and their associated performances. ZModel-group 1 is the worst performing one: only 25% of the grid cells fall in the same class as for the observations. The structure of this model-group shows that it is characterized by an homogeneous amplitude of the seasonal cycle over the whole domain, suggesting a largely reduced upwelling: only one grid point at the coast has an enhanced SST seasonal cycle as compared to the large scale tropical ocean. ZModel-group 2 is the best performing one: 66% of the grid points are assigned to the correct class and the general picture indeed represents a four-class picture fairly consistent with the observed structure (Fig. 7). Important biases yet remain. In particular, the ZRegion-clusters 2 and 4 characterizing the upwelling extend too far offshore. The three other ZModel-groups are intermediate. A relatively reduced upwelling area, with an underestimated SST seasonal cycle, characterizes ZModel-groups 3 and 4. ZModel-group 5 corresponds to a shift of the upwelling region towards the north. Model-All also shows a strongly reduced seasonal cycle, with a large number of pixels in the intermediate ZRegion-cluster 3 and very few in the ZRegion-cluster 4. The ZRegion-cluster 3, representing the southern part of the Senegalo-Mauritanian upwelling, does not appear in the pattern of Model-All.

444   It is notable that all the models forming ZModel-group 2 are included in Model-group 4.
445   For a more precise assessment, we can also project the entire Model-group 4, identified as the
446   best multi-model ensemble over the extended region, on the ZSOM (Fig. 9, right). We notice that
447   the performance of Model-group 4 remains high on this projection, indicating some robustness of
448   this multi-model ensemble. Moreover, this ensemble now outperforms the single best model
449   identified over the extended region (Fig. 9, left panel). This result gives further confidence in the
450   use of multi-model averages, illustrating that one single model can be very skillful over a specific
451   region, or for a specific analysis, but multi-model averages are more robust across various
452   analysis and/or regions.

6 – Impact of climate change on the Senegalo-Mauritanian upwelling

6.1 Representation of the upwelling in the CMIP5 climate models clusters

455   In this section, we compare the representation of the Senegalo-Mauritanian upwelling system
456   given by the two best Model-groups identified above (Model-group 4 and ZModel-group 2). For
457   this evaluation, we use two of the five indices used by (Sylla et al., 2019) to evaluate the full
458   database, namely the intensity of the SST seasonal cycle and the offshore Ekman transport at the
459   coast. The former is specific to the seasonal variability of the Senegalo-Mauritanian upwelling
460   system, and it has been used for the classification. The latter is more general and although it has
461   recently been shown to partly represent the volume of the upwelled waters (Jacox et al., 2018), it
462   is extensively used in the scientific literature to characterize upwelling regions (Cropper et al.,
463   2014; Rykaczewski et al., 2015; Wang et al., 2015). Note also that following Sylla et al., 2019,
464   evaluation is performed on the period [1985-2005]. This period slightly differs from the
465   classification period but the SST seasonal cycle is not significantly different (not shown).

466   Fig. 10 compares the amplitude of the SST seasonal cycle as represented in the
467   observations, Model-All, Model-group 4 and ZModel-group 2 identified above. Consistently with
468   Fig. 6 and 8, Model-All dramatically underestimates the upwelling signature in terms of SST
469   seasonal cycle as compared to the observations. Model-group 4 and ZModel-group 2 yield
470   improved results: the area of enhanced SST seasonal cycle is larger both in latitude and
471   longitude, with stronger SST amplitude values. This confirms the efficiency of the selection
472   operated above. Nevertheless, ZModel-group 2 yields a realistic SST amplitude pattern along the
473   coast but it extends too far offshore. Furthermore, in ZModel-group 2, the subtropical area (in

474   green in Fig 10) extends too far towards the south, in particular in the western part of the basin.

475   The tropical area, characterized by limited amplitude of the seasonal cycle of SST (deep blue in

476   Fig. 10), is shifted to the south as compared to the observations. In other words, the large scale

477   thermal - and thus probably dynamical - structure of the region is poorly represented in ZModel-

478   group 2. Finally, Model-group 4 is the least biased one.

479   The intensity of the wind stress parallel to the coast, inducing offshore Ekman transport

480   and consequently an Ekman pumping at the coast, is generally considered as the main driver of

481   the upwelling. We therefore also tested the representation of this driver in the different Model-

482   groups. The idea is to evaluate the impact of the model selection performed above on the

483   representation of an independent variable by the Model-groups. Fig. 11 shows the latitude-time

484   evolution of the meridional oceanic wind stress, considering that the coast in the studied region is

485   oriented approximately meridionally, so that the offshore Ekman transport is mainly zonal. Note

486   that in Fig. 11, southward winds have positive values so that they correspond to a westward

487   Ekman transport, favorable to upwelling. Panel (a) shows that the observed meridional wind

488   stress is, all year long, favorable to the upwelling north of 20°N. At these latitudes, the

489   meridional wind stress is stronger in summer. Conversely, between 12°N and 20°N, in the

490   latitude band of the Senegalo-Mauritanian upwelling, the wind blows southward with a very

491   weak intensity in summer and it even changes direction in the southern part of this latitude band.

492   It is favorable to the upwelling in winter-spring, which explains why the Senegalo-Mauritanian

493   upwelling occurs during this season with a maximum of intensity in March-April (Capet et al.,

494   2017; Farikou et al., 2015). The main bias of Model-All (Fig. 11b) is due to the fact that the

495   wind stress never reverses between 12°N and 20°N. It weakens in the southern part of the

496   Senegalo-Mauritanian latitude band, i.e. south of the Cape Verde peninsula (15°N), but does not

497   become negative. North of the Cape Verde peninsula, it also blows from the north in summer, so

498   that the Senegalo-Mauritanian upwelling lacks seasonality. This bias is corrected in Model-group

499   4 and ZModel-group 2 (Fig. 11, panels c and d) that are, in this aspect, more realistic than Model-

500   All. Model-group 4 shows a slight extension of the time and latitude range where the oceanic

501   wind stress reverses sign. This constitutes an improvement. The southward wind is nevertheless

502   too strong in winter on the [12°N-20°N] latitude band as well as further south from December to

503   March. These two remaining biases are further reduced in ZModel-group 2. This latter model

504   yields the most realistic seasonal cycle of meridional oceanic wind stress on the latitude band

505   under study. This is consistent with a very localized model selection, as the wind index is itself
506   localized along the coast.

507   To conclude, Model-group 4 and ZModel-group 2 perform in general better than Model-All in
508   reproducing the major, characteristic features of the Senegalo-Mauritanian upwelling. This result
509   confirms the relevance of the multi-model selection we have presented above. Applying the
510   methodology over a relatively large region allows better constraining the spatial extent and
511   pattern of the SST signature of the upwelling than the reduced area. The latter however yields a
512   better representation of the wind seasonality along the coast.

513   **6.2 Response of the Senegalo-Mauritanian upwelling to global warming.**

514   In this section, we examine the response of the upwelling system given by the different
515   multi-model groups we selected to global warming. For this, we compared the two indices
516   analyzed above in present-day and future conditions. The present-day conditions are taken as
517   above as the climatological average of historical simulations over the period [1985-2005]. The
518   future period is taken as the climatological average of the RCP8.5 scenario over the period [2080-
519   2100]. Fig. 12 shows the difference of the SST seasonal cycle amplitude between these two
520   periods. The general behavior is that the SST cycle amplitude will reduce in the upwelling region.
521   Sylla et al., 2019 showed that this is primarily due to a warming of the winter temperature, thus
522   suggesting that the upwelling signature at the surface will reduce. On the other hand, this figure
523   shows that the upwelling signature will increase along the Canary current, which flows along the
524   coast of Morocco, as well as in the subtropical part of our domain. This behavior is observed in
525   the three multi-model ensembles. Yet, the two selected Model-groups suggest a weaker decrease
526   of the SST seasonal cycle in the upwelling region than the one given by Model-All. ZModel-
527   group 2 shows an even weaker decrease mainly confined in the southern part of the upwelling
528   region. This result echoes findings of Sylla et al., 2019 based on another indicator of the
529   upwelling imprint on the SST: they showed that the difference between the SST at the coast and
530   offshore is expected to decrease more in the southern part of the Senegalo-Mauritanian upwelling
531   system (SMUS) than in the north . We hypothesize that the study conducted on the reduced area
532   permits separation of the Senegalo-Mauritanian upwelling system into two clusters, a northern
533   one (ZRegion 4) and a southern one (ZRegion-3) (Fig. 8) which enables to distinguish this
534   specific response.

535   The meridional wind stress also generally weakens under climate change in the [12°N-
536   20°N] latitude band (Fig. 13), suggesting a general reduction of the upwelling intensity. From
537   December to March, this is particularly true in the southernmost region of the Senegalo-
538   Mauritanian band, consistent with the results of (Sylla et al., 2019). The wind pattern inferred
539   from the two Model-groups (Fig. 13, middle and right panels) present a higher seasonal
540   variability than those of Model-All (left panel). The winter reduction of the southward wind
541   stress is slightly more confined to the southern region in ZModel-group 2, especially at the end of
542   the upwelling season (March-April) when the upwelling intensity is the strongest. This may be
543   consistent with the reduced seasonal cycle in the southernmost part of the upwelling identified
544   above.

7 - Discussion and Conclusion

546   This paper proposed a novel methodology for selecting efficient climate models on a specific
547   area with respect to observations and according to well-defined statistical criteria. The present
548   study has specifically focused on the ability of climate models to reproduce the ocean SST annual
549   cycle observed in specific sub-regions of the studied domain during the period 1975-2005 as
550   reported in the ERSST_v3b data set. These sub-regions were defined by a neural classifier
551   (SOM) as clusters having similar seasonal SST cycle anomalies with respect to some statistical
552   characteristics, and were therefore named region-clusters. They correspond to ocean areas having
553   well marked oceanographic specificities.

554   We then checked the ability of the different climate models to reproduce the region-clusters
555   defined on the observation dataset with a SOM. The better a climate model fits the clusters
556   computed with the SST observation, the higher the skill of the model. To evaluate this, we
557   defined geographical regions in the different CMIP5 climate models by projecting the SST
558   annual cycle anomalies of each model grid point onto the SOM. Each grid point is associated
559   with a cluster on the SOM map and consequently to a region-cluster on the geographical map.
560   We built a similarity criterion by counting the number of grid points in a region-cluster of a
561   given model matching the same region cluster defined by processing the observation field.
562   We then computed the ratio between that matching number and the number of pixels of the
563   region-cluster of the model under study. We estimated the total skill of a model by averaging
564   the 7 ratios associated with the 7 region clusters. Note that this procedure presents the advantage

565   of giving the same weight to each region-cluster whatever its number of grid points and its

566   proximity with the upwelling region. This procedure respects the clustering done by the SOM

567   since the different clusters have an equal weight in the skill computation. In its present definition,

568   the total skill is a number between 0 and 1, the higher the skill, the better the fit. Other measures

569   of the total skill of a Model-group could nevertheless be defined depending on the objective of

570   the study. One may compare the skill of individual models over a specific region-cluster of

571   interest, or analyze the pattern of skill in one specific model and its sensitivity to possible various

572   parameterization schemes. The extraction of information embedded in the vector-skill whose 7

573   components are the skills associated with the 7 sub-regions and the resulting efficient multi-

574   model combination imply the use of advanced statistical tools such as the MCA. Moreover the

575   vector skill also contains information behavior of models in terms of large offshore ocean

576   circulation as well as in the upwelling region. It could thus be used to diagnose the deficiencies of

577   some climate models with respect to the modeling of physical processes. Another contribution of

578   the MCA is the visualization of the 47 models and the observations on the plane constituted by

579   the first two MCA axes, which represents 70% of the information embedded in the data. The

580   similarities of the climate models with respect to the observations and the region-clusters can be

581   clearly visualized. The 'mean' skill associated with each climate model and proposed in this

582   study is easy to use but is far less informative than the vector-skill whose 7 components are the

583   skills associated with the 7 sub-regions.

584   Such a multi-model ensemble selection allows sampling a set of models in order to obtain a more

585   realistic climatology over the region of interest. The response of the upwelling to climate change

586   given by the different multi-model ensembles is quite robust in the sense that they give similar

587   qualitative answers. However, a too-selective ensemble of models may lead to noisy patterns. A

588   compromise thus has to be found: a large number of models leads to smoothed biases and

589   unrealistic patterns, but also damps the characteristics of the selection. On the other hand,

590   selecting the most realistic models may yield spurious biases in the ensemble mean.

591   As discussed in the introduction, different criteria have been used for extracting some efficient

592   models from the CMIP5 models used for climatic studies. The most common parameter is the

593   average annual surface mean temperature of the grid points of the region under study.

594   However,(Knutti et al., 2006) used the seasonal cycle in surface temperature, represented by the

seasonal amplitude calculated as summer June–August (JJA) minus winter December–February (DJF) temperatures. This criterion is more informative than the annual mean temperature since the amplitude of the seasonal variability is an important criterion characterizing the validity of a climate model. In the present work, we used a more informative criterion which is formed of the monthly temperature cycle anomaly represented by a 12-component vector, each component representing the average monthly temperature of the year we consider. This new criterion allows account to be taken of the amplitude and phase of seasonal variability while the Knutti et al., 2006 criterion only takes into account the amplitude of the seasonal variability. Note however that it implies a good geophysical knowledge of the region under interest, in order to determine the relevant region-clusters after the SOM. It is also very specific to the Senegal-Mauritania upwelling region. Furthermore, Sylla et al., 2019 extensively discussed the possible differences among several indices aiming at characterizing the upwelling and the need to use some of them to have a complete understanding of this coastal phenomenon. This conclusion is probably general to any physical process of the climate system. In the present study, the model selection is based on only one signature of the SMUS. Several possibilities can be envisaged to improve the resolution of this problem such as merging several indices like SST, temperature at several depths, wind vector or ocean currents. This approach could also allow a selection of models based on the representation of several distinct regional behaviors. In spite of several subjective choices, including the studied domain and the statistical metrics, we argue that this method is a step towards an objective selection of models, based on a quantitative assessment rather than a qualitative analysis of maps of performance.

The methodology is general and can be adapted to any climate or oceanographic phenomenon. Different applications of the multi-model selection strategy proposed in the present study can also be envisaged. Firstly, from a purely modeling point of view, the projection of the models on the SOM (or ZSOM) and the results of the HAC yield a very enlightening description of a given model behavior in terms of region-clusters of the area under study. Such a procedure could advantageously be used by individual modeling groups to identify, analyze and therefore hopefully reduce their model biases in a targeted region. Secondly, from a physical point of view, an identified Model-group can be used to analyze the targeted region (here the SMUS) in terms of processes, with the advantages of a subset of models which have been selected from quantitative criteria. Such an application has been briefly illustrated by showing how the selected

626   Model-group represents an important additional characteristic of the SMUS, not used for the

627   selection, namely Ekman pumping. A promising reduction of biases of the full multi-model mean

628   ensemble has been identified, opening possibilities for process studies based on this sub-

629   ensemble of the CMIP5 database. A third application of the selection lies in the prediction of the

630   future climate. Here, we have shown that selected multi-model ensembles may provide a more

631   precise description of the future behavior of the SMUS. It may nevertheless be important to note

632   that these conclusions are based on the assumption that the CMIP5 models, which have been

633   selected according to their present-day characteristics, are the most reliable in terms of future

634   projections, which can be questioned and refined (Lutz et al., 2016; Reifen and Toumi, 2009).

635   As discussed in the introduction, the concept of "model democracy", suggesting that all models

636   should be equally considered in multi-model ensemble is now strongly questioned (Knutti et al.,

637   2017). The present study proposes a promising way to improve the quality of multi-model

638   ensemble in terms of model selection. Deep advances in the field of multi-model analysis and

639   selection can be expected from the emerging topic of climate informatics (Monteleoni et al.,

640   2016) as it has been shown through the present study. Machine learning can indeed provide

641   efficient tools to make the best out of the extraordinary but imperfect tools that are the climate

642   models and multi-model intercomparison efforts.

643

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656   **Code and Data availability**: The model output used for this study is freely available on the
657   ESGF database for example following this url: https://esgf-node.ipsl.upmc.fr/search/cmip5-ipsl/.
658   The SST data were downloaded from

659   https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v3.html and the winds data

660   here: https://podaac.jpl.nasa.gov . The code developed for the core computations of this study can

661   be found under: 10.5281/zenodo.3476724. This code allows reproducing Fig. 2, 3, 6, 7 and 8.

662   **Author contribution**: JM initially proposed the idea, ST and MC translated it in terms of

663   methodology and coordinated the method development, CS and CM developed the code and

664   produced the figures, CS, CM, MC, ST all contributed to the statistical analysis. As provided the

665   initial definition of the upwelling index and performed the analysis under climate change that is

666   presented in section 6. JM, MC and ST prepared the manuscript with contributions from all the

667   authors.

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846

847

848 **APPENDIX**

849

Model-group 1	Model-group 2	Model-group 3	Model-group 4
ACCESS1-0	bcc-csm1-1	FGOALS-g2	CanCM4
ACCESS1-3	bcc-csm1-1-m	GISS-E2-H	CanESM2
CESM1-CAM5	BNU-ESM	GISS-E2-H-CC	CMCC-CESM
CESM1-CAM5-1-FV2	CCSM4	GISS-E2-R	CMCC-CM
CESM1-WACCM	CESM1-BGC	GISS-E2-R-CC	**CMCC-CMS**
HadCM3	CESM1-FASTCHEM	inmcm4	**CNRM-CM5**
MIROC-ESM	GFDL-CM2p1	IPSL-CM5A-LR	**CNRM-CM5-2**
MIROC-ESM-CHEM	GFDL-ESM2G	IPSL-CM5A-MR	CSIRO-Mk3-6-0
MIROC5	GFDL-ESM2M	IPSL-CM5B-LR	**FGOALS-s2**
NorESM1-M	MPI-ESM-LR	MRI-CGCM3	**GFDL-CM3**
NorESM1-ME	MPI-ESM-MR	MRI-ESM1	HadGEM2-AO
	MPI-ESM-P		HadGEM2-CC
			HadGEM2-ES

850

ZModel-group 1	ZModel-group 2	ZModel-group 3	ZModel-group 4
ACCESS1-0	**CMCC-CMS**	BNU-ESM	ACCESS1-3
bcc-csm1-1-m	**CNRM-CM5**	CanCM4	bcc-csm1-1
CCSM4	**CNRM-CM5-2**	CanESM2	CSIRO-Mk3-6-0
CESM1-BGC	**FGOALS-s2**	CMCC-CM	HadGEM2-AO
CESM1-CAM5	**GFDL-CM3**	FGOALS-g2	HadGEM2-CC
CESM1-CAM5-1-FV2		IPSL-CM5A-LR	HadGEM2-ES
CESM1-FASTCHEM		IPSL-CM5A-MR	MIROC-ESM
CESM1-WACCM		MRI-CGCM3	MIROC-ESM-CHEM
GISS-E2-H		NorESM1-M	MRI-ESM1
GISS-E2-H-CC		NorESM1-ME	
GISS-E2-R			
GISS-E2-R-CC			
HadCM3			**ZModel-group 5**
inmcm4			
IPSL-CM5B-LR			CMCC-CESM
MIROC5			GFDL-CM2p1
MPI-ESM-LR			GFDL-ESM2G
MPI-ESM-MR			GFDL-ESM2M
MPI-ESM-P			

851

852 Table A1: Composition of the different Model-groups identified in the main text. In bold, we

853 show the CMIP5 models which belong to Model-group 4 and ZModel-group 2. We note that all

854 the models belonging to Zmodel-group 2 also belong to Model-group 4.

855

nb	Model Acronym	nb	Model Acronym
1	bcc-csm1-1	25	HadGEM2-ES
2	bcc-csm1-1-m	26	MPI-ESM-LR
3	BNU-ESM	27	MPI-ESM-MR
4	CanCM4	28	MPI-ESM-P
5	CanESM2	29	MRI-CGCM3
6	CMCC-CESM	30	MRI-ESM1
7	CMCC-CM	31	GISS-E2-H
8	CMCC-CMS	32	GISS-E2-H-CC
9	CNRM-CM5	33	GISS-E2-R
10	CNRM-CM5-2	34	GISS-E2-R-CC
11	ACCESS1-0	35	CCSM4
12	ACCESS1-3	36	NorESM1-M
13	CSIRO-Mk3-6-0	37	NorESM1-ME
14	inmcm4	38	HadGEM2-AO
15	IPSL-CM5A-LR	39	GFDL-CM2p1
16	IPSL-CM5A-MR	40	GFDL-CM3
17	IPSL-CM5B-LR	41	GFDL-ESM2G
18	FGOALS-g2	42	GFDL-ESM2M
19	FGOALS-s2	43	CESM1-BGC
20	MIROC-ESM	44	CESM1-CAM5
21	MIROC-ESM-CHEM	45	CESM1-CAM5-1-FV2
22	MIROC5	46	CESM1-FASTCHEM
23	HadCM3	47	CESM1-WACCM
24	HadGEM2-CC		

856

857 Table 1: List of the CMIP5 models used for the comparison. The reader is referred to the CMIP5
858 documentation for more information on each of them. Here, each configuration is furthermore

859 given a number, for easier identification in subsequent figures.

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862
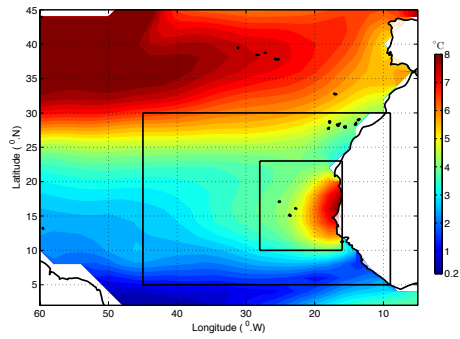
Figure 1: Amplitude of the SST seasonal anomalies in the western tropical north Atlantic. SST
data are from the ERSSTv3b data set averaged between 1975 and 2005. The two black boxes
show the extended and zoomed regions respectively, on which the statistical classifications were
performed (see text for details).

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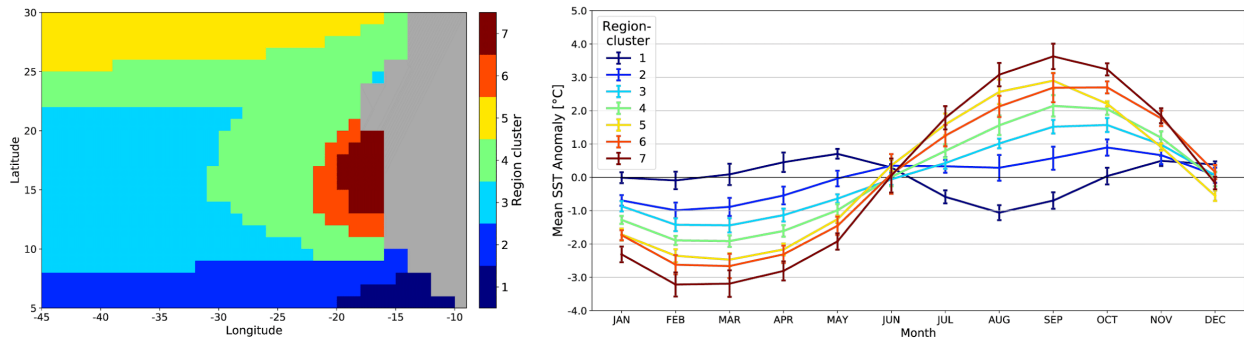
868

869 Figure 2: Left panel: Region-clusters associated with the SOM-clusters obtained after a HAC on
870 a 30x4 neuron SOM learned on ERSSTv3b observations in the extended zone (see text for
871 details). Right Panel: Ensemble-mean monthly climatological SST anomalies for the grid points
872 of the seven Region-clusters. The error bars show the standard deviation of this ensemble mean.
873
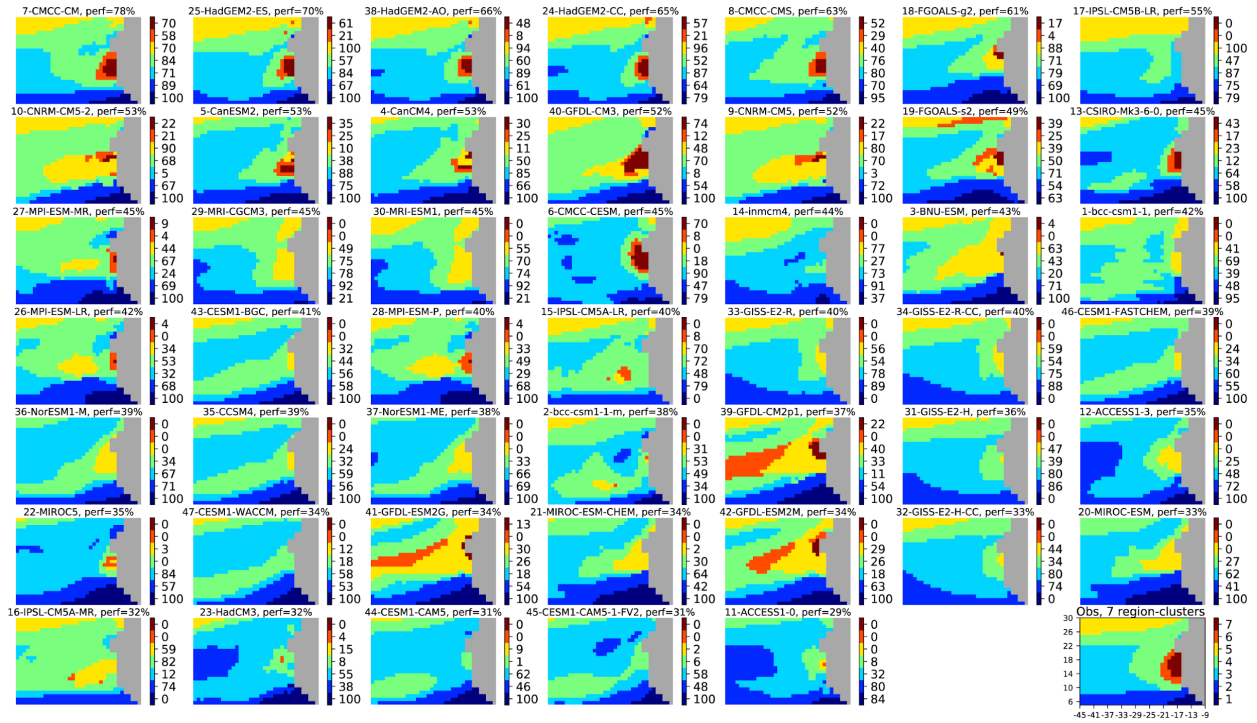
Figure 3: Projection of the 47 climate models of the CMIP5 database onto the SOM learned with ERSSTv3b climatology in the extended zone (see Fig. 1). On top of each panel, we figure: the number referencing the model, its name (Table 1), and its skill given as a mean percentage (see text). The models are ordered according to their skill in decreasing order. The 7 Region-clusters (or SOM-clusters) are defined by applying an HAC to the SOM output learned with the observation field. They are represented by different colors. The numbers in the colorbar at the right of each panel represent the skill for each Region-cluster. The observation field is shown in the bottom right panel and the numbers in front of the colorbar reference the Region-cluster.
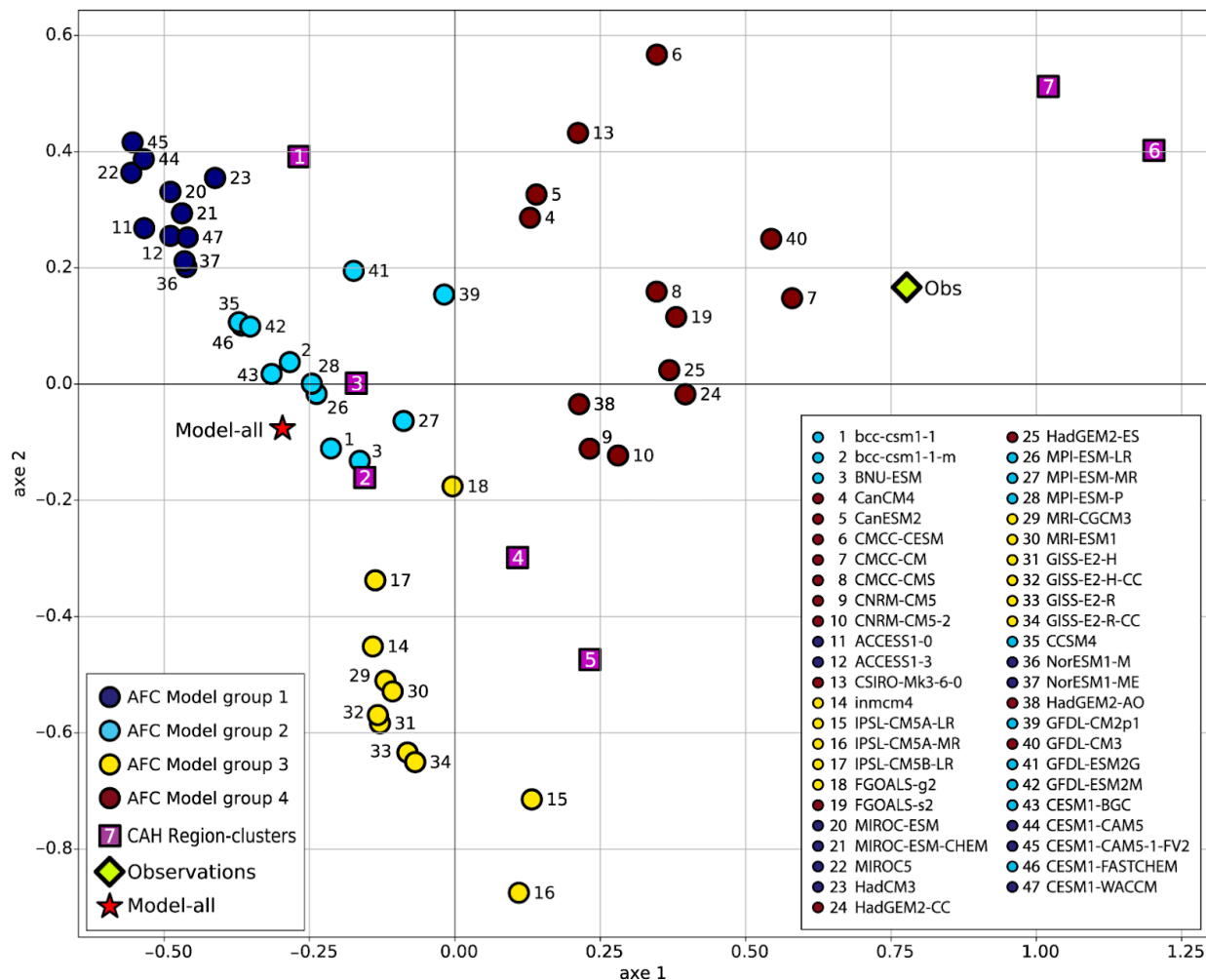
Figure 4: Projection of the CMIP5 models (colored circles) and the observation field (green diamond) defined by their cluster skill vectors on the first two axis of the MCA. The seven region-clusters of the observation field are represented by purple squares. The colours of the circles denote the four groups of models obtained after an HAC was performed on the seven MCA components of the models. The projection of the full multi-model mean (47 models) is represented by a red star. We note that some bias can be introduced in this projection since the projection on the other axes can be of importance
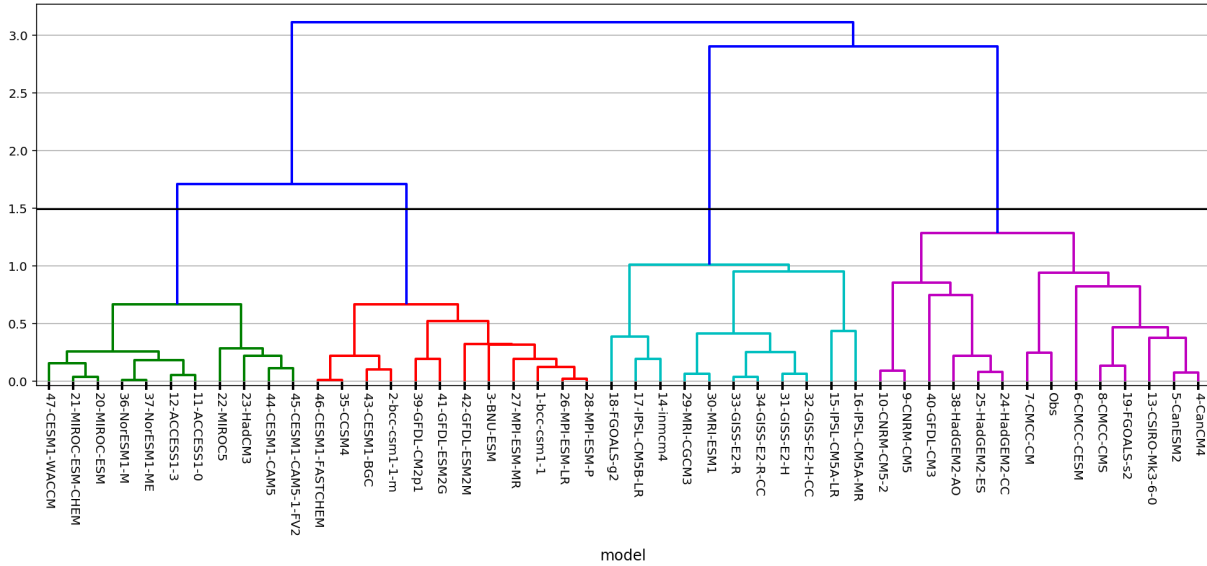
Figure 5: HAC Dendrogram. The horizontal line displays the 47 CMIP5 models, each model being associated with its 7 component skill-vector. As the dendrogram represents a hierarchy of clusters, the numbers on the y axis give the distance between two clusters. We note an optimal 'jump' on this graph: the level 1.5 in the vertical axis (materialized by a horizontal black line) is associated with 4 well-separated clusters corresponding to 4 Model-groups that are very different.

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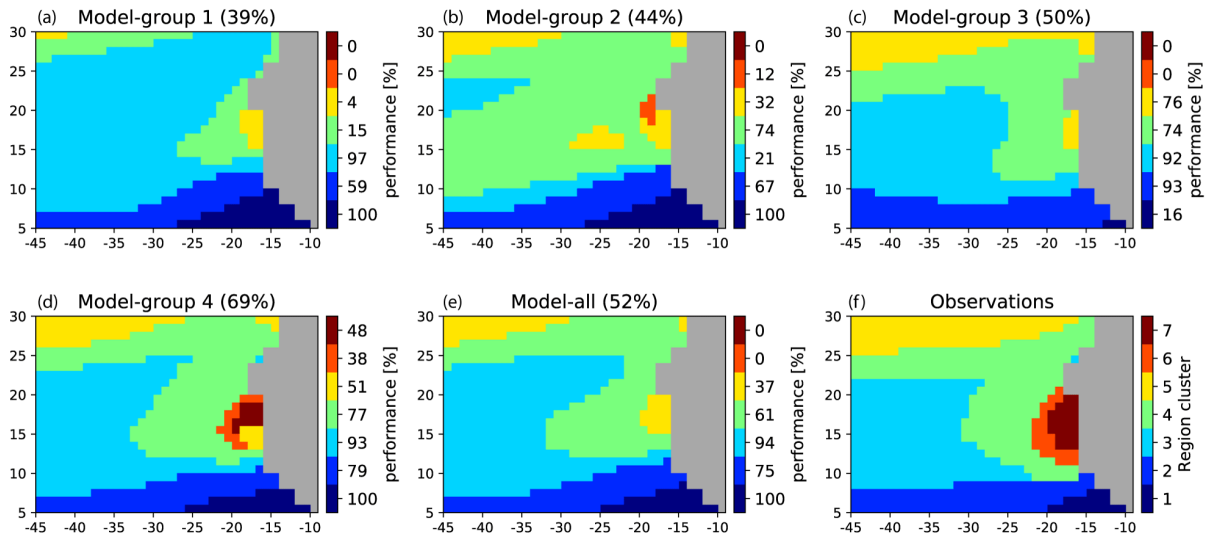
Figure 6: (a)-(d): Projection of the multi-model ensembles (Model-group) onto the SOM learned
with ERSSTv3b climatology in the extended zone. Multi-model ensemble performances are
obtained by averaging the skill of the models forming each group. The performances are given
on top of each panel. The Region-clusters determined by processing the observations in the
extended area and their associated colors are given in the bottom right panel. The colorbars at the
right of each multi-ensemble panel represent the skill (in %) associated with each Region-cluster.
Panel (e) shows the projection for the full multi-model ensemble. Panel (f) reproduces the
Region-clusters based on the observations also shown in Fig. 2.

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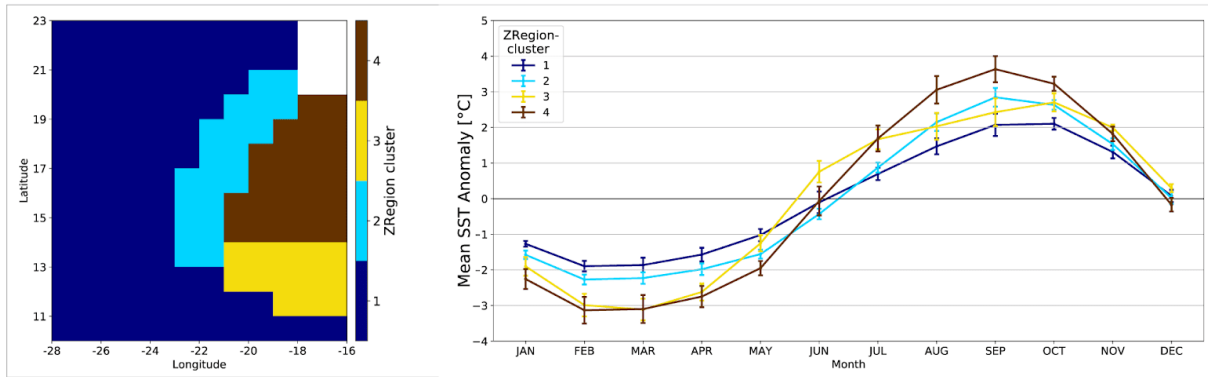
Figure 7: Left panel: ZRegion-clusters associated with the ZSOM-clusters obtained after a HAC on a 10x12 neuron SOM learned on ERSSTv3b observations in the zoomed zone (see text for details). Right Panel: Ensemble-mean monthly climatological SST anomalies for the grid points of the four ZRegion-clusters. The error bars show the standard deviation of this ensemble mean.
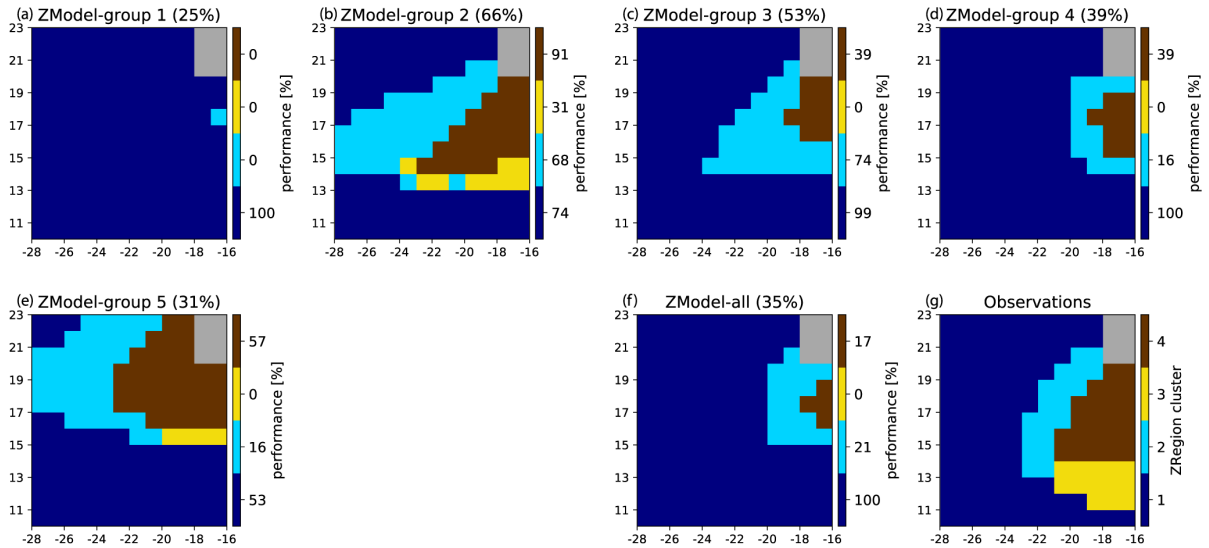
Figure 8: (a)-(e): Projection of the multi-model ensembles (ZModel-groups) onto the ZSOM. The performances are given on top of each panel. The ZRegion-clusters determined by processing the observations in the zoomed region and their associated colors are given in the bottom right panel. The colorbars at the right of each multi-ensemble panel represent the skill (in %) associated with each ZRegion-cluster. Panel (f) shows the same for the full multi-model ensemble. Panel (g) reproduces the Region-clusters based on the observations also shown in Fig. 6.
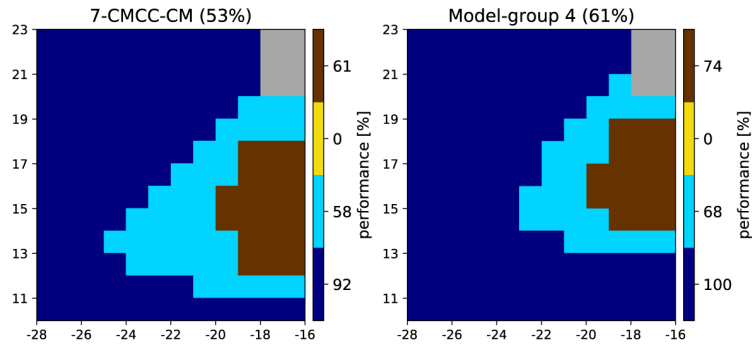
Figure 9 : Same as Fig. 7 but for the individual model CMCC-CM (model 7) (left) and the Model-group 4 (right).
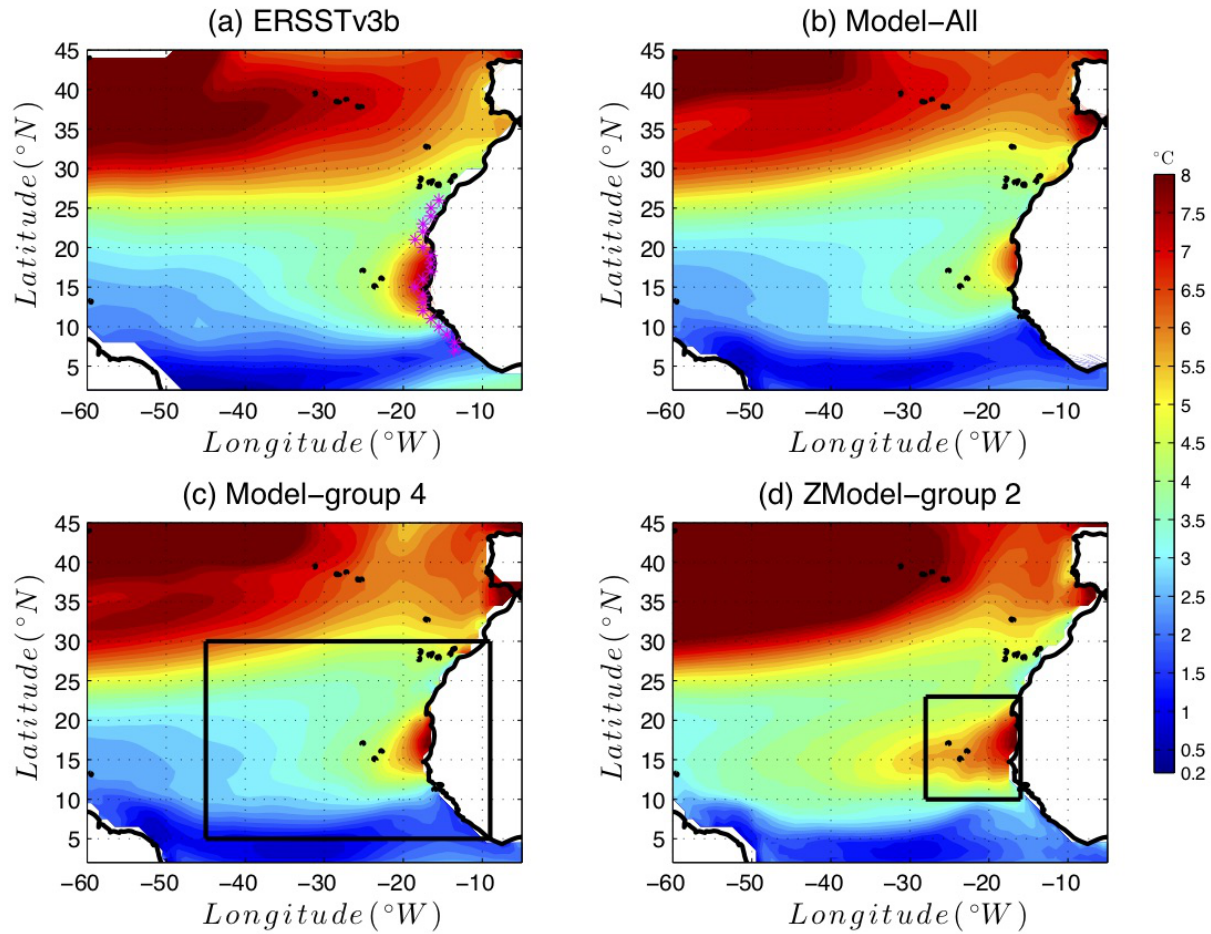
Figure 10: Amplitude of the SST seasonal cycle in the (a) ERSSTv3b Observations (b) Model-All, c) Model-group 4 (best Model-group for the extended area, figured out by the black rectangular box) and (d) ZModel-group 2 (best Model-group for the reduced area, figured out by the small black rectangular box). The SST seasonal cycle is computed over the period 1985-2005
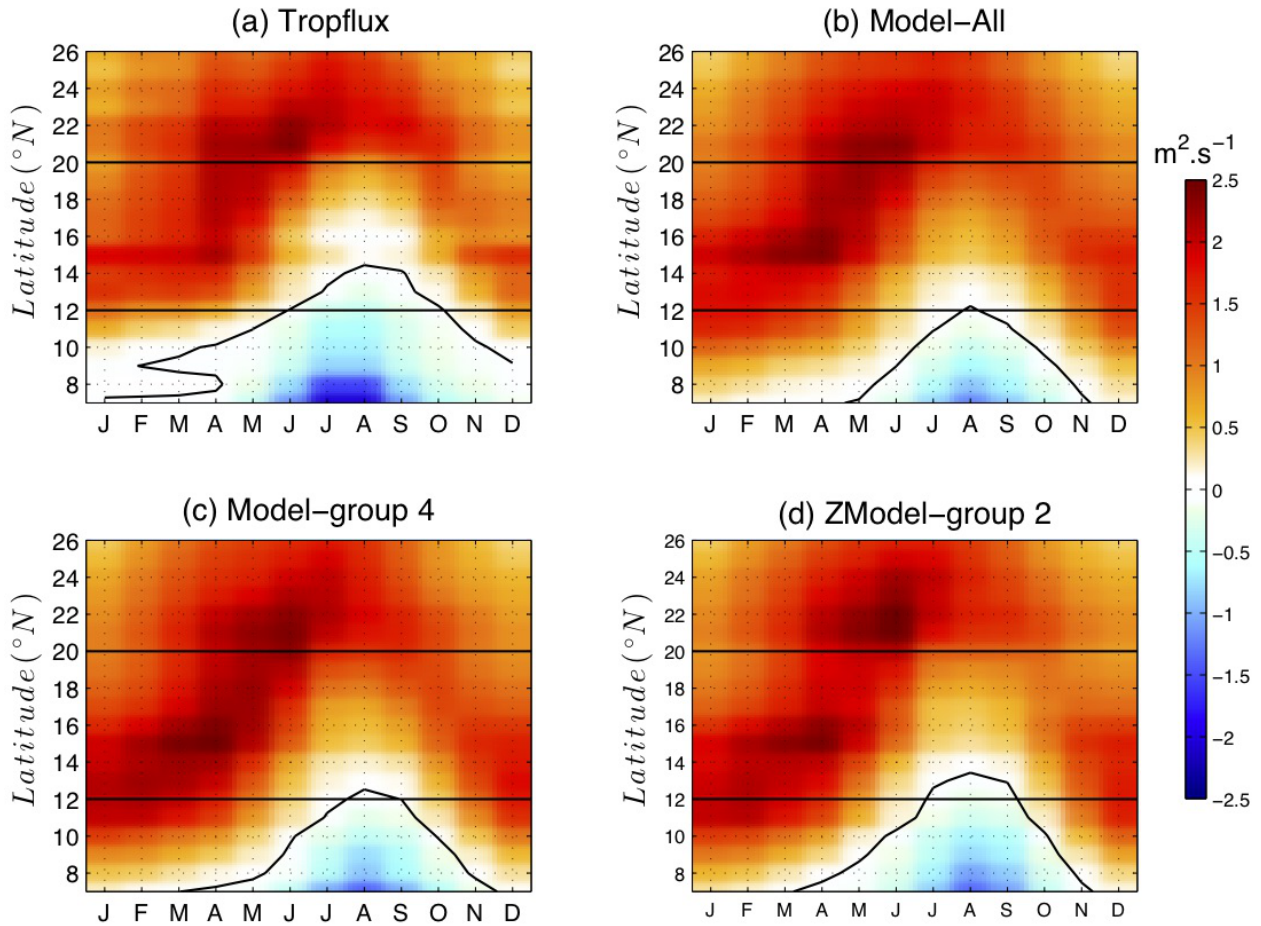
Figure 11: Latitude-time plot of depth integrated Ekman transport computed over the grid point located along the coast (magenta stars in Fig. 9.a). The time axis shows climatological months over the period 1985-2005. Positive (negative) values correspond to upwelling (downwelling) conditions. Panel (a) stands for TropFlux data set (see (Praveen Kumar et al., 2011) (b) Model-All, (c) Model-group 4 and (d) ZModel-group 2. In each panel, the black contour shows the contour zero. The horizontal dashed lines are positioned at 12°N and 20°N and give a rough limitation of the Senegalo-Mauritanian upwelling region.
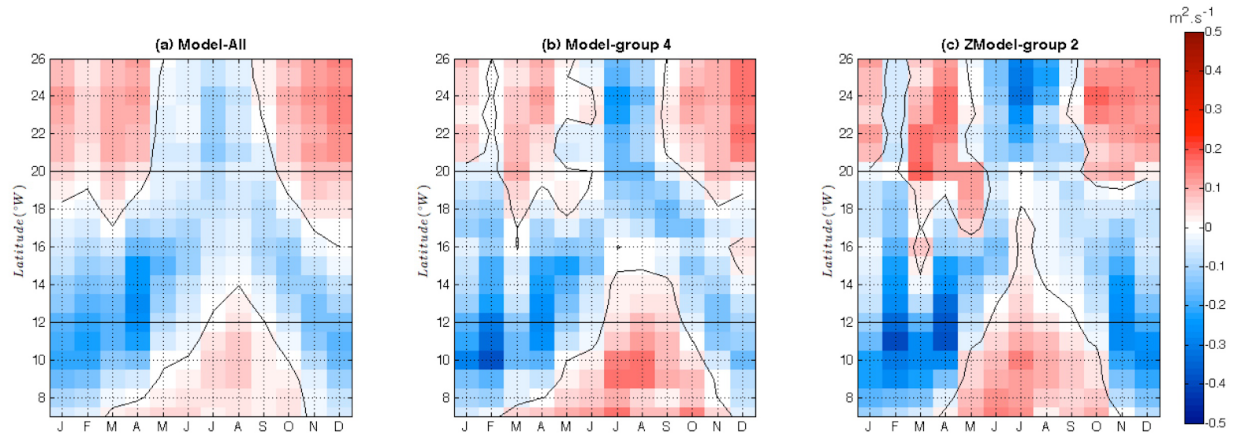
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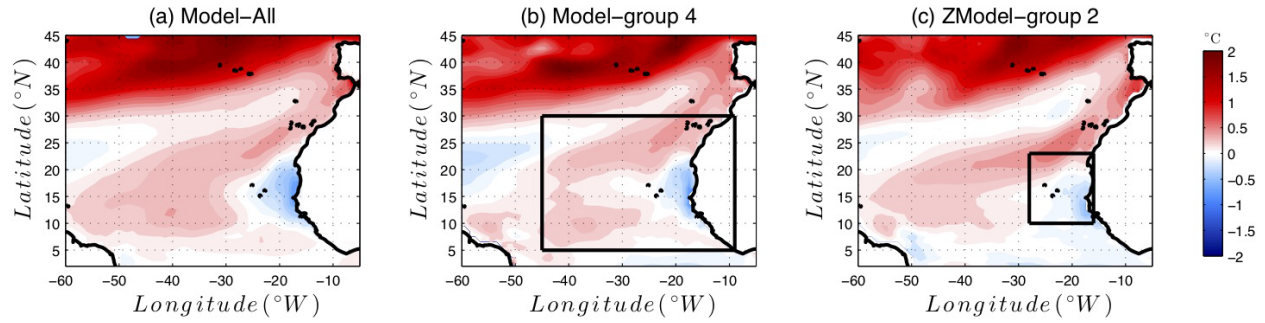
Figure 12: Evolution of the amplitude of the SST seasonal cycle at the end of the 21st century.
The figure shows the difference between the seasonal cycle amplitude averaged over the period
[2080-2100] following the RCP8.5 scenario and the amplitude averaged over the period [1985-
2005] in the historical simulations. A positive value (red) means that the seasonal cycle is more
marked over the period 2080-2100.

Figure 13: Latitude-time diagram of the seasonal shift of the meridional component of the wind-stress with respect to the present days. For each month and at each latitude, we show the meridional wind stress shift with respect to the present days averaged over the period [2080-2100]. Positive values (red) means that the wind stress shift is southward and is thus favorable to upwelling. Panel (a) stands for Model-All, (b) Model-group 4 and (c) ZModel-group 2.