Improving Seasonal Precipitation Forecasts for Agriculture in the Orinoquía Region of Colombia

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(Manuscript received 17 June 2019, in final form 7 October 2019)

ABSTRACT

Canonical correlation analysis (CCA) is used to improve the skill of seasonal forecasts in the Orinoquía region, where over 40% of Colombian rice is produced. Seasonal precipitation and frequency of wet days are predicted, as rice yields simulated by a calibrated crop model are better correlated with wet-day frequency than with precipitation amounts in June–August (JJA). Prediction of the frequency of wet days, using as predictors variables from the NCEP Climate Forecast System, version 2 (CFSv2), results in a forecast with higher skill than models predicting seasonal precipitation amounts. Using wet-day frequency as an alternative climate variable reveals that the distribution of daily rainfall is both more relevant for rice yield variability and more skillfully predicted than seasonal precipitation amounts. Forecast skill can also be improved by using the Climate Hazards Infrared Precipitation with Stations (CHIRPS) merged satellite–station JJA precipitation as the predictand in a CCA model, especially if the predictor is CFSv2 vertically integrated meridional moisture flux (VQ). The probabilistic hindcast derived from the CCA model using CHIRPS as the predictand can successfully discriminate above-normal, normal, and below-normal terciles of over 80% of the stations in the region. This is particularly relevant for stations that, due to discontinuity in their time series, are not included in station-only CCA models but are still in need of probabilistic seasonal forecasts. Finally, CFSv2 VQ performs better than precipitation as the predictor in CCA, which we attribute to CFSv2 being more internally consistent in regards to sea surface temperature (SST)-forced VQ variability than to SST-forced precipitation variability in the Orinoquía region.

Denotes content that is immediately available upon publication as open access.

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/WAF-D-19-0122.s1>.

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1. Introduction

The Orinoquía region, located in the eastern plains of Colombia, is characterized by abundant precipitation and a flat landscape making it ideal for mechanized agriculture. Over 40% percent of Colombia's total rice production comes from the region, where further expansion is planned for the coming years (DNP 2018). Not surprisingly, the demand for improved and tailored

DOI: 10.1175/WAF-D-19-0122.1

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climate information for agricultural applications in Colombia has accelerated in recent years (Delcerce et al. 2016; Esquivel et al. 2018; Loboguerrero et al. 2018). Although real-time seasonal precipitation and temperature forecasts are available to Colombian users from various local and international sources, including the Colombian Instituto de Hidrologia, Meteorologia y Estudios Ambientales (IDEAM), they are not uniformly skillful across the country (Barnston et al. 2010; Krishnamurthy et al. 2018) or available at a spatial scale that is useful for the decision-making process on the ground.

The potentially predictable component of seasonal climate variability is linked, through atmospheric teleconnections, to those due to oceanic forcings such as the El Niño–Southern Oscillation (ENSO) (Rowell 1998). In western and northern Colombia, abundant precipitation is observed during La Niña whereas drought occurs during El Niño (Poveda et al. 2011; Poveda et al. 2001). Tropical South American climate is also impacted by variability in the Atlantic sea surface temperatures (SST) at various time scales (Fernandes et al. 2011; Fernandes et al. 2015; Yoon and Zeng 2010) suggesting that the potential for skillful seasonal forecast in northern South America resides in the combined effect of SSTs in both the Atlantic and Pacific basins (Esquivel et al. 2018; Muñoz et al. 2016; Recalde-Coronel et al. 2014). During the December–February ENSO's peak season, general circulation models (GCMs) produce skillful forecast in areas of Colombia where the ENSO signal is strong, whereas in the Orinoquía region forecast skill tends to be poorer (Barnston et al. 2010), leaving this important agricultural region lacking reliable climate information to support agro-climatological forecasts and agricultural climate services.

One alternative is to use statistical techniques, such as canonical correlation analysis (CCA) to reproduce relationships between the local climate and remote forcings and to correct systematic errors of dynamical (GCMs) outputs (Barnston and Tippett 2017; Tippett and Barnston 2008). CCA has been used extensively in Latin America to produce seasonal forecasts (Alfaro et al. 2018; Muñoz et al. 2016; Recalde-Coronel et al. 2014). In Colombia, Esquivel et al. (2018) assess seasonal forecast skill for five Colombian departments, including Casanare (which is situated in the Orinoquía region). Their findings show Casanare as the department with the poorest forecast skill, regardless of season, predictor, and lead time. Here, we build on those results, and explore the prediction of variables other than the commonly used seasonal precipitation amounts, such as frequency of wet days, as anticipating the behavior of daily precipitation within the rainy season is often of

greater use for agricultural planning (Ndiaye et al. 2009; Revadekar and Preethi 2012) and more skillfully predicted than seasonal precipitation amounts (Maldonado et al. 2013; Moron et al. 2009; Robertson et al. 2009; Verbist et al. 2010). CCA also offers the advantage of exploring how regional physical processes, such as variability of surface wind and atmospheric instability forecasted by GCMs, impact the observed local climate (Alfaro et al. 2018; Muñoz et al. 2016; Ndiaye et al. 2009) and could thus be effectively used as predictors in statistical models.

Our study aims to determine when, during its growing cycle, is rice yield most sensitive to variations in precipitation characteristics. Once that is defined, we design and evaluate the performance of CCA models built using station-only and satellite–station-merged precipitation datasets as predictands paired with traditional predictors, namely, tropical SST and precipitation seasonal forecasts from a dynamical model. Finally, we introduce the use of vertically integrated meridional moisture flux seasonal forecasts as an alternative predictor to regional precipitation in a CCA framework. The paper is structured as follows: the observational datasets, models, and methodological approaches are detailed in section 3, following a description of the Orinoquía region area of study (section 2). The results are described in section 4, whereas in section 5, a discussion is presented followed by conclusions in section 6.

2. The Orinoquía region

The Orinoquía Natural Region of Colombia comprises the departments of Meta, Casanare, Vichada, and Arauca, bordered to the west by the Andean Cordillera Oriental and to the south by the Amazon rain forest. Topography is mostly flat (Fig. 1b), making the region ideal for mechanized agriculture and one of Colombia's focus regions for large-scale agricultural development (DNP 2018).

Over 40% of Colombia's total rice production is grown in the region, with Casanare and Meta containing the majority of the harvested area (Fedearroz 2017). The climate is typical of the humid tropics, with abundant precipitation for most of the year (Fig. 2) and one well defined dry season from December to February. Mean temperature oscillates little seasonally with average values around 22°C in the cooler and wetter months to around 28°C in warmer and drier months (Gutiérrez et al. 2011).

3. Data and methods

a. Station data

Meteorological stations' daily precipitation records from IDEAM were aggregated to monthly precipitation

FIG. 1. Topographic maps of (a) Colombia and (b) the Orinoquía region. Red and yellow dots in (b) represent 48 meteorological stations with less than 15% of data missing over the period 1980–2014. Purple dots represent 30 stations with between 16% and 25% of its total record missing. Labeled yellow dots in (b) show the 8 stations for which rice yield simulations are available (see text for detail).

and number of wet days. Upland rice yields can be adversely affected when nutrient availability is reduced due to prolonged soil water content deficiency (Fageria 2001; Heinemann et al. 2015; Heinemann et al. 2019; Heinemann et al. 2011). Precipitation that is well distributed over the crop's growing phase results in less oscillation in soil water content than precipitation that occurs concentrated in a few days followed by dry spells. Accordingly, frequency of rainy days has been found to impact rice yield variability more significantly than precipitation amounts (Fishman 2016; Revadekar and Preethi 2012). Thus, we choose wet-day frequency as a metric to evaluate rice yield response in the Orinoquía region. Wet days are defined here as the number of days in which daily precipitation surpasses the monthly climatology (in millimeters per day) for the month of interest. For example, if climatological daily precipitation at station X is 10 mm day^{-1} in September, the days in which precipitation is above that value are counted and added for every September in the time series. The choice of monthly climatology as a threshold for wet-day frequency calculation allows for a relative and comparable metric among all stations. The main rice calendar in the Orinoquía region consists of planting from March to May, followed by crop flowering phase in June–August (JJA) and the bulk of the harvest occurs in September–November (SON) (Gutiérrez et al. 2011).

In this study, we use 48 IDEAM stations that contain a maximum of 15% of its record missing over the 1982–2014 period (red and yellow dots in Fig. 1b) and 30 stations (purple dots in Fig. 1b) that contain 16%–25% of its total record missing. Taken all together, precipitation climatology (all 78 stations) is highly seasonal varying from an average of 50 mm in January to 400 mm at the peak of the wet season in June

FIG. 2. Climatological precipitation of IDEAM stations (Fig. 1b) over the 1982–2014 period. The dots represent individual stations' climatology. The red line indicates the mean value among stations.

(Fig. 2). We distinguish the group of stations by their amount of data missing because those with a maximum of 15% of the record missing are used for the station-only CCA models whereas those with a larger amount are not.

b. Climate Hazards Infrared Precipitation with Stations (CHIRPS)

CCA experiments were also designed using CHIRPS satellite–station–merged precipitation (Funk et al. 2015), at a monthly time step for the period 1982–2018 and 0.25° spatial resolution. The spatial domain comprises of the four departments in the Orinoquía region. The primary computing time step for CHIRP (without the stations) is the pentad (5 days) that is aggregated to the secondary monthly time step. There are several publicly available station data sources incorporated into the blending procedure, which is based on modified inverse distance weighting algorithm calculated preliminarily on pentads, and then monthly totals. Our analyses were conducted on seasonal averages processed from the CHIRPS monthly product.

c. NCEP Climate Forecast System

Regional precipitation fields and SST from the NCEP Climate Forecast System, version 2 (CFSv2) (Saha et al. 2014), were used as predictors to seasonal precipitation and number of wet days. Our study aims to complement that of Esquivel et al. (2018) and thus our initial choice of CFSv2 predictors. Although CFSv2 precipitation has shown limited performance in parts of the Orinoquía region (Esquivel et al. 2018) we retain it as a predictor as our area of study comprises a larger domain. Lower atmosphere vertically integrated (1000–500 hPa) meridional moisture flux (VQ) is also used as a predictor as near-surface fluxes have been shown to impact precipitation variability in tropical South America (Fu et al. 2001; Hoyos et al. 2018; Wang and Fu 2002). The CFSv2 model retrospective forecast is available from January 1982 to March 2011, and real-time forecasts are available from April 2011 to the present. The CFSv2 model produces seasonal forecasts with a 9-month lead time, and with four initial conditions for each month (starting at 0000, 0600, 1200, and 1800 UTC), every fifth day to result in 24 ensemble members per month. The ensemble members are averaged and used as predictors to precipitation and wet-day frequency in a CCA framework (Barnston and Smith 1996; Mason and Tippet 2017). Forecast lead time 1 (L-1) refers to, for example, the June–August forecast that is produced in May. Similarly, lead 2 (L-2) and lead 3 (L-3) corresponds to

June–August forecasts that are produced in April and March, respectively.

d. Rice crop model simulations with the ORYZAv3 model

Crop modeling provides time and cost-effective means to simulate a limited number of field and laboratory studies and scale them up to larger spatial and temporal scales. In both lowland and upland rice systems, a large number of application studies have shown that ORYZAv3 (Li et al. 2017) is a robust model that provides reliable predictions for rice growth and yield and it has been used to identify better rice crop management options worldwide (Agustiani et al. 2018; Van Oort and Zwart 2018; Yuan et al. 2017). ORYZAv3 includes modules to simulate plant and soil carbon, water, and nitrogen dynamics, including reproducing nitrogen transformations in response to environmental factors such as soil moisture and temperature. The model accounts for temperature, drought, and nitrogen stress, as well as their interactions (Li et al. 2017). Model parameterization for Fedearroz variety 174 (Gutierrez et al. 2011) was performed following Heinemann et al. (2015) by first calculating phenology parameters (development rate in juvenile, photoperiod-sensitive, panicle development, and reproductive phases) using data on emergence, panicle initiation, flowering and physiological maturity dates, and then calculating growth parameters using a genetic algorithm, whereas model evaluation ensured that simulations were within the range of observations for trials not used for calibration (see the online supplemental material text and Fig. S1 for details). ORYZAv3 simulations are run with IDEAM's meteorological stations daily data at eight locations (Fig. 1b) in which 15% or less of its record is missing (matching the settings for the CCA experiments). Daily precipitation, relative humidity, and maximum and minimum temperatures are available for the period 1982–2014 and used in simulations initialized at various planting weeks every year. Annual yield is an average of simulations with planting dates ranging from the first week of March to the last week of May and have here the sole objective of determining how and when, during the crop growing cycle, yield responds to variations in precipitation characteristics. Once that is determined, more skillful seasonal probabilistic forecast of the desired variable (e.g., precipitation) can provide information on shifts in the probability density function relative to climatology described normally in terms of the terciles being below normal, normal, and above normal. Connecting probabilistic outputs with crop models requires disaggregating seasonal climate forecast into daily information. This can be attained by

employing both parametric and nonparametric statistical downscaling methods (Han and Ines 2017). Regardless of the downscaling method of choice, reliable crop yield simulations can only be accomplished if they are based on skillful seasonal climate forecast.

e. CCA experiments design

The Climate Predictability Tool (CPT) (Mason and Tippett 2017), which enables the user to build CCA models, is employed in this study. The use of CPT provides a computationally inexpensive, efficient and user-friendly implementation of CCA-based seasonal forecast models (Esquivel et al. 2018; Maldonado et al. 2013; Muñoz et al. 2010; Recalde-Coronel et al. 2014). The method consists of first prefiltering predictors and predictands using empirical orthogonal function (EOF) to reduce the dimensionality of the sample space. Then, the CCA-based prediction model optimizes the relationships between the patterns in the predictor and the predictand. Both EOFs and CCA were set to a maximum of five modes in CPT. For models using stations' precipitation or wet-day frequency as predictands, the data are first filtered to retain stations that contain 15% or less of its record missing. Then, if in any given year 10% or more stations are missing data, that year is not included in the CCA model. Once both filters are applied, the remaining data are gap filled using the best near-neighbor method in CPT resulting in the 48 stations previously mentioned. To decrease the chances of skill overestimation, cross validation is conducted by excluding five running consecutive years to predict the one in the center, which is later verified as a simulated independent case outside of the training sample (Barnston and van den Dool 1993; Michaelsen 1987). The overall skill of the models is presented as spatially averaged Kendall's τ rank correlation coefficient (Wilks 2011) or goodness index (GI), where positive values represent model performance superior to using climatological values.

CCA is often used to model patterns that result from teleconnections between a large-scale remote predictor (e.g., tropical SSTs) and a local predictand. It can also correct systematic biases in GCM forecasts through a model output statistics (MOS) by fitting, using linear regression, the GCM predictor to the target local predictand (Barnston and Tippett 2017). The candidate CFSv2 MOS predictors in our study are regional precipitation and VQ.

1) EXPERIMENTS WITH STATION-ONLY PREDICTANDS

The season target (JJA) for our CCA-based experiments was determined by evaluating when, within its

growing cycle, rice yield is most sensitive to fluctuations in precipitation characteristics (see section 4a). A large portion of precipitation variability in tropical South America is due to changes in atmospheric patterns related to anomalous SST in the adjacent tropical oceans (Fernandes et al. 2011; Poveda et al. 2001; Poveda et al. 2006; Ropelewski and Halpert 1987; Yoon and Zeng 2010). With that in mind, our CCA models are fitted using the tropical Atlantic and Pacific basins (20°S–20°N, 100°E–2°W) as the domain for the CFSv2 SST candidate predictor. The domain of choice for the MOS experiments using CFSv2 precipitation seasonal forecast as predictor in CCA covers all of Colombia (7°S–15°N, 80°–63°W), whereas the VQ domain (13°S–24°N, 98°–43°W) extends over tropical South America to account for patterns related to moisture transport from the oceans and the Amazon. The 48 stations included as predictands in the CCA experiments are distributed over the four departments of the Orinoquía region (Fig. 1b). Both precipitation amounts and wet-day frequency are predicted independently as the large-scale climate can impact total precipitation and daily distribution differently within a season (Grimm and Tedeschi 2009; Ropelewski and Bell 2008). A total of 10 total experiments are designed. Six correspond to the use of two predictands (precipitation and frequency of wet days) combined with three L-1 CFSv2 predictors (SST, precipitation, and VQ). Another four consist of combining the two predictands (precipitation and frequency of wet days) with CFSv2 SST as predictor at leads 2 and 3 (L-2 and L-3). The reasoning for the extra four experiments is presented in section 4b.

2) EXPERIMENTS WITH SATELLITE-STATION-MERGED PREDICTANDS

CHIRPS monthly precipitation data over the Orinoquía region (2°–8°N, 75°–67°W) is averaged for the JJA season and used as a predictand in CCA experiments. The same three L-1 predictors of section 3e(1) were used totaling three experiments, but for the period 1982–2018 to take advantage of the longer time series available for both CHIRPS and the CFSv2 hindcasts. The direct use of CHIRPS daily data in crop models is limited. Its calibration depends on the quality of data used in the satellite-station-merging process and on the density of the meteorological stations network reporting daily, which in eastern Colombia is sparse. Thus, we evaluate whether a skillful probabilistic seasonal forecast, using CHIRPS precipitation as a predictand in CCA, can discriminate the stations' above-normal, normal, and below-normal terciles. This is done by calculating the categorical generalized discrimination score (GROC). GROC is a generalization of the relative operating

characteristics (ROC) curve for forecast with more than 2 categories and measures how well the model discriminates observed below-normal, normal, and above-normal precipitation (Mason and Weigel 2009). The JJA probabilistic hindcasts, using CHIRPS as the predictand, is verified locally against observations from each of the 48 stations included in the CCA experiments. The same analysis is conducted for the extra set of 30 stations not included in the station-only models.

4. Results

a. Rice yield variability and climate

A large portion of rice yield interannual variability in Colombia can be explained by variations in seasonal precipitation (Delerce et al. 2016). As mentioned before, in the Orinoquía region, the main rice planting trimester is March–May (MAM), followed by flowering in June–August (JJA), and harvest in September–November (SON) (Gutierrez et al. 2011). In the eight locations where ORYZAv3 simulations are available (labeled yellow dots in Fig. 1b), yields show higher correlations with the variability of precipitation and frequency of wet days during the JJA flowering trimester (Table 1), whereas precipitation fluctuations during the planting trimester (MAM) have the least impact on rice yields followed by SON. Moreover, the daily distribution of precipitation in JJA, in the form of frequency of wet days, relates more significantly to the interannual variability of rice yield.

In sectors of the Orinoquía region however, forecast skill performance is the poorest in JJA compared to the other two trimesters (Esquivel et al. 2018). Thus, we initially focus on improving seasonal forecast skill of station-only JJA precipitation variables, given that station data are the primary source of meteorological variables for crop model simulations.

b. Improving forecast skill–station-only predictands

Table 2 describes the experiments designed using station-only data as predictands in CCA. Lead-1 (May) CFSv2 JJA precipitation does not perform well as predictor using CCA, especially to forecast seasonal precipitation (experiment 2), in agreement with poor precipitation forecast skill out of GCMs in eastern Colombia (Barnston et al. 2010; Krishnamurthy et al. 2018).

Better skill is obtained using CFSv2 VQ as a predictor to both station precipitation (experiment 3) and frequency of wet days (experiment 6). This is consistent with the work of Ndiaye et al. (2009), who found that low-level winds and related moisture transport can

TABLE 1. Pearson correlation between rice yield as estimated by the ORYZA crop model (1980–2014) and precipitation, and frequency of wet days in parentheses. March–May (MAM), June–August (JJA), and September–November (SON) correspond to the main planting, flowering, and harvest trimesters, respectively. Values in bold font are significant at $P < 0.05$ (t test).

	MAM	JJA	SON
Arauca	0.12 (−0.04)	0.38 (0.67)	0.37 (0.37)
Aguazul	−0.02 (−0.02)	0.5 (0.59)	0.17 (−0.03)
Orocué	−0.07 (0.02)	0.58 (0.73)	0.07 (0.35)
Cumaral	−0.27 (−0.09)	0.31 (0.34)	0.0 (0.07)
Granada	0.11 (0.1)	0.37 (0.43)	0.17 (0.07)
P. Gaitán	0.0 (−0.07)	0.35 (0.6)	0.12 (0.18)
V. Vicencio	0.09 (0.11)	0.21 (0.47)	0.41 (0.35)
Cumaribo	0.2 (0.16)	0.62 (0.63)	0.55 (0.37)

contain more of the SST-forced predictive information than precipitation in the Sahel, making the former a potentially more adequate predictor in a MOS configuration.

The best performance as measured by the GI is obtained using CFSv2 JJA tropical Pacific and Atlantic SSTs as a predictor to both precipitation and frequency of wet days and thus, experiments 1 and 4 are examined further. The spatial loadings of the first CCA mode (Figs. S2 and S3 show all CCA modes) describe patterns in the Pacific and Atlantic SSTs that are very similar in both experiments (Figs. 3a and 3b), but with slightly different responses in JJA precipitation amounts (Fig. 3c) and frequency of wet days (Fig. 3d). The first CCA mode suggests, for example, that a La Niña accompanied by warm North Atlantic results in more precipitation in the northern sector of Meta (positive values in Fig. 3c), but fewer than normal wet days (negative values in Fig. 3d), indicating that seasonal precipitation is distributed over fewer days with heavier daily precipitation rates. The counterpart of this behavior is an El Niño accompanied by cold Atlantic SST causing reduced seasonal precipitation amounts in northern Meta distributed over more days with lighter precipitation. Elsewhere in the region, the behavior is more straightforward describing a response in which above (below) average precipitation occurs concomitantly with higher (lower) frequency of wet days in response to an El Niño + cool Atlantic (La Niña + warm Atlantic).

The spatial distribution of GROC is shown in Fig. 4 for experiments 1 and 4. An overall similar performance is observed for both predictands although the spatial distribution of GROC differs slightly between precipitation and wet-day frequency.

Our results indicate that improvements in JJA forecast skill (Table 2), as measured by GI, can be obtained

TABLE 2. Station-only CCA experiments. Stations' JJA precipitation forecast experiments. GI stands for goodness index or Kendall's τ . Experiments with the highest skill for each predictand are marked in bold.

Predictand IDEAM stations	No. of stations	Predictor	Domain	Period of analysis	GI
Target season JJA		CFSv2 JJA SST (L-1, May forecast)			
1) Precipitation	48	Tropical SST	20°S–20°N, 100°E–2°W	1982–2014	0.14
2) Precipitation	48	Precipitation	7°S–15°N, 80°–63°W	1982–2014	0.04
3) Precipitation	48	Vertically integrated VQ	13°S–24°N, 98°–43°W	1982–2014	0.10
4) Wet day frequency	48	Tropical SST	20°S–20°N, 100°E–2°W	1982–2014	0.18
5) Wet day frequency	48	Precipitation	7°S–15°N, 80°–63°W	1982–2014	0.10
6) Wet day frequency	48	Vertically integrated VQ	13°S–24°N, 98°–43°W	1982–2014	0.16

by relying on wet-day frequency as the predictand variable. The usefulness of these results is limited to crop management decisions that are taken after planting given the forecast is available in May (JJA SST, L-1). The ideal set of seasonal climate scenarios for crop modeling in the Orinoquía region, would contain skillful forecast for the most climate-wise relevant season for rice development (JJA) *before* or *early in* the planting phase (March–May). With that in mind, we conducted four extra CCA experiments retaining the predictor that resulted in the highest GI (CFSv2 JJA SST) but with longer forecast leads as described in Table 3.

Using L-3 CFSv2 JJA SST forecast as the predictor (Table 3, experiments 7 and 8) to precipitation variables results in model skill only slightly better than climatology. In contrast, the use of JJA SST forecast released in April (L-2) results in more skillful CCA model performance specially for wet-day frequency (experiment 10) and describes patterns in SSTs and wet-day frequency very similar (not shown) to those of experiment 4. The poorest CCA model performance for longer leads is to be expected as GCMs' forecast skill naturally decays over longer lead times (Barnston et al. 2010).

Having skillful forecasts available in April does not meet the ideal scenario as stated previously, but it does allow for crop modeling of May late season planting dates and for crop management decisions made through later phases of the growing season, such as planning for irrigation. At the specific localities where ORYZAv3 crop simulations are available, the CCA models' ability to discriminate between above-normal, normal, and below-normal categories varies according to the predictand and predictor's lead time. In five out of eight locations (Fig. 5), the wet-day frequency predicted in April results in GROC that surpasses the 50% threshold for reliable discrimination of terciles. Notably, the performance of seasonal precipitation amounts as the predictand results in highest GROC skill index in only two stations (black bars in Fig. 5). Using the frequency of wet days as the predictand in CCA provides an alternative to seasonal precipitation forecast that performs poorly, without the need to resort to any additional dataset. Nonetheless, station-only-based forecast is restricted to the locations with low amount of missing data, leaving usually large areas of interest deprived from climate information. We thus explore how the use of

FIG. 3. Canonical patterns of the first CCA mode (CCA1). (a),(b) Spatial loadings of predictor JJA CFSv2 SST. Spatial loadings of JJA station-only (c) precipitation and (d) wet-day frequency.

FIG. 4. JJA (a) precipitation and (b) wet-day frequency forecast GROC skill score (%) using CFSv2 tropical Atlantic and Pacific SSTs as the predictor. GROC is an indication of how often the forecast is correct in distinguishing between the above-normal, normal, and below-normal categories. Values above 50% are considered a skillful forecast.

satellite-station-merged dataset can improve forecast performance and availability in the Orinoquía region of Colombia.

c. Improving forecast skill—satellite-station-merged predictand

In contrast to stations-only derived forecast, the highest goodness index skill score ($GI = 0.2$) results from MOS using JJA vertically integrated meridional moisture flux as the predictor and CHIRPS JJA precipitation as the predictand (Table 4).

The CCA first mode patterns shown in Fig. 6 describe a relationship between southerly (northerly) moisture transport over the Orinoquía region with positive (negative) anomalies in precipitation (Fig. S4 shows all CCA modes). Our results are consistent with previous findings (Wang and Fu 2002) showing increased lower atmosphere southerly winds associated with moisture transport from the Amazon and increased precipitation in central Colombia.

The experiments using CHIRPS were designed with the goal of determining whether the probabilistic forecast from a skillful experiment (e.g., experiment 13, $GI = 0.2$) using a predictand from a dataset that is not

directly useful for use in crop models, can be relied on to discriminate categories of an observational dataset that is. To that effect, we calculated categorical GROC based on the JJA probabilistic hindcasts, using CHIRPS as predictand, and verified against JJA precipitation from each of the 48 stations included in the CCA experiments and the extra set of 30 stations not included in the station-only CCA.

CHIRPS-based probabilistic forecast from experiment 13 can be effectively used to discriminate above-normal, normal, and below-normal precipitation categories ($GROC > 50\%$) in over 80% of the stations used in the station-only CCA (blue line in Fig. 7). For the remaining 30 stations, the CHIRPS-based probabilistic forecast is also successful in discriminating the categories (red line in Fig. 7), performing poorly ($GROC < 50\%$) in only 10% of the stations. This has important implications for agricultural applications, as stations with no direct forecast can still be included in temporal downscaling schemes for use in crop model simulations (Han and Ines 2017), provided that CHIRPS probabilistic forecast can discriminate the stations' tercile categories. Another advantage of relying on satellite gridded datasets relates to their high spatial coherence and thus, greater

TABLE 3. IDEAM Stations JJA precipitation forecast experiments. GI stands for goodness index, a measure of overall model skill. The experiment with highest skill is marked in bold.

Predictand IDEAM stations	No. of stations	Predictor	Domain	Period of analysis	GI
Target season JJA					
7) Precipitation	48	CFSv2, JJA (L-3, March forecast)			
		Tropical SST	20°S–20°N, 100°E–2°W	1982–2014	0.05
8) Wet day frequency	48	Tropical SST	20°S–20°N, 100°E–2°W	1982–2014	0.05
Target season JJA					
9) Precipitation	48	CFSv2, JJA (L-2, April forecast)			
		Tropical SST	20°S–20°N, 100°E–2°W	1982–2014	0.10
10) Wet day frequency	48	Tropical SST	20°S–20°N, 100°E–2°W	1982–2014	0.15

FIG. 5. JJA precipitation (black) and wet-day frequency (light yellow) forecast GROC skill score (%) using CFSv2 tropical Atlantic and Pacific SSTs as the predictor (X) at leads 1 (L-1) and 2 (L-2). GROC is an indication of how often the forecast distinguishes between the above-normal, normal, and below-normal categories. Values above 50% are considered a skillful forecast.

potential for predictability using CCA (Moron et al. 2009). In addition, the CHIRPS dataset is publicly available and often more up to date than meteorological stations making it an ideal resource for research and development of CCA forecast models and subsequent applications in the agricultural sector.

5. Discussion

Tailoring climate services involves the production, translation, transfer and use of climate information designed to address significant problems and create solutions (Vaughan et al. 2016). In the Orinoquía, the challenge begins at producing skillful seasonal forecast due in part to stations' sparse distribution and irregular record over time (Esquivel et al. 2018) and to poor performance of dynamical models' precipitation forecast in the region (Barnston et al. 2010; Krishnamurthy et al. 2018). In this study, we presented approaches to work around these limitation by exploring the following: (i) the forecast performance of wet-day frequency as an alternative to seasonal precipitation amounts;

(ii) the use of CFSv2 vertically integrated meridional moisture flux (VQ) seasonal forecasts as an alternative predictor to regional precipitation variables in a CCA framework; and (iii) the potential for relying on seasonal probabilistic forecasts, generated using CHIRPS as a predictand in CCA, to determine stations' above-normal, normal, and below-normal precipitation categories.

We first determined that rice yield, as simulated by the ORYZAv3 crop model, responds more consistently to variability of wet-day frequency than to seasonal precipitation amounts. This is especially true during JJA, which is the season following the main planting trimester (MAM). By using CFSv2 L-1 SST JJA forecast as predictor to frequency of wet days in a CCA-based model, we find that forecast skill is improved in comparison with seasonal precipitation amounts. Precipitation totals can be expressed in terms of intensity times frequency. Monthly precipitation is then equivalent to the number of rainy days multiplied by the month's average daily precipitation. Whether it rains or not is a more consistent metric across a region than daily rainfall intensity. Some of the high spatial variability of daily precipitation intensity related to small-scale convection is filtered out by using a more uniform representation of large-scale processes (rain versus no-rain), which in turn respond more consistently to remote climate forcings, such as SST anomalies (Moron et al. 2007). This is consistent with previous findings showing that the signal of large-scale oceanic forcings, such as ENSO, can manifest in the distribution of daily precipitation more significantly than in the total seasonal amounts (Grimm and Tedeschi 2009; Ropelewski and Bell 2008). Similarly, wet-day frequency forecast using April (L-2) JJA SST as predictor in CCA results in forecast skill comparable to forecast released in May, which allows for longer-term planning, such as provisions to reduce the impact of dry conditions (e.g., covering the soil with mulch), or determining the timing and amount of fertilizer application based on midcycle forecast. Moreover, the use of frequency of wet days as a predictand in CCA provides an alternative to seasonal precipitation forecast that performs poorly, without the need to resort to any additional dataset.

Although it is most desirable for agricultural applications to use station data directly as predictands in

TABLE 4. CHIRPS precipitation forecast experiments.

Predictand CHIRPS precipitation	Domain	Predictor	Domain	Period	GI
Target season JJA		CFSv2, JJA (L-1, May forecast)			
11) Precipitation	2°–8°N, 75°–67°W	Tropical SST	20°S–20°N, 100°E–2°W	1982–2018	0.08
12) Precipitation	2°–8°N, 75°–67°W	Precipitation	7°S–15°N, 80°–63°W	1982–2018	0.07
13) Precipitation	2°–8°N, 75°–67°W	Vertically integrated VQ	15°S–20°N, 85°–45°W	1982–2018	0.2

FIG. 6. Canonical patterns of the first CCA mode (CCA1). Spatial loadings of (a) predictor JJA CFSv2 vertically integrated meridional moisture flux (VQ) and (b) predictand CHIRPS JJA precipitation. Positive values in (a) correspond to southerly moisture transport, whereas negative correspond to northerly moisture transport.

statistical models, it limits the seasonal forecast availability to locations where the stations' time series comply with the stipulated missing elements threshold for inclusion in CCA. Stations with a moderate amount of missing data are either left out or need to have its records filled using mathematical methods for data gap filling. In this study, we explored an alternative approach involving the use of CHIRPS satellite–station–merged precipitation as predictand in CCA. Using precipitation forecast from the CCA experiment with highest skill, we find that CHIRPS probabilistic hindcast can successfully

discriminate JJA precipitation historical below-normal, normal, and above-normal categories at the majority of stations in the Orinoquía region. This has implications especially for locations not included in a CCA station-only model but still in need of agro-climatic probabilistic forecasts.

CHIRPS experiments have also revealed the potential for using CFSv2 VQ as a predictor to precipitation in the Orinoquía region. This is consistent with studies showing that GCM variables other than precipitation may contain more of the relevant SST-forced predictive information and thus be more adequate in a MOS scheme (Alfaro et al. 2018; Muñoz et al. 2016; Ndiaye et al. 2009). To check if that is the case in CFSv2, we evaluated the model's internal tropical SSTs and regional VQ coupling as well as SSTs and precipitation using CCA. We found an overall better performance of VQ than the corresponding response in precipitation over the Orinoquía region (Fig. 8) when tropical SST is used as predictor. In addition, the VQ response to SST variability in CFSv2 is remarkably consistent over the Orinoquía region in contrast to a patchy distribution of SST-forced precipitation variability. This helps to explain why the CCA experiments that used CFSv2 VQ as a predictor performs better than those that use precipitation.

FIG. 7. Cumulative probability of categorical GROC based on CHIRPS probabilistic hindcasts (experiment 13) verified against stations included (blue) in the station-only CCA experiments and stations not included in CCA (red). GROC values above 50% are considered a skillful forecast.

6. Conclusions

Improved climate seasonal forecast skill in the Orinoquía region of Colombia can be achieved by using alternative predictands and predictors in CCA

FIG. 8. JJA (a) CFSv2 precipitation and (b) CFSv2 VQ forecast skill score (Spearman correlation) using CFSv2 tropical Atlantic and Pacific SSTs as the predictor.

schemes. Frequency of wet-day forecast skill is normally higher than it is for the more traditional seasonal precipitation forecast, especially in stations where rice yield simulations are run. Moreover, rice yield variability responds more significantly to frequency of wet days than to precipitation amounts. This is the case in our study area and in other rice-producing regions (Fishman 2016; Revadekar and Preethi 2012), suggesting that our findings can be reproduced and applied beyond the Orinoquía region.

Alternatively, CHIRPS precipitation probabilistic forecast can also be relied on to discriminate stations' above-normal, normal, and below-normal terciles, which is especially relevant to stations that lack a consistent and long enough time series to be included in CCA. Last, the use of predictors in CCA that contain a higher fraction of SSTs predictive information, such as VQ, can result in precipitation seasonal forecast with higher skills at the same time that advances our knowledge of the Orinoquía regional climate system.

Our methodological approach and new understanding can be adapted to include the next generation of forecasts in which SST, precipitation, and vertically integrated meridional moisture flux are likely to be more skillfully represented in GCMs and with a longer lead time allowing for a more precise and advanced agricultural planning for rice cultivation in the Orinoquía region.

Acknowledgments. This work was carried out under the Climate Services for Resilient Development (CSRD)-U.S. Agency for International Development (USAID) Award AID-BFS-G-11-00002-10 towards the CGIAR Fund (MTO 069018), the Climate Change, Agriculture and Food Security (CCAFS) project Agroclimas (<http://bit.ly/2i3V0Nh>), and by ACToday, the first of Columbia University's World Projects. CCAFS is carried out with

support from CGIAR Fund Donors and through bilateral funding agreements <https://ccaafs.cgiar.org/donors>. We also gratefully acknowledge the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM) for providing access to their meteorological station data, the Federación Nacional de Arroceros (FEDEARROZ) for providing data necessary for ORYZAv3 calibration and simulations and two anonymous reviewers for providing feedback that helped to improve our manuscript.

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