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CONFIGURATION AND HINDCAST QUALITY ASSESSMENT OF A

BRAZILIAN GLOBAL SUB-SEASONAL PREDICTION SYSTEM

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ABSTRACT

1

2   This paper presents the Center for Weather Forecast and Climate Studies (CPTEC)

3   developments for configuring a global sub-seasonal prediction system and assessing

4   its ability in producing retrospective predictions (hindcasts) for meteorological

5   conditions of the following 4 weeks. Six Brazilian Global Atmospheric Model

6   version 1.2 (BAM-1.2) configurations were tested in terms of vertical resolution,

7   deep convection and boundary layer parameterizations, as well as soil moisture

8   initialization. The aim was to identify the configuration with best performance when

9   predicting weekly accumulate precipitation, weekly mean 2-meter temperature

10   (T2M) and the Madden and Julian Oscillation (MJO) daily evolution. Hindcasts

11   assessment was performed for 12 extended austral summers (November to March -

12   1999/2000 to 2010/2011) with two start dates for each month for the six

13   configurations and two ensemble approaches. The first approach, referred to as

14   Multiple Configurations Ensemble (MCEN), was formed of one ensemble member

15   from each of the six configurations. The second, referred to as Initial Condition

16   Ensemble (ICEN), was composed of six ensemble members produced with the

17   chosen configuration as the best using an Empirical Orthogonal Function (EOF)

18   perturbation methodology. The chosen configuration presented high correlation and

19   low root mean squared error (RMSE) for precipitation and T2M anomaly

20   predictions at the first week and these indices degraded as lead time increased,

21   maintaining moderate performance up to week 4 over the tropical Pacific and

22   northern South America. For MJO predictions, this configuration crossed the 0.5

23   bivariate correlation threshold in 18 days. The ensemble approaches improved the

24 correlation and RMSE of precipitation and T2M anomalies. ICEN improved

25 precipitation and T2M predictions performance over eastern South America at week

26 3 and over northern South America at week 4. Improvements were also noticed for

27 MJO predictions. The time to cross the above mentioned threshold increased to 21

28 days for MCEN and to 20 days for ICEN.

29 **Keywords**: MJO, Intraseasonal Variability, Forecast Verification.

30 **1. INTRODUCTION**

31 Forecasting for the time scale between two weeks and two months is known as sub-

32 seasonal prediction (Vitart et al., 2017). This type of forecast is a major challenge

33 because the predictability contribution from the atmospheric initial conditions is

34 reduced compared to shorter (weather) timescales, and the predictability from slowly

35 varying boundary conditions is small for 1-2 week averages, typically the focus of sub-

36 seasonal prediction, compared to seasonal timescales (Kumar et al., 2011; Lin et al.,

37 2016). The main source of predictability for sub-seasonal forecasting is the Madden -

38 Julian Oscillation (MJO) (Zhang, 2013). However, General Circulation Models (GCMs)

39 still show limitations in simulating this oscillation (Green et al., 2017; Wang et al.,

40 2018) even with important improvements achieved in recent years (Saha et al., 2014;

41 Vitart, 2014). As a consequence of these limitations, the predictive ability of GCMs in

42 the sub-seasonal scale is lower than in the weather and seasonal scales (Zhu et al.,

43 2014). For example, de Andrade et al. (2019) showed the limited predictive ability of

44 GCM for sub-seasonal precipitation predictions for lead times beyond 15 days. In

45 general, the GCMs show modest performance in specific areas such as the equatorial

46   regions of the Atlantic and Pacific oceans and over a few regions in South America at

47   this lead time.

48   In spite of these results, a tendency towards improvements in GCMs for sub-seasonal

49   predictions is seen and several meteorological centres currently operationally produce

50   this type of forecasts (Vitart, 2004; Hudson et al., 2011; Mastrangelo et al., 2012; Liu et

51   al., 2017; Weber and Mass, 2017; Liang and Lin, 2018). The Center for Weather

52   Forecast and Climate Studies [Centro de Previsão de Tempo e Estudos Climáticos

53   (CPTEC)], which plays a leading role in South America with respect to weather and

54   seasonal forecasts, is now following the trend of these meteorological centres and

55   started to develop a sub-seasonal prediction system. This is motivated by the fact that,

56   as in seasonal forecasting, South America is located in a privileged region for sub-

57   seasonal prediction, with GCMs showing better predictive ability in this region when

58   compared to other continental regions (Li and Robson, 2015; de Andrade et al., 2019).

59   The identified evolution in sub-seasonal predictions is mainly due to improvements in

60   the representation of the MJO in GCMs. For example, The European Centre for

61   Medium-Range Weather Forecasts (ECMWF) showed a mean gain of one day in MJO

62   prediction performance per year (Vitart, 2014). This indicates that in addition to

63   improvements in predictive ability for a phenomenon that manifests in the tropical

64   region, there is also associated improvement in the extratropics due to teleconnections

65   generated by the MJO (Vitart, 2017).

66   These findings are documented, in large part, thanks to the effort generated by Sub-

67   seasonal to Seasonal (S2S) Prediction Project. This project was launched jointly by the

4

68   World Weather Research Program (WWRP) and the World Climate Research Program

69   (WCRP) of the World Meteorological Organization (WMO) and aims to improve

70   forecast skill and understanding on the sub-seasonal to seasonal time scales and also to

71   promote its uptake by operational centres and by the applications community. Currently,

72   the S2S Prediction Project stores and disseminates near-real-time forecasts and

73   hindcasts of eleven operational and research centres for research purposes (Vitart et al.,

74   2017).

75   The Brazilian Global Atmospheric model [BAM (Figueroa et al., 2016)] is the current

76   CPTEC global atmospheric model for weather forecasting. The performance of this

77   model for sub-seasonal predictions has not been documented yet. Therefore, this study

78   presents the first outcomes of this model for sub-seasonal predictions and aims to

79   determine which model configuration presents the best performance for this time scale.

80   Special attention is given to characteristics such as vertical resolution, deep convection

81   and boundary layer parameterizations and as well as initialization of the soil moisture

82   because they have an important influence on the MJO and sub-seasonal predictions. A

83   similar approach was taken by Green et al (2017) in order to identify a model

84   configuration with best performance when producing MJO predictions. Green et al

85   (2017) evaluated the MJO predictive ability in multiphysics and multimodel global

86   ensembles, by performing two sets of hindcasts in order to test the impact of using the

87   Grell–Freitas (2014) versus the revised simplified Arakawa–Schubert (Han and Pan,

88   2011) deep convection parameterization. They revealed that the Grell–Freitas (2014)

89   convection parameterization showed better MJO prediction performance than the

90   revised simplified Arakawa–Schubert scheme.

91 The paper is organized as follows. Section 2 presents the model description, datasets

92 used for model initialization and hindcast quality assessment, the definition of the

93 experiments, ensemble approaches and the metrics used for evaluation. The

94 retrospective performance of the produced precipitation, 2-meter temperature (T2M)

95 and MJO predictions with different BAM configuration experiments, including two

96 ensemble approaches, is shown in section 3. The final section is intended for the

97 conclusion.

98 **2. MODEL   DESCRIPTION,   DATASETS   AND   EXPERIMENTAL**

99 **CONFIGURATIONS,   EVALUATION   METRICS   AND   ENSEMBLE**

100 **APPROACHES**

101   2.1. Model description

102 The model version used in this study is the current operational CPTEC global spectral

103 atmospheric model developed for numerical weather forecasting, which is known as

104 BAM version 1.2 (BAM-1.2). This model version has different options for dynamical

105 and physics parameterizations. The Eulerian advection scheme option with a two-time-

106 level Semi-Lagrangian scheme for moisture transport and microphysics prognostic

107 variables is used in this study. The physical processes of this recent operational version

108 are similar to the previous version (BAM-1.0) and are described in Figueroa et al.

109 (2016), which are: microphysics from Morrison et al. (2009), the IBIS-CPTEC surface

110 model (Kubota, 2012), the long-wave radiation scheme developed by Chou et al. (2001)

111 (CLIRAD-LW), the short-wave radiation scheme developed by Chou and Suarez (1999)

112 (CLIRAD-SW), the latter modified by Tarasova and Fomin (2000), the modified

113 Mellor-Yamada diffusion scheme for the planetary boundary layer (PBL), which is

114   based on Mellor-Yamada (1982) and is referred to as dry-PBL, and the modified Grell-

115   Dévényi deep convection scheme, which is based on Grell-Dévényi (2002). The two

116   new BAM-1.2 components are Bretherton-Park moist diffusion scheme (Bretherton and

117   Park, 2009) for the PBL, which is referred to as moist-PBL, and the revised version of

118   the simplified Arakawa-Shubert deep convection scheme (Han and Pan. 2011), which

119   were recently implemented. Following Yu et al. (2006) aerosol optical depth in the first

120   2 km of the atmosphere is specified as 0.22 over the continents and as 0.14 over the

121   oceans. The horizontal resolution used in this study is triangular truncation at 126 waves

122   (TQ126, corresponding to a grid of approximately 1.0° in latitude and longitude) and

123   two vertical resolutions are examined: 42 (L42) and 64 (L64) sigma vertical levels.

124   One of the objectives of this study is to investigate the performance of the two PBL and

125   deep convection schemes mentioned above for sub-seasonal predictions. The main

126   difference of the newly implemented moist-PBL Bretherton-Park scheme compared to

127   the dry-PBL modified Mellor-Yamada diffusion scheme is the use of moist-conserved

128   variables and an explicit entrainment closure for convective layers. Regarding the

129   convection schemes, the revised simplified Arakawa-Shubert and the previously

130   implemented modified Grell-Dévényi deep convection parameterization schemes were

131   both derived from Grell (1993), in which the cloud spectrum of the original Arakawa-

132   Schubert (1974) scheme is reduced to a single cloud using a single mass flux closure.

133   The main differences between these convection schemes implemented in BAM-1.2 are

134   the fractional entrainment rate and convection trigger formulations [see Han and Pan

135   (2011) and Figueroa et al., (2016) for additional information].

136   2.2. Datasets and experimental configurations

137 Sub-seasonal hindcasts were performed over the period defined as the extended austral

138 summer (from November to March) over the 1999/2000-2010/2011 period. Two

139 hindcasts for two selected start dates were produced for each month of a given year.

140 Starts dates vary from one month to the next and are presented in Table 1. Each hindcast

141 was run for the following 35 days after the start date (35 days of lead time). For the

142 production of these hindcasts, BAM-1.2 was not coupled with an ocean model. Instead,

143 the total Sea Surface Temperature (SST) field (not the anomaly) of each start date was

144 kept constant during the 35 days of integration (persisted SST). It is worth highlighting

145 that coupled ocean-atmosphere processes are recognized as being important on these

146 timescales (Reichler and Roads, 2005; Chen et al., 2010, Kumar et al., 2011; Shelly et

147 al., 2014), but a number of centres contributing to the S2S database [e.g., Japan

148 Meteorological Agency (JMA) and Environment and Climate Change Canada (ECCC)]

149 produce operational sub-seasonal forecasts using un-coupled systems (Vitart et al.,

150 2017). The CPTEC couple ocean-atmosphere model version which uses BAM-1.2 as

151 atmospheric component is under development. The sub-seasonal hindcast quality

152 assessment of this coupled model version will be reported in future work.

153 ERA-Interim reanalyses (Dee et al., 2011) produced by ECMWF were used in two

154 ways. Firstly, the reanalyses were used as atmospheric initial conditions for the

155 hindcasts produced with BAM-1.2. The variables required for initialization are zonal

156 and meridional wind, specific humidity, virtual temperature and ozone in 35 vertical

157 levels between 1000 hPa and 50 hPa, surface pressure and SST. The horizontal

158 resolution chosen for initialization was 1.5° x 1.5° degrees in latitude and longitude,

159 which was interpolated to the model spectral resolution (TQ126L42, ~100km).

160   Secondly, ERA-Interim data were used as reference to assess the quality of the

161   produced hindcasts. The variables selected for this assessment are T2M and zonal and

162   meridional winds at 850 hPa and 200 hPa.

163   To assess precipitation hindcasts quality, daily data from the Global Precipitation

164   Climatology Project (GPCP) were used (Huffman, 2001). GPCP is a product derived

165   from observed rainfall data and precipitation estimates by geostationary and polar-

166   orbiting satellites. The spatial resolution of GPCP is 1° x 1° degrees in latitude and

167   longitude. Additionally, estimates of Outgoing Longwave Radiation (OLR) from

168   National Oceanic and Atmospheric Administration (NOAA), with a spatial resolution of

169   2.5° x 2.5° degrees in latitude and longitude, were used for assessing the model ability

170   to represent the MJO in conjunction with zonal wind at 850 and 200 hPa from ERA-

171   Interim. This OLR estimation is generated through interpolations in time of polar-

172   orbiting satellite data (for additional information, see Liebmann and Smith, 1996).

173   Six BAM-1.2 configurations for sub-seasonal prediction have been defined for

174   evaluation. Characteristics such as vertical resolution, convection and boundary layer

175   parameterizations were evaluated as well as the impact of soil moisture initialization.

176   Single member hindcasts over the 1999/2000 – 2010/2011 extended austral summer

177   period were produced for each configuration. Five of the configurations were defined by

178   combining two convection schemes, the revised simplified Arakawa Shubert and the

179   modified Grell-Dévényi, and two vertical diffusion schemes for the PBL, the moist-PBL

180   Bretherton-Park scheme and the dry-PBL modified Mellor-Yamada, and two vertical

181   resolutions, 42 and 64 sigma levels. These physical processes and vertical resolutions of

182   the model were selected because they have an important influence on the predictive

183   ability of the MJO (Vitart, 2014; Boyle et al., 2015; Wang and Chen, 2017) and

184   consequently in the sub-seasonal precipitation and T2M predictions. It is important to

185   highlight that other aspects such as horizontal resolution, radiation and microphysics

186   parameterizations are also important for the good representation of the MJO (Zhang,

187   2005; Vitart, 2014; Wang et al., 2018). However, such characteristics were not

188   evaluated in the present work.

189   The sixth configuration evaluates the impact of soil moisture. This characteristic is a

190   source of predictability for the sub-seasonal timescale and has a positive impact on

191   GCM predictive ability, especially in longer lead times such as when predicting weeks 3

192   and 4 (Koster et al., 2010). In this part of the study, the mean soil moisture from the

193   previous month of the start date of each hindcast from the Global Land Data

194   Assimilation System (GLDAS) version 2 product (Rui and Beaudoing, 2017) was used

195   to initialize the soil moisture rather than using the monthly climatological soil moisture

196   estimate in order to assess whether a more realistic soil moisture condition has an

197   impact on the predictive ability of BAM-1.2. The monthly climatological soil moisture

198   data estimates used in this study were obtained from the balance analyses of Willmott et

199   al. (1985). Both GLDAS and climatological soil moisture data estimates were

200   interpolated to the model Gaussian grid and converted to soil moisture fraction for

201   hindcasts initialization.

202   The six examined configurations are defined in Table 2 and are summarized below:

203   • 42ABC: BAM-1.2 with 42 vertical levels, revised simplified Arakawa-Schubert

204   deep convection parameterization, moist Bretherton-Park boundary layer

205   parameterization, and climatological soil moisture initialization;

206   • 64ABC: BAM-1.2 with 64 vertical levels, revised simplified Arakawa-Schubert

207   deep convection parameterization, moist Bretherton-Park boundary layer

208   parameterization, and climatological soil moisture initialization;

209   • 42ABG: BAM-1.2 with 42 vertical levels, revised simplified Arakawa-Schubert

210   deep convection parameterization, moist Bretherton-Park boundary layer

211   parameterization, and soil moisture initialized through the GLDAS version 2

212   product;

213   • 42GBC: BAM-1.2 with 42 vertical levels, modified Grell-Dévényi deep

214   convection parameterization, moist Bretherton-Park boundary layer

215   parameterization, and climatological soil moisture initialization;

216   • 64GBC: BAM-1.2 with 64 vertical levels, modified Grell-Dévényi deep

217   convection parameterization, moist Bretherton-Park boundary layer

218   parameterization, and climatological soil moisture initialization;

219   • 42AMC: BAM-1.2 with 42 vertical levels, revised simplified Arakawa-Schubert

220   deep convection parameterization, dry modified Mellor-Yamada boundary layer

221   parameterization, and climatological soil moisture initialization.

222

223   2.3. Evaluation metrics and ensemble approaches

224   We assessed the ability of the six BAM-1.2 configurations to predict precipitation, T2M

225   and the MJO. For precipitation and T2M, the deterministic assessment consists of

226   computing the Pearson correlation and Root-Mean-Square Error (RMSE) between the

227   prediction and observed anomalies. Each metric was calculated for each grid point and

228   for four lead times: days 1-7 (week-1), 8-14 (week-2), 15-21 (week-3) and 22-28 (week-

229   4). The results were evaluated in the form of weekly averages because the model is

230   expected to have a greater ability to predict weekly anomalies than daily values when

231   producing sub-seasonal predictions (Vitart, 2014).

232   The performance of MJO prediction was evaluated using the Real-time Multivariate

233   MJO indices (RMMs) (Wheeler and Hendon, 2004). Reference RMMs were calculated

234   using the meridional wind at 850 and 200 hPa from the ERA-Interim reanalyses and

235   satellite observed OLR. RMMs for hindcasts were calculated as proposed by Rashid et

236   al. (2011). The metrics used for the MJO prediction quality assessment were bivariate

237   correlation and RMSE (Lin et al., 2008) with lead times in days.

238   In addition to the single member deterministic prediction assessment, we evaluated the

239   ability of the Multiple Configurations Ensemble (MCEN) mean prediction formed by

240   the six here investigated BAM-1.2 configurations with each configuration representing

241   one ensemble member. This was compared to an Initial Condition Ensemble (ICEN)

242   produced with an Empirical Orthogonal Function (EOF) perturbation methodology

243   (Mendonça and Bonatti, 2009), using the configuration that showed the best

244   performance among the six evaluated configurations for producing six ensemble

245   members. The EOF-based perturbation methodology is in operation at CPTEC for

246   extended range forecasts up to 15 days. The methodology produces optimally perturbed

247   analyses by applying the EOFs to n time series formed by the differences between a

248 model run initialized with a control initial condition and n model runs initialized with

249 randomly perturbed initial conditions. The initial random perturbations are drawn from

250 a Gaussian distribution with zero mean and standard deviation comparable to the model

251 short length forecast error [e.g., 3 ms-1 for the horizontal wind field components, 0.6 K

252 for the air temperature field, 1 hPa for the surface pressure field and a vertical standard

253 deviation profile for the specific humidity derived from the ECMWF background error

254 covariance matrix (Derber and Boutier, 1999)]. The EOF analysis is performed over the

255 Northern and Southern Hemispheres, over the tropical domain and also regionally over

256 southern and northern South America. The EOF perturbations are the ones associated

257 with the fast growth coefficients. To be used as optimal perturbations, these fast growth

258 modes are rescaled in order to have a standard deviation of the same order of magnitude

259 as the initial perturbations. Finally, the optimal perturbation is added and subtracted

260 to/from the control analysis and an ensemble of $2n$ initial perturbed states is produced.

261 A more detailed revision of the EOF-based perturbation methodology used at CPTEC

262 can be found in Cunningham et al. (2015).

263 The above mentioned deterministic metrics for precipitation and T2M anomaly

264 hindcasts, as well as for the hindcast MJO indices, were calculated for the ensemble

265 mean of the two equal size (six members) ensemble (MCEN and ICEN) to assess and

266 compare the value of utilizing multiple sub-seasonal predictions using two approaches.

267 In order to have an assessment of the differences in the obtained scores for the

268 investigated model configurations and the two ensemble mean approaches, 95%

269 confidence intervals were computed for the mean correlation and RMSE (for

270 precipitation and T2M anomalies), globally averaged between 60° N and 60° S, and for

271 the bivariate correlation and RMSE (for the MJO) using a bootstrap resampling

272 procedure with replacement with 1000 samples.

3. HINDCAST QUALITY ASSESSMENT

3.1. Deterministic evaluation of the six investigated BAM-1.2 configurations

275 Figure 1 shows the correlation between predicted and observed (GPCP) precipitation

276 anomalies for the six BAM-1.2 configurations (first 6 rows) and four lead times (four

277 columns representing week-1, week-2, week-3 and week-4). The 10 hindcasts per

278 extended austral summer (5 months times 2 start dates) over 12 austral summers

279 produce a sample with a total of 120 hindcasts. Applying a two-side Student's t test, the

280 correlation value of 0.2 is statistically significant, different from zero at the 5% level.

281 For the six configurations, in general, the correlation is high during the first week in

282 most regions and drops rapidly as lead time increases. This fall is more pronounced

283 between the first and second week for all six configurations as the forecasts extend

284 beyond the deterministic limit of predictability for many scales and we are considering

285 only a single member for this initial analysis. It is noted that all configurations show

286 greater correlation over the North Hemisphere than the South Hemisphere during week-

287 1 and week-2. This is because GCMs are more likely to predict winter baroclinic

288 weather systems and associated fronts (Zhu et al., 2014). As of the third week, BAM-

289 1.2 correlation values are smaller than 0.2 in practically all extratropical regions. This

290 illustrates that the predictive ability of BAM-1.2 over mid-latitudes beyond 15 days is

291 limited for single member hindcasts. For weeks 3 and 4, significant correlation values

292 are only seen in the Tropical Pacific Ocean, over a few areas in northern South America

293 and in the equatorial Atlantic Ocean. The high correlation values in the first two lead

294 times, especially at week-1, are associated to the predictability provided by the initial

295 conditions, and the high correlation values observed in the last two lead times over the

296 equatorial Pacific Ocean are mainly associated to the predictability provided by the El

297 Nino-Southern Oscillation (ENSO) and the MJO (Li and Robertson, 2015; de Andrade

298 et al., 2019). All six configurations show negligible correlation values near the

299 Subtropical Highs and desert regions from week-1. These characteristics are also

300 noticed in other GCMs configured for sub-seasonal predictions (Zhu et al, 2014; Li and

301 Robertson, 2015; Wheeler et al., 2017; de Andrade et al., 2019) and are associated with

302 the low capacity of GCMs to simulate small precipitation rates in these regions.

303 The spatial correlation pattern is similar for the four weeks of each of the six BAM-1.2

304 configurations. However, this pattern for the configurations with revised simplified

305 Arakawa-Schubert (deep convection) and moist Bretherton-Park (boundary layer)

306 parameterizations shows slightly larger values in the first two weeks than for the other

307 configurations (Figure 1, first two columns of configurations 42ABC, 64ABC and

308 42ABG vs. first two columns of configurations 42GBC, 64GBC and 42AMC). In the

309 week-3 and week-4 (last two columns of Figure 1), correlation levels are similar in

310 terms of both spatial pattern and intensity for the six configurations. Increasing the

311 vertical resolution shows very little change in the precipitation correlation levels at any

312 lead time. For example, the 42 vertical level configuration, 42ABC (first row of Figure

313 1), and the 64 vertical level configuration, 64ABC (second row of Figure 1), have

314 nearly identical correlation values for most regions. The same is noticed for

315   configurations 42GBC (fourth row of Figure 1) and 64GBC (fifth row of Figure 1).

316   Initialization of the soil moisture also shows no increase in the correlation values for all

317   four investigated weeks. Hindcasts initialised with climatological soil moisture

318   (42ABC, first row of Figure 1) have the same correlation levels as 42ABG (third row of

319   Figure 1) hindcasts, which were initialized with GLDAS soil moisture.

320   Figure 2 shows the precipitation anomaly RMSE spatial features for the six BAM-1.2

321   configurations. Highest RMSE values are found over the Intertropical Convergence

322   Zone (ITCZ), Indian Ocean, Maritime Continent, South Pacific Convergence Zone

323   (SPCZ) and South American Convergence Zone (SACZ), which are regions of strong

324   sub-seasonal variability (Liu et al., 2014). The errors grow as lead time increases. As for

325   the correlation assessment, the errors grow more between week-1 and week-2 than from

326   weeks 2 to 3. Again, configurations with revised simplified Arakawa-Shubert and moist

327   Bretherton-Park parameterizations have the fewest errors and do not differ greatly from

328   each other (rows 42ABC, 64ABC and 42ABG in Figure 2). Configurations with

329   modified Grell-Dévényi parameterizations (rows 42GBC and 64GBC in Figure 2) also

330   do not differ much from each other and have larger errors when compared to

331   configurations with revised simplified Arakawa-Shubert parameterizations. That is, the

332   revised simplified Arakawa-Shubert parameterization seems to be better than the

333   modified Grell-Dévényi parameterization and increase of the vertical resolution and soil

334   moisture initialization do not reduce the errors of the hindcasts in any lead time.

335   To better note the differences between the six configurations, the mean global

336   correlation between 60°N and 60°S was calculated as a function of lead time (Figure

337   3a). Vertical bars represent bootstrap 95% confidence intervals. The six configurations

338 show a near-exponential drop in correlation as a function of lead time. The

339 configurations with the revised simplified Arakawa-Shubert and moist Bretherton-Park

340 parameterizations (black, orange and blue lines) have the largest correlation values

341 when compared to the other configurations in the week-1 and week-2. Important

342 improvements are noticed when comparing the configurations with revised simplified

343 Arakawa-Shubert and modified Grell-Dévényi deep convection parameterizations at the

344 first two lead times For example, 42ABC (black line) has a global mean correlation

345 equals to 0.45 at week-1 and drops to 0.18 at week-2, whereas 42GBC (yellow line) has

346 a global mean correlation values equals to 0.40 at week-1 and drops to 0.14 at week-2.

347 The 95% confidence intervals for the 42ABC (black vertical bars on top of solid black

348 line) do not overlap the 95% confidence intervals for the 42GBC (yellow vertical bars

349 on top of solid yellow line), illustrating the superiority of 42ABC over 42GBC.

350 However, the six configurations show similar correlation levels at week-4. As noted in

351 the previous figures, the increase of vertical resolution does not result in an increase in

352 the correlation values. This feature is noticed when we compare the 42ABC (black line)

353 and 64ABC (orange line) configurations or the 42GBC (yellow line) and 64GBC (green

354 line) configurations, which show practically the same behaviour, with the differences

355 between configurations smaller than the 95% confidence intervals (vertical bars). This is

356 also noticed for soil moisture initialization, where the 42ABG configuration (blue line)

357 shows similar correlation levels to the 42ABC configuration (black line).

358 The global RMSE mean between 60°N and 60°S (Figure 3b) further emphasizes the

359 differences between the revised simplified Arakawa-Shubert and modified Grell-

360 Dévényi deep convection parameterizations. The modified Grell-Dévényi

361 parameterization (green and yellow lines) produces larger errors than the revised

362 simplified Arakawa-Shubert parameterization (other lines) at all lead times. The

363 differences between the errors of these two parameterizations are much larger than the

364 95% confidence intervals (vertical bars) shown in Figure 3b, illustrating the superiority

365 of the revised simplified Arakawa-Shubert over the modified Grell-Dévényi

366 parameterization. The configurations 42ABC (black line) and 64ABC (orange line)

367 show very similar values at the four lead times, with overlapping 95% confidence

368 intervals. This is also noticed with the 42GBC (yellow line) and 64GBC (green line)

369 configurations. These results suggest that increasing the vertical resolution does not

370 decrease the RMSE. The initialization of soil moisture also does not contribute to the

371 reduction of error (black vs. blue lines). An interesting aspect is that the configuration

372 with dry modified Mellor-Yamada boundary layer parameterization (red line) has the

373 smallest error in the last two lead times.

374 Figure 4 shows the correlation between predicted and reanalyses (ERA-Interim) T2M

375 anomalies for the six configurations and four lead times. The six BAM-1.2

376 configurations show better prediction performance for T2M anomalies than

377 precipitation anomalies (see Figures 1 and 4). The correlation values decrease with lead

378 time. The highest correlation values are seen over cloud free oceanic regions (e.g.,

379 42ABC row in Figure 4). However, significant sub-seasonal correlation values exist

380 over a large portion of the global land domain. Over extratropical continental regions,

381 strong correlation values are observed in restricted regions at week 3 and 4, for

382 example, over the southeast of the United States and some regions over Asia. Over

383   tropical regions, correlation values are low in regions with high convective activity

384   (e.g., over the Maritime Continent).

385   The spatial correlation pattern is similar for the four weeks of the six BAM-1.2

386   configurations. The difference in performance between configurations with revised

387   simplified Arakawa-Shubert and modified Grell-Dévényi deep convection

388   parameterizations is not observed for T2M (e.g., row 42ABC vs. row 42GBC in Figure

389   4). Configurations with these two parameterizations have the same performance level

390   for the four weeks of lead time. There are differences when comparing the two

391   boundary layer parameterizations. The configuration with the dry modified Mellor-

392   Yamada parameterization (row 42AMC in Figure 4) shows reduced performance than

393   the other five configurations at all lead times, which were configured with the moist

394   Bretherton-Park boundary layer parameterization. Increasing vertical resolution from 42

395   (rows 42ABC and 42GBC in Figure 4) to 64 (rows 64ABC and 64GBC in Figure 4)

396   levels seems to slightly reduced prediction performance of extratropical T2M anomalies

397   in the first two weeks of lead times. Predictions with the initialisation of soil moisture

398   (row 42ABG in Figure 4) rather than the climatology soil moisture (row 42ABC in

399   Figure 4), show a slight improvement in correlation in the continental regions

400   (Australia, South and North Americas and Africa) at week 2 and 3 lead time.

401   Figure 5 shows the T2M anomaly RMSE spatial features for the six BAM-1.2

402   configurations. In all configurations, RMSE values grow with the lead time and are

403   generally lower over oceanic regions than over continental regions for all 4 lead times.

404   The highest RMSE values are noticed over Northern Hemisphere regions where there

405   are interactions between mid-latitude baroclinic system, and tropical convective

406   anomalies, which are usually associated with the MJO and circulation teleconnections

407   through Rossby waves (Stan et al., 2017; Hu et al., 2019). Over northern Asia, high

408   RMSE values are also noticed. The RMSE values are lower over the Southern

409   Hemisphere because there are fewer continental regions than over the Northern

410   Hemisphere, and baroclinic instability is lower at this time of the year in the Southern

411   Hemisphere. The latter makes the interaction between the convective anomalies over

412   tropical regions and circulation over mid-latitudes regions less pronounced. As a result,

413   the sub-seasonal variability over the Southern Hemisphere extratropical regions is also

414   reduced during the austral summer.

415   Configurations with the revised simplified Arakawa-Shubert and modified Grell-

416   Dévényi deep convection parameterizations present similar RMSE patterns (Figure 5).

417   Some differences are found in specific regions. For example, the 42GBC configuration

418   shows slightly lower RMSE values over southern South America than the 42ABC

419   configuration at week 3. The opposite is noticed over the Iberian Peninsula. Similar

420   features are noticed for the increase in vertical resolution. Concerning the initialization

421   of soil moisture, subtle differences are noticed between 42ABC and 42ABG, with slight

422   improvements over continental regions such as Australia, South America, southern

423   Africa and North America with initialized soil moisture (42ABG). Large differences are

424   found when comparing configurations with moist Bretherton-Park and dry modified

425   Mellor-Yamada boundary layer parameterizations. For example, the RMSE values are

426   lower in high latitude regions over North America and Asia for the 42AMC

427   configuration when compared to the 42ABC configuration. The opposite is over tropical

428   and medium latitudes regions.

429   Figure 6 shows the global mean T2M anomaly correlation (Figure 6a) and RMSE

430   (Figure 6b) averaged between 60°N and 60°S as a function of lead time with 95%

431   confidence intervals (vertical bars). The six configurations show a similar drop (rise) in

432   correlation (RMSE) as a function of lead time. The increase of vertical resolution from

433   42 to 64 levels, change of deep convection scheme and soil moisture initialization do

434   not influence the levels of correlation and error values for T2M anomalies predictions

435   for the global perspective. This feature is noticed by the proximity or overlap of

436   correlation and RMSE lines of most investigated configurations shown in Figure 6, with

437   overlapping 95% confidence intervals. Differences in performance levels are noticed

438   when comparing moist Bretherton-Park and dry modified Mellor-Yamada boundary

439   layer parameterizations. The dry modified Mellor-Yamada parameterization (red line)

440   produces smaller correlation values and larger errors than the other five configurations

441   at all lead times, with the differences between these configurations and the others larger

442   than the 95% confidence intervals (vertical bars) illustrating the superiority of the other

443   configurations.

444   Figures 7a and 7b show MJO bivariate correlation and bivariate RMSE of all six BAM-

445   1.2 configurations, respectively. Vertical bars represent bootstrap 95% confidence

446   intervals. The MJO predictive ability is determined when the bivariate correlation is

447   lower than 0.5 and the bivariate RMSE grows to $\sqrt{2}$. The lead times for these two

448   thresholds to be reached are usually found to be close (Rashid et al., 2011). The

449   bivariate correlation decreases with the increase in lead time and crosses the threshold

450   of 0.5 in 18-19 days for all configurations, except for the 42AMC configuration (red

451   line), which uses the dry modified Mellor-Yamada boundary layer parameterization and

452 has a much reduced performance, with the bivariate correlation reaching the 0.5

453 threshold in 12 days. The bivariate RMSEs (Figure 7b) increase with lead time and each

454 configuration reaches the bivariate RMSE value of $\sqrt{2}$ at approximately the same lead

455 time as the bivariate correlation. The 42AMC configuration crosses the threshold value

456 of $\sqrt{2}$ in 11 days, whereas the other five configurations cross the threshold value of $\sqrt{2}$

457 in around 18 to 19 days. The overlap of the 95% confidence intervals (vertical bars) for

458 most configurations (expect 42AMC) illustrates their similarity in MJO predictive

459 ability.

460   3.2.Deterministic assessment of two investigated ensemble approaches

461 With the precipitation anomalies, T2M anomalies and MJO hindcast evaluation of the

462 six configurations shown in the previous section, a preferred BAM-1.2 configuration

463 was determined for defining an ensemble sub-seasonal forecasting system for CPTEC.

464 The increase of the vertical resolution from 42 levels to 64 levels did not result in

465 increase in predictive ability, therefore a vertical resolution of 42 levels was selected.

466 The moist Bretherton-Park boundary layer parameterization was selected because it

467 contributed to a better performance than the dry modified Mellor-Yamada boundary

468 layer parameterization, especially for T2M anomalies and MJO predictions. The revised

469 simplified Arakawa-Shubert and modified Grell-Dévényi deep convection

470 parameterizations showed similar ability for T2M anomalies and MJO prediction with a

471 slight advantage to the modified Grell-Dévényi parameterization for MJO prediction.

472 On the other hand, the revised simplified Arakawa-Shubert parameterization showed a

473 large advantage for sub-seasonal precipitation, with higher correlation and smaller

474 errors values than the modified Grell-Dévényi parameterization. Based on this

22

475   assessment, the revised simplified Arakawa-Shubert deep convection parameterization

476   was chosen. Soil moisture initialization instead of the climatology led to subtle

477   improvements in T2M anomalies predictions in specific regions (e.g., Australia).

478   However, these improvements were lower than expected and given limitations in the

479   availability of accurate real-time soil moisture data, the use of climatological soil

480   moisture was selected for the BAM-1.2 system. Therefore, the chosen BAM-1.2 version

481   for ensemble sub-seasonal forecasting was the 42ABC configuration.

482   The possible physical reasons why the selected configuration (42ABC) performed better

483   than the other investigated configurations, particularly in terms of the tested boundary

484   layer and deep convections parameterizations are as follows. The use of the moist

485   Bretherton-Park boundary layer parameterization resulted in better MJO and T2M

486   predictions performance than the use of the dry modified Mellor-Yamada boundary

487   layer parameterization. This is because the moist Bretherton-Park has several

488   advantages compared to the dry modified Mellor-Yamada parameterization. The main

489   contribution of the moist Bretherton-Park parameterization is to improve the

490   representation of the stable night boundary layer, where the predominant physical

491   process in flat areas such as the oceans is the surface radiative cooling. The evolution of

492   the stable nocturnal boundary layer depends on the radiative cooling rate, and therefore

493   the presence of clouds is essential for reducing radiative loss. At sunrise, the state of the

494   stable boundary layer will be important for the evolution of vertical instability and the

495   mixing boundary layer. Therefore, the higher or lower the energy released during the

496   evolution of the stable boundary layer this energy surplus or deficit will contribute to

497   the formation of shallow and deep clouds, and consequently impacts the daytime

498   temperature and precipitation cycle. The energy scales produced by these processes

499   directly or indirectly impact the atmospheric conditions on the sub-seasonal time scale.

500   As for the comparative performance of sub-seasonal precipitation predictions, important

501   differences were noted when changing the deep convection parameterizations. The

502   revised simplified Arakawa-Shubert parameterization showed better performance than

503   the modified Grell-Dévényi parameterization. This is likely due to the revision made by

504   Han and Pan (2011) in the simplified Arakawa-Shubert parameterization to suppress

505   unrealistic grid point storms due to remaining instability in the atmospheric column.We

506   next further assess BAM-1.2 sub-seasonal hindcast quality through a deterministic

507   evaluation of ensemble mean predictions. Two ensemble types are evaluated and

508   presented here. The first ensemble consists of one ensemble member from each of the

509   six configurations previously presented, which was denominated Multiple

510   Configurations Ensemble (MCEN). The second ensemble was denominated Initial

511   Condition Ensemble (ICEN) and is composed of six members produced with the chosen

512   42ABC configuration consisting of a control member and five perturbed members

513   produced with an EOF method (Mendonça and Bonatti, 2009; Cunningham et al.,

514   2015).

515   The assessment of the ensemble mean of the two ensemble types (MCEN and ICEN)

516   revealed important increase in global mean performance at four lead times for

517   precipitation anomalies predictions when compared to the single member assessment of

518   the six investigated BAM-1.2 configurations (Figure 3), with the increase in

519   performance larger than the 95% confidence intervals (vertical bars). The two ensemble

520   mean approaches show similar correlation levels (dashed lines in Figure 3a) and

521 overlapping 95% confidence intervals (vertical grey and black bars on top of dashed

522 lines). This shows that BAM-1.2 performance increases when more (six) members are

523 used to form an ensemble with the 42ABC configuration or when using the six

524 configurations as an ensemble. The predictive ability of GCMs increases as the number

525 of members increases because the ensemble mean acts as a filter for decreasing the

526 uncertainties of the initial conditions used to run the model (Cheung, 2001). This is

527 noticed over several regions in the four investigated lead times (e.g., Figure 1). For

528 example, over extratropical regions at week 2, over eastern South America at week 3

529 and over northern South America at week 4. Precipitation anomaly hindcasts also show

530 lower RMSE values for both ICEN and MCEN at all four lead times (dashed lines in

531 Figure 3b), with the reduction of error much larger than the 95% confidence intervals

532 (vertical bars). Improvements are noticed primarily over the ITCZ, Indian Ocean,

533 Maritime Continent, SPCZ and SACZ regions (last two rows in Figure 2). This suggests

534 that the ensemble mean helps BAM-1.2 to better represent the sub-seasonal variability

535 in these regions. The same feature is noticed for the T2M hindcasts ensemble means.

536 The two ensemble means show improved T2M anomalies performance when compared

537 to the single member performance with increased correlation values and decreased error

538 (see last two rows in Figure 4 and 5 and dashed lines in Figures 6). Improvements in

539 MJO forecast performance are also noticed when using the two ensemble approaches.

540 The prediction ability limits are around lead times 18 and 19 days for the single member

541 configurations, except for the 42AMC which is much reduced (solid lines in Figures 7).

542 For the MCEN this limit increases to 21 days (dashed grey line in Figures 7a-b) and to

543 20 days (dashed black line in Figures 7a-b) for the ICEN. However, these improvements

25

544 are less prominent than those identified for precipitation and T2M, because the 95%

545 confidence intervals of the two ensemble approaches largely encompass the 95%

546 confidence intervals of the single members of the individual investigated configurations.

547 **4. CONCLUSIONS**

548 Vertical resolution and physical parameterizations (deep convection and boundary

549 layer) were changed in BAM-1.2 to form five model configurations to determine the

550 model configuration with greater performance for sub-seasonal predictions. These

551 components were selected because these parameters have an important impact on

552 GCMs simulated MJO (Zhang, 2005; Wang and Chen, 2017; Wang et al., 2018). Given

553 the soil moisture initialization potential to increase the sub-seasonal predictions

554 performance (Koster et al., 2010; Koster et al., 2011; Guo et al., 2012), a further

555 configuration initialized with monthly soil moisture from the previous month, rather

556 than the climatological mean soil moisture, was formed to investigate the impact of soil

557 moisture initialization on BAM-1.2 predictive ability. The configuration with the best

558 result was selected to form an initial condition ensemble (ICEN) with six members, one

559 control member and five perturbed members produced using an EOF-based

560 methodology. The six configurations, individually evaluated in the first part of this

561 work, were also used to form another ensemble (multiple configurations ensemble-

562 MCEN) to compare the improvements inherent in the ensemble mean between ICEN

563 and MCEN.

564 All six BAM-1.2 configurations produced high precipitation and T2M anomalies

565 correlation levels for the first week and decreased correlation levels for weeks 2-4. For

566 weeks 3-4, moderate precipitation anomaly correlation levels were restricted to the

26

567 Equatorial Pacific Ocean region. This feature was also noticed in other models (e.g., Li

568 and Robertson, 2015; de Andrade et al., 2019). Precipitation anomaly RMSE increased

569 with lead time and the highest RMSE values were found over regions with strong sub-

570 seasonal variability, for example, over the ITCZ, Indian Ocean, Maritime Continent,

571 SPCZ and SACZ (Liu et al., 2013). For T2M, this characteristic was identified over the

572 Northern Hemisphere where interaction between anomalous convection and mid-

573 latitudes circulation anomalies are noticed (Hu et al., 2019). The six BAM-1.2

574 configurations showed better prediction performance for T2M anomalies than for

575 precipitation anomalies.

576 The increase of the vertical resolution from 42 levels to 64 levels did not result in an

577 increase in predictive ability. Comparing 42ABC with 64ABC (revised simplified

578 Arakawa-Shubert deep convection configurations with 42 and 64 levels, respectively)

579 and 42GBC with 64GBC (modified Grell-Dévényi deep convection configurations with

580 42 and 64 levels, respectively), it was noticed that the correlation and RMSE showed

581 nearly identical levels for all lead times for precipitation anomalies, T2M anomalies and

582 MJO predictions. These results may sound contradictory since other studies have shown

583 that the increase in vertical resolution contributes to improvements in predictive ability

584 in the sub-seasonal timescale (Zhang, 2005; Vitart, 2014). Other factors might be

585 contributing to this finding. For example, the use of initial conditions with only 37

586 vertical levels, which had to be interpolated to cover 42 and 64 levels.

587 BAM-1.2 configurations with revised simplified Arakawa-Shubert deep convection

588 parameterization showed better performance than BAM-1.2 configurations with

589 modified   Grell-Dévényi   deep   convection   parameterization   for   sub-seasonal

590   precipitation prediction, with the largest correlation levels found in the first two weeks

591   and the smallest RMSE in the four lead times. However, these two parameterizations

592   showed practically the same performance for T2M anomalies and MJO, with the

593   commonly used performance thresholds reached at 18/19 days of lead time. The fact

594   that the BAM-1.2 model presents increased ability for sub-seasonal precipitation

595   forecast with the revised simplified Arakawa-Shubert deep convection parameterization

596   compared to modified Grell-Dévényi and very similar ability for T2M and MJO is

597   intriguing. Han and Pan (2011) provided a revision of the simplified Arakawa-Shubert

598   deep convection in the National Centers for Environmental Prediction's (NCEP) global

599   forecast system. This revision aimed to suppress unrealistic gridpoint storms due to

600   remaining instability in the atmospheric column. This might be a possible reason for the

601   better BAM-1.2 performance in sub-seasonal precipitation anomaly forecasting with

602   revised simplified Arakawa-Shubert deep convection parameterization.

603   The moist Bretherton-Park boundary layer parameterization produced better

604   performance for precipitation anomalies, T2M anomalies and MJO predictions than the

605   dry modified Mellor-Yamada boundary layer parameterization. The greatest differences

606   were noticed for MJO predictions, where the bivariate correlation decreased more

607   sharply as a function of lead time with the configuration using the dry modified Mellor-

608   Yamada parameterization (42AMC) than for the other configurations. For this, the

609   42AMC has correlation below 0.5 and RMSE above $\sqrt{2}$ around the 11th day of lead

610   time. Large discrepancies were also noticed for T2M anomalies predictions when

611   comparing 42AMC with the other configurations.

612　We did not find important impacts of soil moisture initialization when compared to

613　climatological initialization on the predictive ability of precipitation anomalies in the

614　four investigated lead times. Slight improvements were seen for T2M anomaly

615　predictions in some continental regions. These improvements were smaller than those

616　found in Koster et al. (2010), Koster et al. (2011), Guo et al. (2012) and Van den Hurk

617　and et al. (2012), and might be related to differences in the investigated seasons, time

618　window, experiments or/and even to low BAM-1.2 sensitivity to soil moisture

619　initialization.

620　With the evaluation of the six configurations, it was possible to determine a

621　configuration for use as CPTEC sub-seasonal ensemble system. For this, the determined

622　configuration was the 42ABC. This configuration consists of a model version at TQ126

623　spatial resolution, 42 vertical sigma levels, revised simplified Arakawa-Shubert deep

624　convection parameterization, moist Bretherton-Park boundary layer scheme,

625　initialization with climatological soil moisture, CLIRAD-LW, CLIRAD-SW, Morrison

626　microphysics and the IBIS-2.6-CPTEC surface model.

627　The deterministic evaluation of ensembles (MCEN and ICEN), through the computation

628　of the ensemble means, presented considerable improvements when compared to the

629　single (control) member evaluation (42ABC). For precipitation and T2M anomalies

630　predictions, this improvement was noticed mainly in extratropical continental regions.

631　For MJO predictions, the ensemble means extended in two days the MJO prediction

632　ability limit (e.g., up to 20 days). It is interesting to note that the MCEN mean, formed

633　from the six configurations, showed very similar level of improvements to ICEN when

634　compared to the control member.

This work focused on determining a global CPTEC model configuration for sub-seasonal prediction through a deterministic assessment using a limited number of ensemble members (six). The results presented in this paper suggest that BAM-1.2 has competitive performance to other S2S models (Vitart et al., 2017; Lim et al., 2018; de Andrade et al. 2019). In a forthcoming paper, we plan to perform a probabilistic assessment of the defined configuration with an increased number of ensemble members and a more detailed comparison of BAM-1.2 with other S2S models. It is worth mentioning that although the extended austral summer is a fundamental season for Brazil (particularly in terms of precipitation) further work is needed in order to evaluate the performance of the Brazilian model during other seasons for identifying regions where best to trust the model for issuing operational sub-seasonal predictions.

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659

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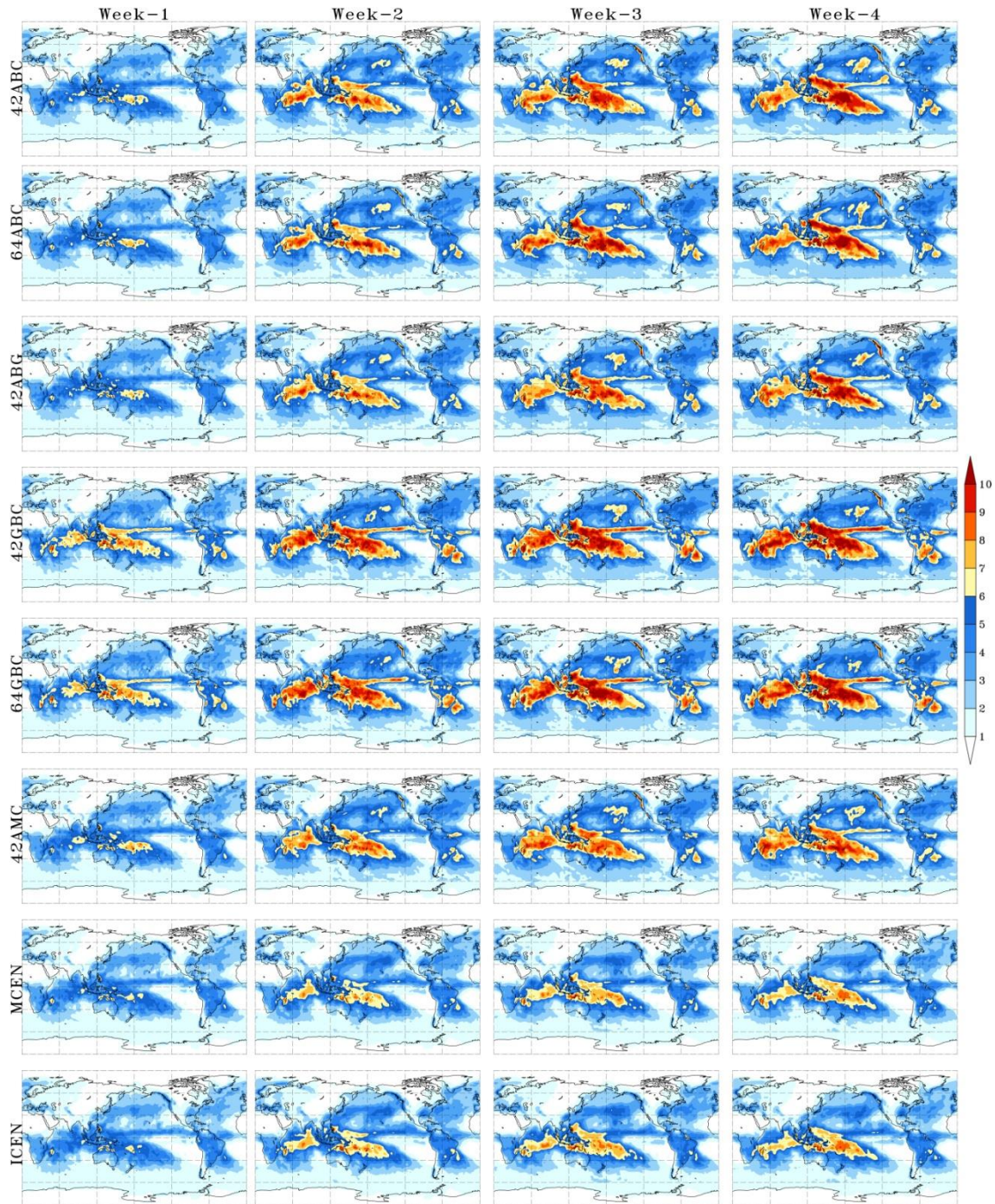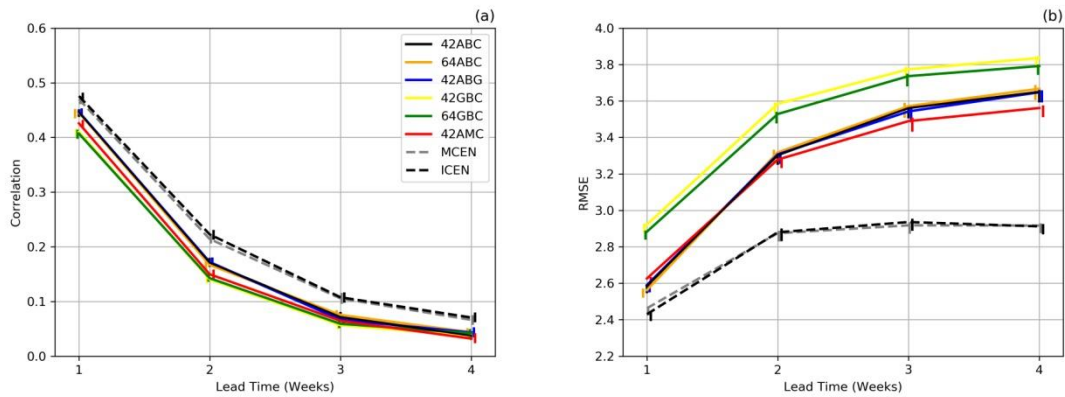
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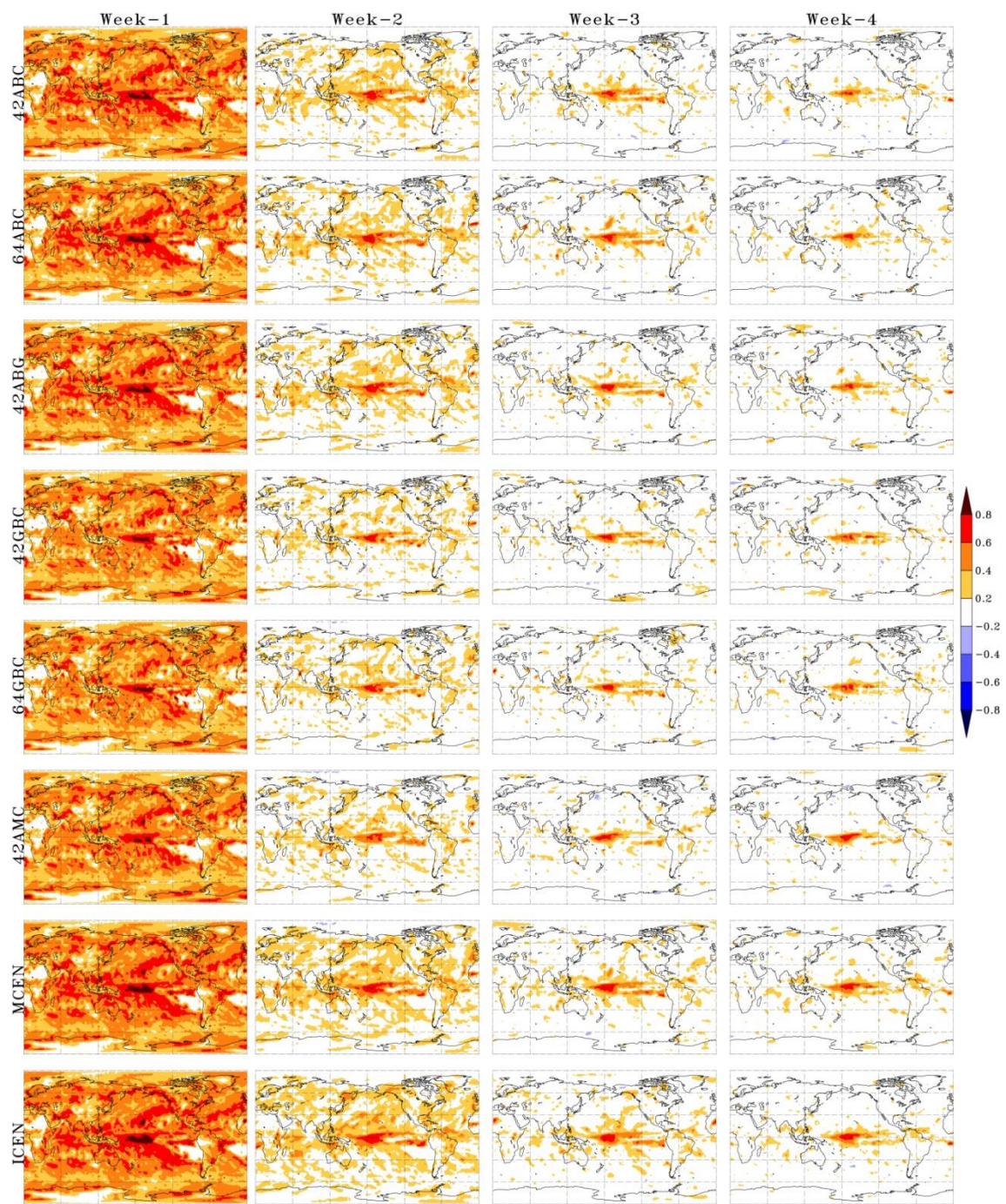
Figure 1: Correlation between the predicted and observed (GPCP) precipitation anomalies for the six BAM-1.2 configurations (42ABC, 64ABC, 42ABG, 42GBC, 64GBC and 42AMC) and two ensemble means (MCEN and ICEN) (rows) for week-1, week-2, week-3 and week-4 (columns). The hindcasts were initialized within the

827   extended austral summer period (from November to March 1999/2000 – 2010/2011) on

828   the dates shown in Table 1.

829

830   Figure 2: Six configurations (42ABC, 64ABC, 42ABG, 42GBC, 64GBC and 42AMC)

831   and two ensemble means (MCEN and ICEN) (rows) RMSE precipitation anomaly

832   (units are mm day-1) for week-1, week-2, week-3 and week-4 (columns). The hindcasts

833   were initialized within the extended austral summer period (from November to March

834   1999/2000 – 2010/2011) on the dates shown in Table 1.

835

836   Figure 1: Global mean correlation between predicted and observed precipitation

837   anomalies (a) and RMSE (b) for six BAM-1.2 configurations (42ABC, 64ABC,

838   42ABG, 42GBC, 64GBC and 42AMC) and two ensemble approaches (MCEN and

839   ICEN) assessed against GPCP averaged over the latitudinal band 60°N-60°S for four

840   lead times (weeks 1 to 4). The hindcasts were initialized within the extended austral

841   summer period (from November to March 1999/2000 – 2010/2011) on the dates shown

842   in Table 1. The vertical bars plotted around the four lead times represent 95%

843   confidence intervals produced using a bootstrap resampling procedure with replacement

844   with 1000 samples. These vertical bars are slightly displaced from the exact lead time

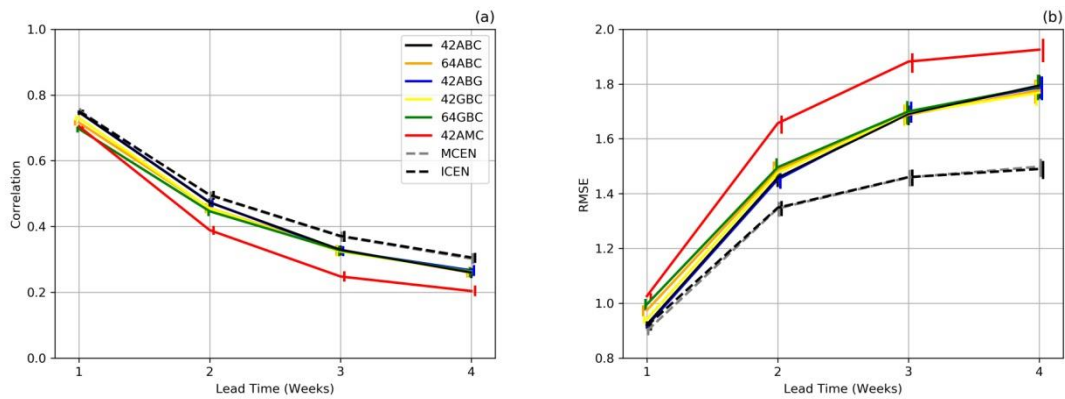845   location in the horizontal axis to facilitate visualization.
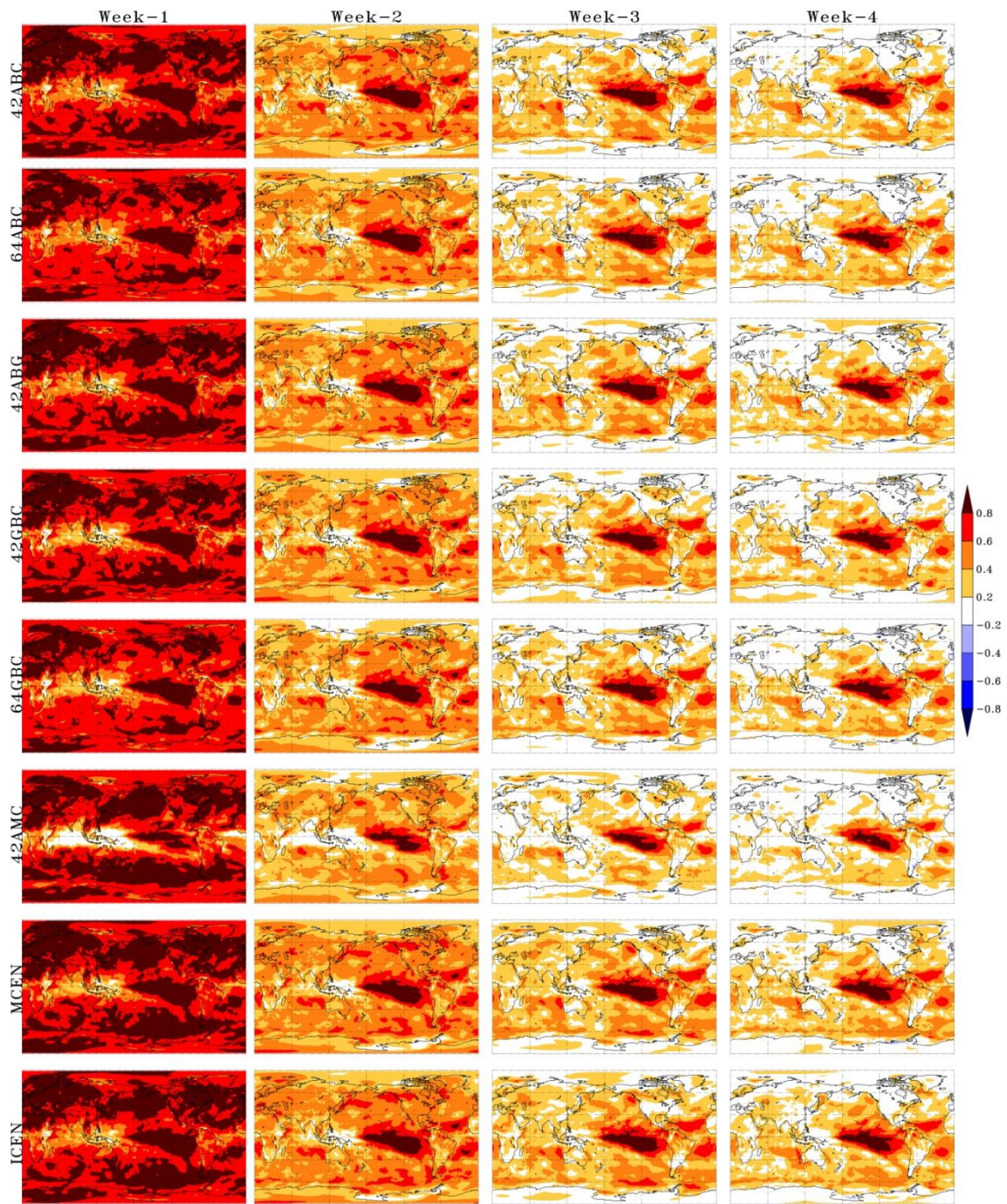
847   Figure 4: Same as Figure 1, except for T2M anomaly.
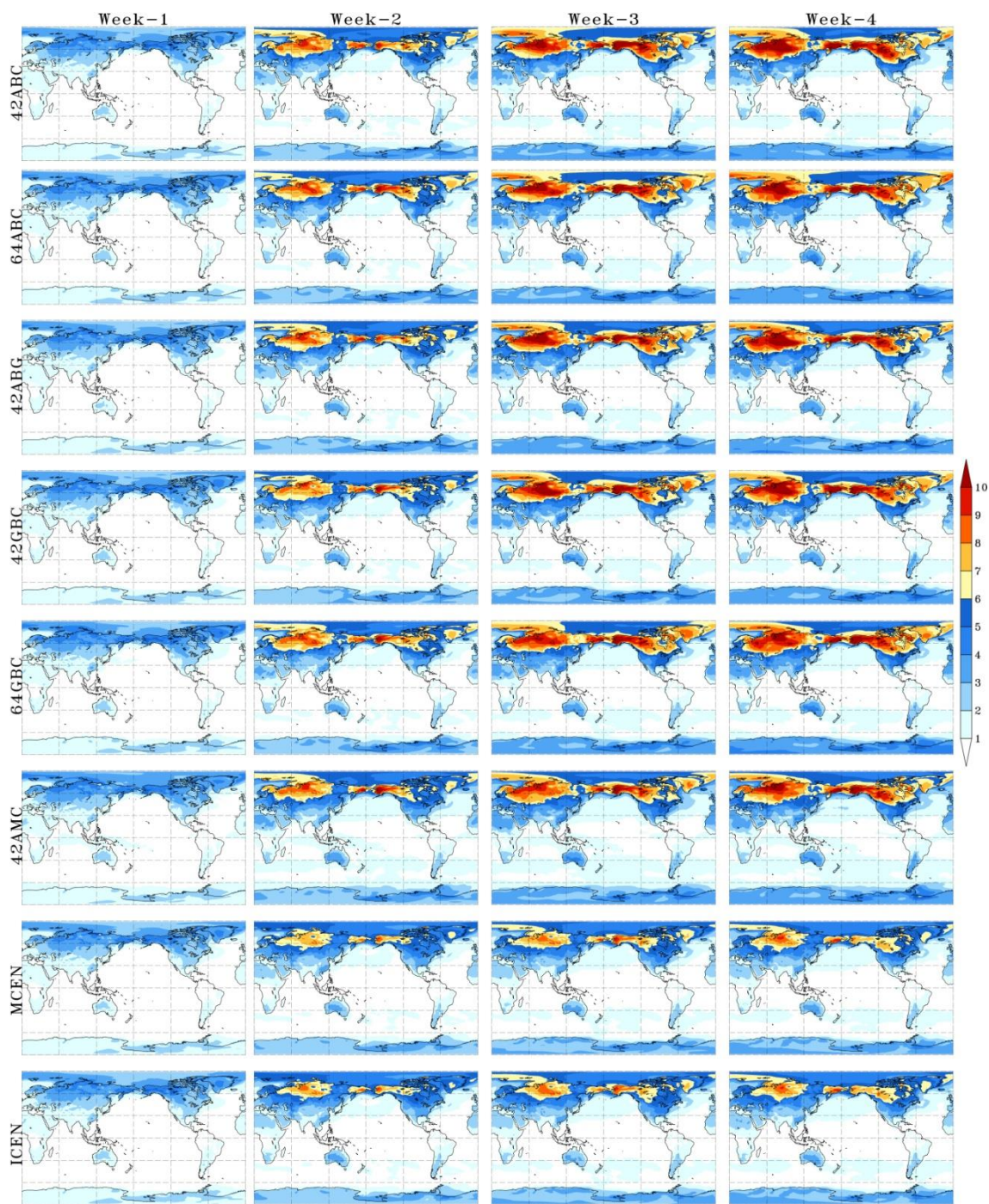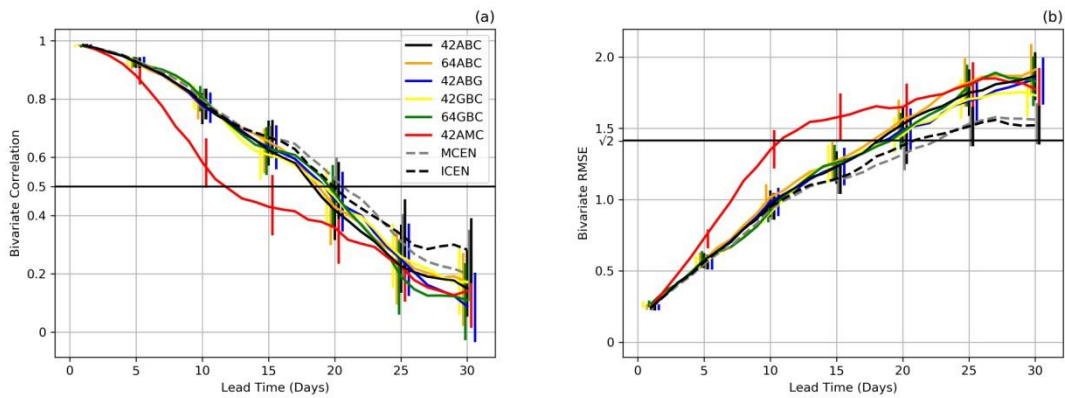
848

849   Figure 5: Same as Figure 2, except for T2M anomaly (units are °C).

850

851 Figure 6: Same as Figure 3, except for T2M anomaly.

852

853 Figure 2: Bivariate correlation (a) and bivariate RMSE (b) for six BAM-1.2 configurations
854 (42ABC, 64ABC, 42ABG, 42GBC, 64GBC and 42AMC) and the two ensemble approaches
855 (MCEN and ICEN) as a function of forecast lead time (in days). The hindcasts were initialized
856 within the extended austral summer period (from November to March 1999/2000 – 2010/2011)
857 on the dates shown in Table 1. The vertical bars around lead times 1 to 30 days plotted every 5
858 days represent 95% confidence intervals produced using a bootstrap resampling procedure with
859 replacement with 1000 samples. These vertical bars are slightly displaced from the exact lead
860 time location in the horizontal axis to facilitate visualization. Note that two black vertical bars
861 are plotted every 5 days, with the first of these bars corresponding to 42ABC and the second
862 corresponding to ICEN.

863