SHORT COMMUNICATION

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A perspective for advancing climate prediction services in Brazil

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Abstract

The Climate Science for Service Partnership Brazil (CSSP-Brazil) project provides Brazil and UK partners the opportunity to address important challenges faced by the climate modeling community, including the need to develop subseasonal and seasonal prediction and climate projection services. This paper provides an overview of the climate modeling and prediction research conducted through CSSP-Brazil within the context of a framework to advance climate prediction services in Brazil that includes a research-to-services (R2S) and a services-to-research (S2R) feedback pathway. The paper also highlights plans to advance scientific understanding and capability to produce beneficial climate knowledge and new products to improve climate prediction services to support decisions in various industries in Brazil. Policy-relevant outcomes from climate modeling and prediction exercises illustrated in this paper include supporting stakeholders with climate information provided from weeks to months ahead for (a) improving water management strategies for human consumption, navigation, and agricultural and electricity production; (b) defining crop variety and calendars for food production; and (c) diversifying energy production with alternatives to hydropower.

The Climate Science for Service Partnership Brazil (CSSP-Brazil) is a research project supported by the UK and Brazilian governments, which aims to establish a strong and sustainable partnership between research institutions and climate scientists in the two countries. The project is supported by the UK Newton Fund and Brazilian research and education funding agencies (CNPq [National Council for Scientific and Technological Development] and CAPES [Coordination for the Improvement of Higher Education Personnel]). Brazilian research partners include the National Institute for Space Research (INPE), the National Institute for Amazon Research (INPA), and the National Centre for Monitoring and Early Warnings of Natural Disasters (CEMADEN). INPE collaborates with Brazilian and UK partners in this project on various climate modeling scientific aspects, to configure and evaluate the performance of global models in representing relevant physical processes to produce climate simulations and predictions for Brazil, including assessing these predictions against observational datasets. Such evaluations are fundamental to implement climate services that support climate-resilient economic development and social welfare.
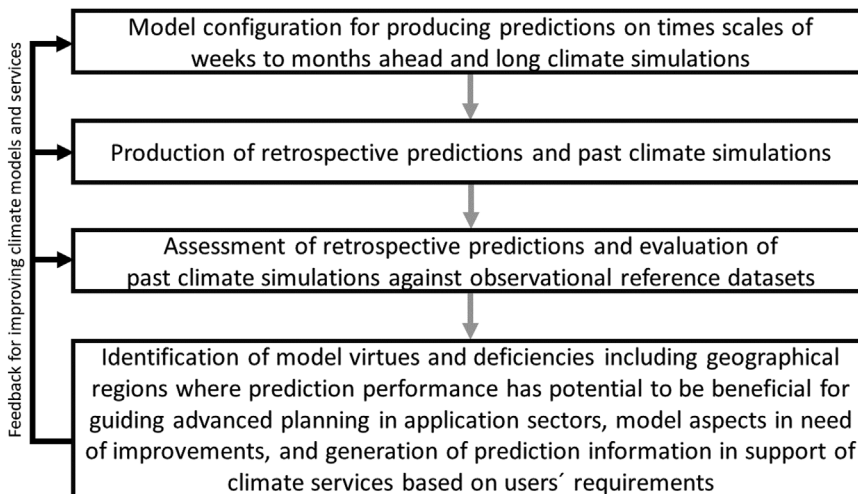
CSSP-Brazil is providing INPE and UK partners the opportunity to address important challenges faced by the climate modeling community, including the need to develop subseasonal and seasonal prediction and climate projection services, which are relevant to various industries in Brazil (e.g., agricultural and fishery production, water management, and energy production to name a few). All these sectors are affected by future weather and climate conditions on scales of weeks, months, and decades. Prediction of rainfall characteristics, such as the expected number of wet and dry days and rainy season onset timing, is a long-standing demand of these sectors, the latter also commonly required by the general public and the media. Developing and evaluating climate model prediction capabilities to deliver novel prediction products and services across these time scales is therefore fundamental to build a resilient and sustainable future for our society.

Figure 1 illustrates a framework to advance climate prediction services in Brazil, which contains four pillars, a research-to-services (R2S) and a services-to-research (S2R) feedback pathway. The first pillar consists of configuring the model for producing weekly to monthly predictions, and long (on the order of 30 years) climate simulations. The second pillar involves performing retrospective predic-

tions and historical climate simulations. Retrospective predictions are those produced using only information (such as initial conditions) that was available prior to the prediction period after the events were observed; these are also known as hindcasts (Coelho et al., 2006; Lee et al., 2006). They are essentially identical to real-time predictions, but performed for past dates. These retrospective predictions allow assessing model performance against observations gathered afterward. The third pillar comprises such a quality assessment (verification) of the retrospective predictions and an evaluation of historical climate simulations against observational reference datasets. The fourth pillar consists of identifying model virtues and deficiencies, including geographical regions where prediction performance can guide advanced planning in application sectors, model aspects in need of improvements, and the generation of prediction information to support climate services based on users' requirements. Through the services-to-research (S2R) feedback pathway (back arrows in Figure 1) users' and climate scientists can interact and exchange information to improve climate models and prediction services. Below we provide a brief overview of the research conducted in CSSP-Brazil through this framework.

Subseasonal predictions provide information for the expected (mean) atmospheric conditions usually for the forthcoming 4 weeks, although other time-averaging periods (e.g., over two consecutive weeks) are sometimes considered. These predictions are important to enable the abovementioned sectors to plan activities within the month following the prediction issuance date. As part of CSSP-Brazil modeling research activities, Brazil and UK scientists configured and assessed retrospective prediction quality of a new Brazilian global subseasonal prediction model (Guimarães et al., 2020). The performance of weekly precipitation predictions from this model was next compared by Guimarães et al. (2021) and Klingaman et al. (2021) to other international models including the European Centre for Medium-Range Weather Forecasts (ECMWF), the Australian Bureau of Meteorology (BoM), the Japanese Meteorological Agency (JMA), the Environment and Climate Change Canada (ECCC), the USA National Centers for Environmental Predictions (NCEP), and the United Kingdom Met Office (UKMO). The Brazilian model performed competitively with other similar models during extended austral summer (November to March) when predicting weekly precipitation anomalies

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FIGURE 1 A framework for advancing climate prediction services in Brazil. The gray arrows illustrate the research-to-services (R2S) and the black arrows the services-to-research (S2R) feedback pathway.

Feedback for improving climate models and services

Model configuration for producing predictions on times scales of weeks to months ahead and long climate simulations
Production of retrospective predictions and past climate simulations
Assessment of retrospective predictions and evaluation of past climate simulations against observational reference datasets
Identification of model virtues and deficiencies including geographical regions where prediction performance has potential to be beneficial for guiding advanced planning in application sectors, model aspects in need of improvements, and generation of prediction information in support of climate services based on users' requirements

(measured through the correlation between predicted and observed anomalies as illustrated in figures 1 and 2 of Guimarães et al. [2021]), the daily evolution of the Madden and Julian Oscillation (MJO)—one of the main sources of subseasonal predictability (measured through the bivariate correlation and mean squared error [Lin et al., 2008] of the Real-time Multivariate MJO indices [Wheeler and Hendon, 2004] as illustrated in figure 9 of Guimarães et al. [2021]), and in representing South American precipitation patterns during different MJO phases (assessed through composite maps [i.e., mean conditions] during strong MJO events as illustrated in figure 12 of Klingaman et al. [2021]). Although subseasonal precipitation prediction performance (assessed using deterministic metrics for the ensemble mean anomaly and probabilistic metrics for the event positive precipitation anomalies, as described in Coelho et al. [2018]) was much lower at longer leads (weeks 3 and 4) than at shorter leads (weeks 1 and 2), moderate performance with some level of association (i.e., predicted anomalies positively correlated with observed anomalies) and discrimination (i.e., probabilistic predictions successfully distinguishing occurrence from nonoccurrence of the assessed event, assessed using the area under the Relative Operating Characteristics curve [AROC, Mason and Graham, 2002]) was still found over parts of the north, northeast, southeast, and south regions in Brazil as illustrated in figures 1, 2, and 5 of Guimarães et al. (2021). Improving model representation of the MJO using models capable of simulating ocean–atmosphere interactions is likely to improve precipitation predictions.

In a fourth study, Chevuturi et al. (2021a) evaluated subseasonal prediction performance for South American land–atmosphere coupling through soil moisture–evapotranspiration–precipitation and soil moisture–sensible heat flux–air temperature feedback pathways (Seneviratne et al., 2010) during extended austral summer in the Brazilian model (Guimarães et al., 2020),

as well as the international models assessed by Klingaman et al. (2021). This is important because land–atmosphere interactions through water and energy exchanges provide another source of predictability for the hydrological cycle. As land surface conditions usually evolve more slowly than atmospheric conditions, land surface conditions modulate atmospheric variability on scales longer than daily weather (synoptic) fluctuations (Dirmeyer et al., 2015; Dirmeyer et al., 2018; Koster and Suarez, 2001). The land surface can affect atmospheric variability when the following conditions are satisfied: (i) the atmosphere is sensitive to land surface state variations (coupling); (ii) the land surface state fluctuates (variability); and (iii) these fluctuations persist (memory). Chevuturi et al. (2021a) highlighted deficient representation of feedbacks between soil moisture and precipitation over the Amazon in the Brazilian and American models due to initial dry soil moisture biases. The study also found deficient feedbacks between soil moisture and temperature for all investigated models over southeastern South America, due to erroneous representations of sensible heat flux in the soil moisture to air temperature pathway. These deficiencies are associated with models' misrepresentation of the terrestrial leg of this pathway, which measures the strength of coupling between a surface variable (soil moisture) and a flux variable (evapotranspiration or sensible heat flux), and of the atmospheric leg of the pathway, which measures the relationship between the flux variable (evapotranspiration or sensible heat flux) and the atmospheric variable (air temperature or precipitation).

Improving Brazil's capability in simulating and predicting seasonal climate variability (average climate conditions usually over 3 months) is also a topic of great interest within the context of the collaborative CSSP-Brazil project. As part of CSSP-Brazil modeling research activities, Brazil and UK scientists produced and evaluated climate simulations with the Brazilian global atmospheric

climate model at two spatial resolutions (Coelho et al., 2021a). Aspects such as the representation of precipitation interannual variability, El Niño-Southern Oscillation (ENSO) precipitation teleconnections, and daily precipitation characteristics were assessed. Precipitation interannual variability was investigated by examining the correlation between model simulated and observed seasonal precipitation. ENSO teleconnections were assessed by examining global maps of correlation values between seasonal precipitation and the Southern Oscillation Index (SOI, Philander, 1985) and checking whether the model represents the patterns typically manifested during El Niño and La Niña conditions (Karoly, 1989; Wallace and Gutzler, 1981). Characteristics such as persistence, intermittency, and spatial structure (size and orientation) of daily precipitation were assessed using the methods of Klingaman et al. (2017) and Martin et al. (2017). The model's capability to represent interannual precipitation variability at both resolutions was linked to the adequate representation of ENSO teleconnections, measured through the pattern correlation between the simulated and observed seasonal teleconnection patterns. As ENSO is the main source of predictability on the seasonal time scale (Goddard et al., 2001), having diagnosed that the Brazilian global atmospheric climate model can simulate the observed ENSO precipitation teleconnections provides confidence for using this model for issuing predictions in real time for delivering climate services. The daily precipitation assessment revealed that light precipitation was overestimated, and heavy precipitation underestimated by the model over the southeast of South America. Increasing spatial resolution slightly reduced some of the identified biases, for example, by making the probability density function of model-simulated daily precipitation at the same grid point on consecutive days better resemble the corresponding observed probability density function, and therefore largely correcting the light precipitation overestimation and heavy precipitation underestimation reported above.

The monsoon is one of the most important phenomena in terms of both scientific and societal interests, as a large portion of the world's population lives in regions affected by monsoon climate features. In a second climate-related CSSP-Brazil study, Coelho et al. (2021b) assessed the representation of South American Monsoon features in simulations produced with the Brazilian (Coelho et al., 2021a) and UK (Ridley et al., 2018; Williams et al., 2018) global climate models. The assessment evaluated the models' ability to represent major climate features, such as the South American summer and winter precipitation contrast and associated atmospheric circulation, key elements of the South American monsoon system during spring and summer, and the climatological distributions of rainy season onset and demise dates over the core South American monsoon

region. Despite the identified model deficiencies, including misrepresentation of cloud–radiation interactions in the Brazilian model, both models depicted the monsoon-affected region, and adequately represented the main monsoon features including the regional Walker circulation during both the premonsoon (spring) and peak monsoon (summer) seasons. Investigating new approaches to represent clouds for improving cloud optical properties and parameters such as cloud fraction, and liquid and ice water content in future versions of the Brazilian model could improve the representation of cloud–radiation interactions. Both models captured the main observed climatological features of rainy season onset and demise dates, although the UK model overestimated the interannual variability of onset dates.

In another collaborative CSSP-Brazil study, Baker et al. (2021a) assessed land–atmosphere interactions on annual to seasonal time scales over South America in the same Brazilian (Coelho et al., 2021a) and UK (Ridley et al., 2018; Williams et al., 2018) global climate models. Key features of South American land–atmosphere interactions were identified in both observations and model simulations, including seasonal variations in coupling strength, large-scale spatial variations in the sensitivity of evapotranspiration to surface moisture, and a dipole in evaporative regime across the continent (Figure 2). In regions where models and observations disagreed on the strength and direction of land–atmosphere interactions (e.g., along the tropical North Atlantic coast; Figure 2), precipitation biases and misrepresentations of processes controlling surface soil moisture, such as soil water storage capacity, runoff rate, and vegetation water uptake, were implicated as likely drivers for the disagreement. These results illustrated regions where improved representations of the physical processes controlling soil moisture could reduce uncertainty in the modeled climate responses to land-use change, and highlighted areas where model soil moisture biases could unrealistically amplify drying or wetting trends in future climate projections. Besides identifying the importance of soil moisture, it was not possible to use the existing AMIP-type simulations to identify more precisely which model mechanisms contributed to the misrepresentation of land–atmosphere interactions over some parts of South America. Future work could use model experiments to address this question in more detail. Model experiments could be designed to test the impacts of new land initialization procedures on soil moisture, evapotranspiration, precipitation, and temperature conditions. In situ observations and satellite-derived datasets are key ingredients for both model initialization and evaluation.

Baker et al. (2021a) also found that the Brazilian and UK climate models were consistent with the median response
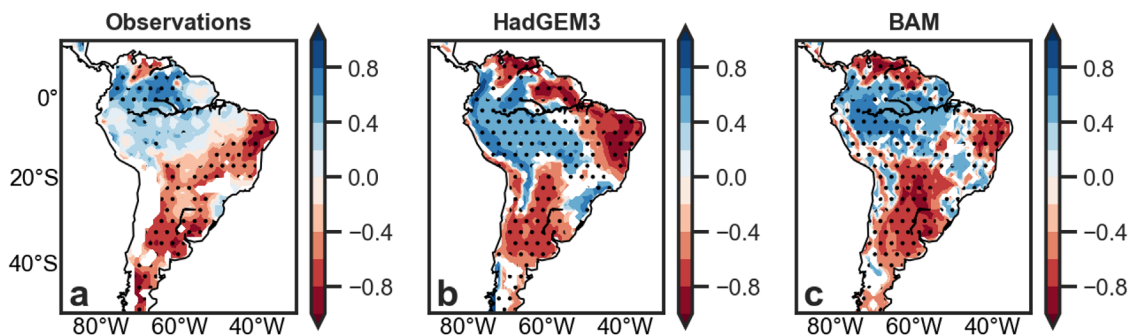
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FIGURE 2 Variation in evaporative regime across South America. Maps show results from the temperature–evapotranspiration metric (correlation between these two variables) in December–February for observations (a), HadGEM3 (b), and BAM (c). Blue shading indicates a radiation-limited evaporative regime (temperature and evapotranspiration are positively related) and red shading indicates a water-limited evaporative regime (temperature and evapotranspiration are negatively related). Stippling indicates relationships that are statistically significant at $p < 0.05$. Observations of land surface temperature come from Atmospheric Infrared Sounders (AIRS) and evapotranspiration data come from Moderate Resolution Imaging Spectroradiometer (MODIS). For full details of the analysis, see Baker et al. (2021a). The land–atmosphere coupling diagnostic scripts used in Baker et al. (2021a) are available from https://github.com/jcabaker/land_atm_coupling.

of an ensemble of nine Coupled Model Intercomparison Project (CMIP6) models, illustrating they are broadly representative of the latest generation of climate models in simulating land–atmosphere interactions. In a related collaborative CSSP-Brazil study, Baker et al. (2021b) assessed the credibility of Amazon precipitation projections in CMIP5 models based on model representation of land–atmosphere interactions. The ensemble mean of models presenting realistic land–atmosphere interactions in past (historical) simulations revealed a robust drying signal over the eastern Amazon and in the dry season in future projections, with precipitation increasing in the western Amazon. Another recent study showed that the eastern Amazon has already experienced greater land-use and climate change over the past four decades than other areas of the basin, resulting in higher moisture stress, tree mortality, and fire occurrence, causing the region to become a source of carbon emissions to the atmosphere (Gatti et al., 2021). The analysis from Baker et al. (2021b), which used model projections based on a high-emissions scenario (RCP8.5), indicates that drying over the eastern Amazon could continue for the duration of the century, with serious implications for the regional carbon balance. Furthermore, Baker at al. (2021b) showed that the factors controlling Amazon evapotranspiration evolved over time in realistic CMIP5 models, reducing climate stability and suggesting that the Amazon may become more vulnerable to climate change as the century progresses.

The CSSP-Brazil collaborative modeling studies discussed here identified model aspects requiring improvements or new developments, several of which have also been identified in modeling studies outside CSSP-Brazil. For the Brazilian model, the following aspects were highlighted: improving spatial resolution to refine predictions

for regional applications (Prodhomme et al., 2016); improving model parameterization schemes (Freitas et al., 2021), particularly cloud parameterizations to improve cloud–radiation interactions; implementing new land initialization procedures, to improve land–surface modeling and the simulation and prediction of land–atmosphere interactions (Koster et al., 2004); coupling to an interactive ocean to improve the representation of the diurnal cycle of the sea surface temperature and MJO predictions, in the light of the importance of ocean–atmosphere interactions for a better representation of this phenomenon (DeMott et al., 2015; Woolnough et al., 2007); and testing new approaches for ensemble generation to improve probabilistic subseasonal prediction quality. The use of multiple sources of observations (in situ and satellite estimates) is fundamental to evaluate the impacts of these model changes for improving predictions and simulations.

The CSSP-Brazil studies discussed here can also provide support for the use of model predictions for delivering improved climate services for various societal sectors. Such a research-to-services (R2S) pathway (illustrated by the gray arrows in Figure 1) was successfully paved with the Brazilian climate model evaluated in CSSP-Brazil, which has been used to produce real-time seasonal predictions at INPE's Center for Weather Forecast and Climate Studies (CPTEC) since May 2020. This is well aligned with the CSSP-Brazil overall concept: collaborative science performed between Brazil and UK scientists to advance and improve climate services. Figure 3 (left panel) shows the probabilistic precipitation seasonal prediction, expressed as probabilities for the most likely tercile category, for October–December (OND) 2020 produced with the Brazilian CPTEC/INPE model (Coelho et al., 2021a) in September 2020 (i.e., near the peak of the 2020/21 La Niña
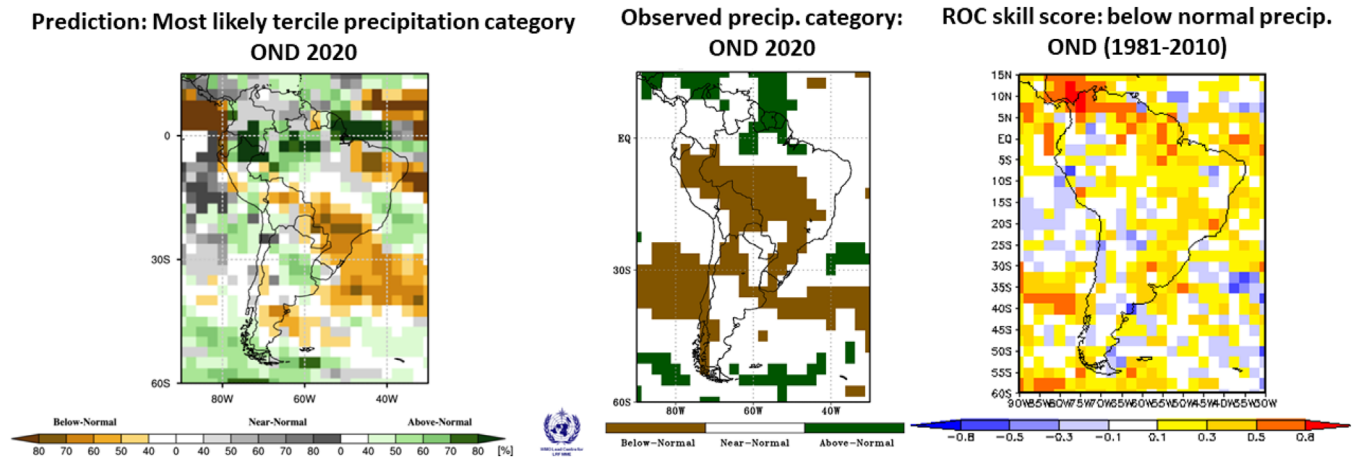
FIGURE 3 First column: Most likely tercile precipitation probability prediction for OND 2020 produced in September 2020 with the Brazilian CPTEC/INPE model (Coelho et al., 2021a). Green, gray, and brown colors indicate that the upper tercile (above normal), central tercile (normal), and lower tercile (below normal) categories are predicted as the most likely, respectively. Second column: Observed precipitation category (GPCP, Adler et al., 2003) in OND 2020. Third column: A measure of prediction performance expressed as twice the area under the Relative Operating Characteristics curve (AROC) minus one computed for retrospective predictions over the 1981–2010 period for the model probabilistic predictions for the event precipitation in the lower tercile (below normal) category. Values above 0 indicate that the model-predicted probabilities are better able to distinguish occurrence from nonoccurrence of precipitation in the lower tercile than the random (50%) reference value.

event). The prediction indicated that the most likely category was the lower tercile (below normal) in part of central and south Brazil and the upper tercile (above normal) in part of northern Brazil. Figure 3 (central panel) shows that over central and south Brazil below normal precipitation was observed, and over part of north Brazil above normal precipitation was observed in OND 2020, illustrating that over these regions the predictions indicated well the expected conditions 1 month in advance. Figure 3 (right panel) shows that over these regions, the model produced probabilistic predictions that better distinguished occurrence from nonoccurrence of below-normal precipitation than the random (50%) reference value when evaluated retrospectively. The value 50% is the probability of correctly discriminating (distinguishing) an event from a nonevent by chance (guessing). These predictions could, for example, be integrated into fire alert systems (Anderson et al., 2021).

Figure 4 shows another example, this time a subseasonal prediction produced with the Brazilian CPTEC/INPE model (Guimarães et al., 2020) on November 3, 2019 for the following 4 weeks. The probabilistic predictions (first row) indicate high probabilities of dry anomalies over northeast Brazil during the first 2 weeks, which agree with the observations (second row). The probabilistic predictions also indicate high probabilities of wet anomalies over northern South America during the last 2 weeks, which also agree with the observations. Over these regions, the model showed a better retrospective ability to distinguish occurrence from nonoccurrence of a positive anomaly than the

random (50%) reference value (third row). This illustrates the sort of subseasonal prediction information that can be produced and disseminated for the benefit of various application sectors, including hydrological predictions (Chevuturi et al., 2021b).

Future CSSP-Brazil collaboration plans involving INPE and UK partners for advancing climate prediction services include the assessment of the Brazilian and UK climate models in the representation of tropical–extratropical cloud bands, and assessment of a configuration of the Brazilian model for subseasonal predictions, consisting of the current atmospheric model (Guimarães et al., 2020) coupled to a mixed-layer ocean model, following Hirons et al. (2015) for the UK model. The South Atlantic converge zone (Kodama, 1992, 1993) is the tropical–extratropical cloud band that manifests over Brazil during austral spring and summer, contributing to a large portion of the observed annual precipitation. Evaluating the ability of models to represent this cloud band and developing associated prediction products for subseasonal and seasonal time scales will enrich the portfolio of information for dissemination. Advancing research and prediction services by producing probabilistic predictions of rainy season onset (Coelho et al., 2017) is another avenue to be explored. Further research should also evaluate the ability of models to reproduce characteristics such as the number of wet and dry days within a week, month, and season and the quality of associated prediction products. These research topics are based on previous experience with users, ranging from the general public to the media and government agencies,
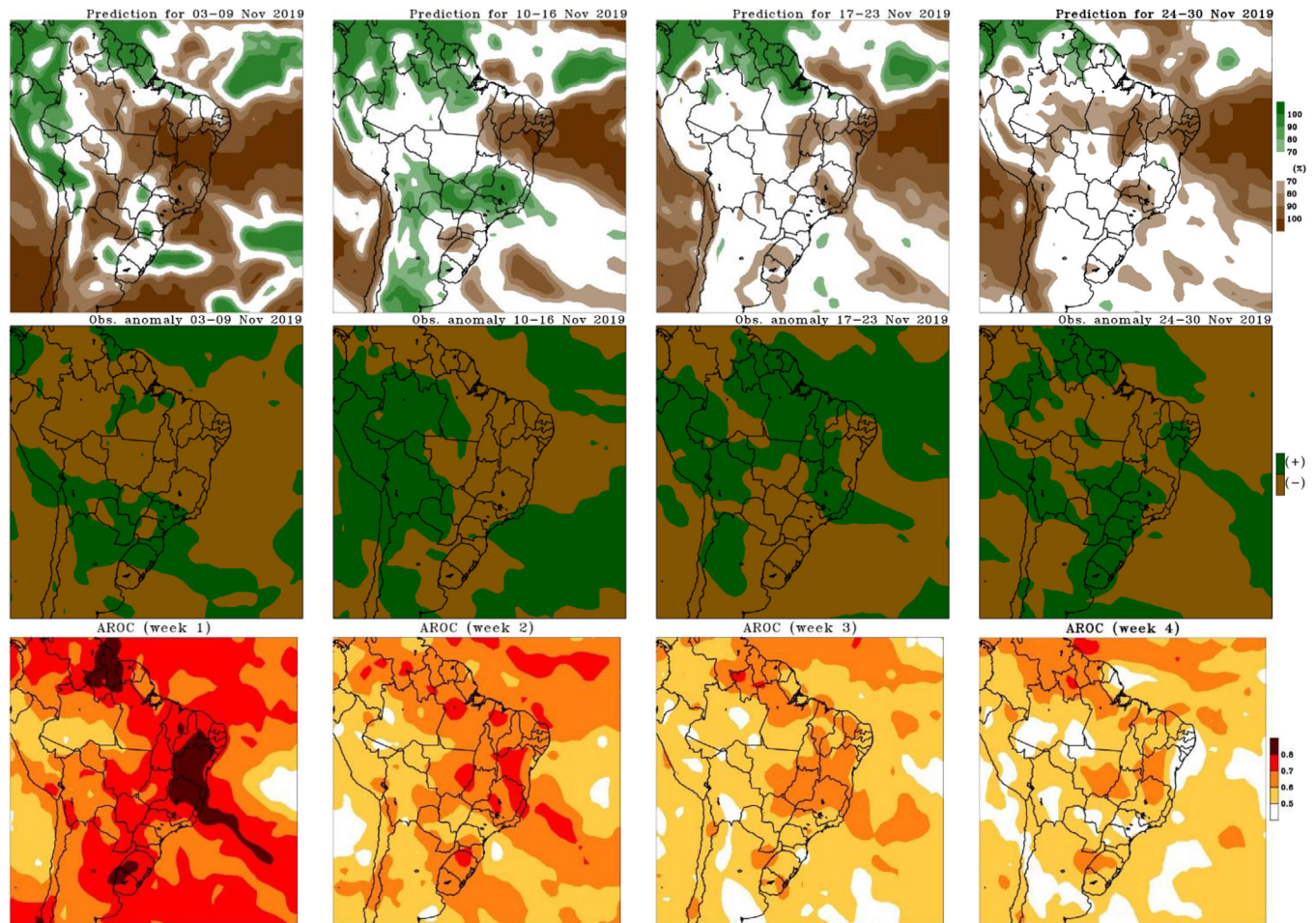
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FIGURE 4 First row: Precipitation predictions expressed in terms of probability for a wet anomaly (green) and for a dry anomaly (brown) produced with Brazilian global subseasonal prediction model (Guimarães et al., 2020) on November 3, 2019 and valid for the weeks of November 3–9, 2019 (first column), November 10–16, 2019 (second column), November 17–23, 2019 (third column), and November 24–30, 2019 (fourth column). Second row: Corresponding observed precipitation anomalies (GPCP, Huffman et al., 2001) for the 4 weeks (columns). Positive (negative) precipitation anomalies are illustrated in green (brown). Third row: A measure of prediction performance given by the area under the Relative Operating Characteristics curve (AROC) for the 4 weeks (columns) computed over the 1999–2010 period for the model probabilistic predictions for the event positive precipitation anomaly (see Guimarães et al., 2021 for full details of this assessment). Values above 0.5 indicate that the model-predicted probabilities are better able to distinguish occurrence from nonoccurrence of a positive anomaly than the random (50%) reference value.

that seek such additional climate information for planning activities in various socioeconomic sectors in Brazil. In addition to developing these products to deliver new prediction services, an important component of the process is to promote the adequate interpretation of the new prediction products, including the limitations.

Envisaged societal benefits as outcomes from CSSP-Brazil climate modeling and prediction research activities include access to novel and improved subseasonal and seasonal prediction products to support planning of weather and climate-sensitive activities from weeks to months ahead. Benefits also include improved understanding about the expected climate conditions in the next

few decades to support the development of adaptation plans, particularly for the most vulnerable regions and populations.

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