A Coffee Yield Next-Generation Forecast System for Rain-Fed Plantations: The Case of the Samalá Watershed in Guatemala

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ABSTRACT: The provision of climate services has the potential to generate adaptive capacity and help coffee farmers become or remain profitable by integrating climate information in a risk-management framework. Yet, to achieve this goal, it is necessary to identify the local demand for climate information, the relationships between coffee yield and climate variables, and farmers' perceptions and to examine the potential actions that can be realistically put in place by farmers at the local level. In this study, we assessed the climate information demands from coffee farmers and their perception on the climate impacts to coffee yield in the Samalá watershed in Guatemala. After co-identifying the related candidate climate predictors, we propose an objective, flexible forecast system for coffee yield that is based on precipitation. The system, known as NextGen, analyzes multiple historical climate drivers to identify candidate predictors and provides both deterministic and probabilistic forecasts for the target season. To illustrate the approach, a NextGen implementation is conducted in the Samalá watershed in southwestern Guatemala. The results suggest that accumulated June–August precipitation provides the highest predictive skill associated with coffee yield for this region. In addition to a formal cross-validated skill assessment, retrospective forecasts for the period 1989–2009 were compared with agriculturalists' perception on the climate impacts to coffee yield at the farm level. We conclude with examples of how demand-based climate service provision in this location can inform adaptation strategies like optimum shade, pest control, and fertilization schemes months in advance. These potential adaptation strategies were validated by local agricultural technicians at the study site.

SIGNIFICANCE STATEMENT: In this study we wanted to provide climate services to coffee farmers in Guatemala who currently face challenges associated with climate variability and change. To do this, we first assessed what climate information they currently have at the farm level, how they use it in decision-making processes, and what improvements would benefit their risk-management framework (e.g., shade management). In addition, we evaluated farmers' perceptions related to the impact of climate to their coffee productivity. We verified the historical impact of several climate variables on coffee yield at the study site location and found that total rainfall for June–August is associated with coffee yield as originally referred by farmers. After identifying rainfall as one of the critical factors associated with coffee yield in this particular watershed of Guatemala, we moved to create a model that could help coffee farmers to forecast precipitation and the associated coffee yield months in advance. We then validated each of the management activities that could be put in place at the farm level with local technical and extension agricultural services in the region, including managing shade, adapting fertilization schemes, and managing weed removal at the farm level.

KEYWORDS: Seasonal forecasting; Seasonal variability; Climate variability; Agriculture; Climate services; Decision-making

1. Introduction

International coffee trade generates over \$220 billion (U.S. dollars) annually and supports the livelihoods of 100 million people worldwide (ICO 2019). Over 70% of the coffee production supporting this worldwide market exchange is produced by smallholder farmers in more than 60 countries in Latin America, Asia, and Africa (Waller et al. 2007; Jayakumar et al. 2016; Chengappa

et al. 2017; Hannah et al. 2017; Imbach et al. 2017). Although each country has its own particularities in terms of local production strategies, market fluxes, and environmental factors, there are some common features. For instance, less-developed economies in some of these countries exhibit a relatively high dependence on climate-sensitive agriculture including smallholder coffee farmers in places like Indonesia, Nigeria, Ruanda, Ethiopia, Perú, México, Guatemala, Nicaragua, Honduras, Puerto Rico, and Jamaica (Meza 2015; Quiroga et al. 2015; Lechthaler and Vinogradova 2017; Fain et al. 2018; Guido et al. 2018; Hirons et al. 2018; Sujatmiko and Ihsaniyati 2018; Hakorimana and Akcaoz 2019; Hernández 2019; Oko-Isu et al. 2019). In Guatemala, coffee (*Coffea arabica*) is planted on 677 000 acres (1 acre = 0.4 ha), positioning the country among the

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historical top ten coffee producers in the world from 1990 to 2020 (ICO 2021). Coffee farming in Guatemala supports around 700 000 people, all of whom are economically dependent on its productivity (Tucker et al. 2010; MAGA 2013; Lechthaler and Vinogradova 2017). Price instability, changes in the climate, and incidence of pests have been identified as the major challenges for coffee production in Guatemala (Castellanos et al. 2013). The negative impacts associated with climate variability and change can have drastic effects on coffee yield, which can lead to poverty, malnutrition, and food insecurity among rural families (Caswell et al. 2012; Lechthaler and Vinogradova 2017).

The provision of climate services to coffee farmers has the potential to generate adaptive capacity and therefore reduce vulnerability under the IPCC risk management framework (IPCC 2012) because it can help coffee farmers become or remain profitable by timely informing critical actions at the farm level that could result in increased productivity or avoided losses. The IPCC compound risk framework integrates the climatic hazard, exposure of the agricultural system to the hazard, and the vulnerability of the system(s) to determine climate risk. In certain coffee-producing countries in Central America, the impacts of extreme rainfall are not necessarily associated with the geographic extent of the climatic events, suggesting that consideration of social determinants like vulnerability of local populations need to be taken into account to successfully manage risk (Maldonado et al. 2013).

Understanding how climate variability and change impacts coffee production at a local level is therefore essential to support management strategies aimed at increasing coffee farmers' resilience to climate-related hazards, that is identifying the climatic hazard within the IPCC framework mentioned earlier. In addition to this it is necessary to identify the local demand for climate information beyond bold regional estimates (see García-Solera and Ramirez 2012), the capacity to forecast relevant climate variables at a local level, and the relationships between coffee yield and climate variables (see Vezy et al. 2020). Once this is accomplished, the next step is to identify the potential actions that can be realistically put in place by farmers at the local level taking into consideration their socioeconomic capabilities to transform the forecast into adaptation strategies at the farm level.

With socioeconomic capabilities being considered, timely, reliable, and tailored forecasts of the climate events associated with coffee productivity can inform appropriate management strategies to increase profitability, reduce or even avoid losses by adjusting management activities (e.g., fertilizer requirements, pesticide inputs, and labor costs). This study first aims to better understand what the concrete demand is and how coffee farmers access and use climate information for decision-making at farm level within the Samalá watershed, as an example of how to apply the general approach of climate service provision to coffee farmers. Given the demand for reliable coffee yield predictions, an objective system (see WMO 2020) to produce deterministic and probabilistic forecasts of coffee yield is developed and evaluated. To the best of the authors' knowledge, this is the

first coffee yield forecast system of its kind in Central America, and probably in several other regions of the world.

The paper is organized as follows. Section 1 presents information on the association between coffee and climate, coffee farmers' perception on climate variability and change, and the provision of climate services for the coffee sector. Section 2 presents information on the study region as well as the data and methods used. Section 3 presents the main results, and the discussion and concluding remarks are presented in section 4. We have included a set of management strategies that could be implemented at the farm level in this location, after the forecast has been translated and transferred to the farmers and that have the potential to lead to increased resilience and adaptation to climate-related risks. This set of activities was validated by technicians and extension service agents from the National Coffee Association [Asociación Nacional del Café (ANACAFÉ)], in charge of providing agricultural technical advice to the coffee farmers in the Samalá region.

2. Coffee, climate, and the provision of climate services to farmers

a. Coffee yield and climate

Coffee crops are very sensitive to changes in climate, especially to variations in temperature and precipitation, which can have an impact on the coffee plant phenology (e.g., early or late flowering blooms, see Camargo 1985; Fournier and Di Stefano 2004; DaMatta and Ramalho 2006; Villers et al. 2009; Rahn et al. 2014; Bunn et al. 2015; Magrach and Ghazoul 2015; Rahn et al. 2018; Hernández 2019).

In the case of temperature, the optimum for *Coffea arabica* varies with the phenological stage of the plant, but the average annual temperature in an established plantation should be around 18°–21°C (Alègre 1959; Camargo 1985; DaMatta and Ramalho 2006). Although new experimental research suggests that heat resistance from *Coffea arabica* might be higher than originally estimated (Rodrigues et al. 2016; DaMatta et al. 2019), temperatures that exceed the optimum still affect quality by accelerating the ripening of the fruits with an overall loss in the quality of coffee (Camargo 1985; Vaast et al. 2006; Bosselmann et al. 2009). While new research suggests that CO₂ fertilization could mitigate some of the negative impacts of increasing temperatures on coffee yield, precipitation extremes might still bring large uncertainties to coffee yield estimates (DaMatta et al. 2019). Hence, managing water availability at the farm level remains critical for the overall healthy development and productivity of the coffee plants. For instance, adequate hydrological stress after harvest could trigger flowering over vegetative growth resulting in more fruits being produced. On the other hand, intense rainfall after bud formation could initiate abortion of the flowers and/or reduce productivity *via* pests, infestations and fruit dropping (DaMatta 2004). Excessive rainfall has been associated with a decline of up to 30% in coffee production due to coffee leaf rust infestations (Cristancho et al. 2012; CEDICAFÉ 2018). Changes in rainfall characteristics, like amounts and frequency remain a major climatic limitation for

coffee production in Guatemala (Castellanos et al. 2013; Tucker et al. 2010; Haggart et al. 2013; Schmitt-Harsh 2013). Altogether, climate variability and change are already exerting challenges on coffee production, including high yield variability (Imbach et al. 2017).

When it comes to long-term expected impacts of climate on coffee, several climate projections for Guatemala suggest a reduction in precipitation in both the dry and wet seasons, which might impact coffee production, especially among smallholder producers (Hannah et al. 2017). However, uncertainties in the models used in these estimates remain high, especially for the Central American region (Neelin et al. 2006; Läderach et al. 2011; Karmalkar et al. 2011; Baca et al. 2014; Magrin et al. 2014; Ovalle-Rivera et al. 2015; Hidalgo et al. 2017; Imbach et al. 2018; Durán-Quesada et al. 2020).

Although knowing the long-term (i.e., climate change) background climate signal is important, farmers might require information at shorter time scales (Vaughan and Dessai 2014). Providing clear, reliable climate information on the typical past behavior of key variables, as well as their most recent behavior and their expected future comportment, from hours to months or even years ahead allows for a better assessment of risks and improved planning than when only a single time scale is considered. This approach, known as “Ready-Set-Go” (Goddard et al. 2014; Koh et al. 2020), helps decision makers to contextualize predictions and stratify their identified strategic actions across multiple time scales, considering both the natural climate variability and the anthropogenic climate change signals for a better-informed decision. For instance, a long-term projection for coffee suitability toward 2050 could inform the development of new genetic traits aimed at producing new varieties of coffee with drought-resistant properties in an incremental manner (Läderach et al. 2017). However, current interannual precipitation variability affecting coffee production needs to be addressed with the provision of climate services at time scales valuable for decision-making at the farm level in the short term. The provision of climate services as an adaptation framework to climate variability is critical under high-cost production schemes and low international market prices in the coffee sector.

Changes in precipitation and the associated impacts to coffee yield need to be placed in the context of tolerable and optimum rainfall thresholds for *Coffea arabica* plantations for the particular region of interest (Ridley 2011). For instance, most of the coffee farms within the Samalá River watershed (Fig. 1), are located at the piedmont of the Santa María and Santiaguito volcanoes, where they experience a total annual precipitation of up to 4000 mm. This amount of precipitation exceeds the 800–2500 mm considered *tolerable* for *Coffea arabica* plants and surpasses by far the 1200–1800 mm considered *optimum* for the species (Ridley 2011). According to the national meteorological institute (INSIVUMEH), the accumulated precipitation for the June–July–August season in the region usually averages 1200 mm (INSIVUMEH 2018). Relatedly, the impact of El Niño–Southern Oscillation (ENSO) associated with drier (wetter) than normal conditions in the Samalá region linked to the warm (cold) phase of ENSO, has diverse

effects on the coffee productivity elsewhere in the country (ANACAFÉ 2018, 12–13). According to ANACAFÉ, in dry regions of Guatemala, where coffee is grown under low-precipitation regimes, the effects of ENSO during a warm phase would manifest on the ground as increased lack of soil humidity, further limiting the nutrient absorption from the plant. In high-humidity, high-precipitation regions where coffee is grown (like the Samalá region), the effects of a warm ENSO phase are associated with better coffee productivity due to more uniform flowering and adequate soil moisture for fruit development (ANACAFÉ 2018, 12–13). In addition to the influence of ENSO, there are many known climate mechanisms behind the precipitation regime in Guatemala (Giannini et al. 2000; Li et al. 2011; Hidalgo et al. 2017; Alfaro et al. 2018; Anderson et al. 2019; Anderson et al. 2020 a,b; Durán-Quesada et al. 2020; Maldonado et al. 2018), yet no objective predictive system has been developed to date involving climate predictors and coffee yield, especially for Guatemala at scales useful for the farmers at the local level (Karmalkar et al. 2011; Steinhoff et al. 2015).

b. Climate services and coffee farmers' perceptions on climate variability

The provision of climate services (generation, translation, transfer, and use of climate information; see Vaughan and Dessai 2014) has the potential to generate adaptive capacity and help coffee farmers become or remain profitable by integrating climate information into a risk management context following the IPCC framework (IPCC 2013). In order for climate services to be successful, it is necessary to work with farmers at the local level to identify their perceptions on climate impacts and their demand for climate information, and to examine the potential actions that can be realistically put in place by them at the local level while considering social, economic, and infrastructural constraints.

Research on coffee production in India suggests that the identification of coffee farmers' perceptions allows researchers and farmers to determine the adequate adaptation strategies to reduce the risks associated with climate variability (Chengappa et al. 2017). According to Chengappa et al. (2017), coffee farmers indicated that climate variability was considered a high-risk factor for coffee production and identified that the rainfall distribution over time concerned them more than the total annual rainfall, consistent with previous studies (e.g., Robertson et al. 2009; Moron et al. 2010). Similarly, in Rwanda, it was the incorporation of local leaders into the evaluation processes that helped researchers to identify limitations on adaptation strategies associated with climate services and coffee, which included lack of research and climate data, restricted access to technologies, and insufficient communication, among other factors (Hakorimana and Akcaoz 2019).

Recent studies in coffee producing countries in America related to the gap between climate knowledge and its transformation into actionable information for coffee farmers, suggest that climate services provision can be used as an adaptation strategy because it has the potential to incorporate farmers' perceptions and collaboration with scientists to respond to the challenges associated with agricultural production. For instance,

FIG. 1. Map of Guatemala highlighting the Samalá River Watershed.

in Jamaica, a recent study on climate information products with the potential to help coffee farmers manage climate risks helped to identify the role of climate service provision to build adaptive capacity (Guido et al. 2018). The study suggests that the more traditional “science push” unidirectional transfer of information from climate scientists to farmers might not be enough to overcome local barriers that hinder farmers from using the climate information provided (Cash et al. 2006; Feldman and Ingram 2009; Goddard et al. 2010; Dilling and Lemos 2011; Lemos et al. 2012; Hansen et al. 2019). Their analysis indicates that a continued dialogue among farmers, extension services agents, and scientists had a positive impact in the identification of successful climate service provision (Hansen et al. 2004; Sivakumar and Hansen 2007; Rengalakshmi 2007; Hansen et al. 2011; Daly and Dessai 2018; Guido et al. 2018). In Perú, climate service provision for coffee production provided useful infrastructural support with potential to inform key adaptation mechanisms, including fertilizer choice, field size, dams, and

irrigation systems (Lechthaler and Vinogradova 2017). Similarly, in Nicaragua, farmers’ perceptions of climate risks were considered essential to overcoming the barriers that hindered coffee farmers from implementing adaptation strategies (Quiroga et al. 2015). Coffee farmers in Guatemala are becoming more aware of local climate variability yet, similarly to coffee farmers in other regions of the world, they still face limited adaptation strategies (Dang et al. 2014). The realization of the benefits of incorporating local demands and knowledge to enable adaptive capacity building on the base of climate information has been widely studied and is the approach used in this study (Dilling and Lemos 2011; Lemos et al. 2012).

In Guatemala, ANACAFÉ and INSIVUMEH, in partnership with international research organizations, developed a Regional Program for Climate Change, specifically targeting coffee farmers to identify the adaptive capacity of the coffee sector in the country (PRCC 2016). The program was coproduced and validated with coffee farmers in three different departments of Guatemala (San

Marcos, Cobán, and Guatemala). This technical document laid out several approaches identified by the coffee farmers with the potential to increase adaptive capacity of coffee systems to climate change. According to the PRCC document, there are several factors to consider achieving a certain degree of adaptive capacity, among them knowledge and planning capacity. Knowledge in the context of the document referred to anticipating the state of the climate and understanding the potential changes in the coffee systems associated with these expected changes in the climate system. Planning capacity was associated with the factors involving the decision-making processes after the climate knowledge was provided in order to reduce vulnerabilities (PRCC 2016). The identification of historical impacts of climate on coffee plantations in different regions of the country allowed the study to draw several general adaptation strategies that are evaluated and validated in this research for the particular study area. A new seasonal climate forecast system in Guatemala, described below and that follows international standards (WMO 2020), allows for these historical impacts to be assessed using cross-validation methods at a local scale, and to derive locally relevant information for agricultural management at the farm level, including the identification of key climate variables associated with coffee yield.

c. Seasonal climate information for agriculture

The premise behind the use of seasonal climate forecasts for agriculture is that the information provided to the farmer is in fact of relevance to the decision-making processes on the ground, leading to an overall improvement of the farmers' finances or quality of life (Hansen 2002; Hansen et al. 2009). This level of improvement could potentially be accomplished by the farmers by managing risks associated with climate variability and extremes, or by taking advantage of the information to assume other risks that could improve the overall economic return (Hansen 2002; Iizumi et al. 2018). These optimal management strategies can be determined by not only the climate information but also the associated yield estimates (Brown et al. 2018). Incorporating climate models into crop models can therefore offer the farmers an additional piece of information to evaluate and ultimately choose from a set of potential actions at the farm level, although the process tends to also involve propagation of uncertainty from the climate models to the crop ones, which needs to be adequately managed (Vezy et al. 2020).

Applied research in Latin America has made use of pattern-based statistical models, like canonical correlation analysis (CCA), to improve the overall skill of uncalibrated seasonal forecasts (e.g., Muñoz et al. 2010; Recalde-Coronel et al. 2014; Muñoz et al. 2016 a,b; Alfaro et al. 2018; Doss-Gollin et al. 2018). In these studies, precipitation—the predictand—was estimated to then be incorporated into the decision-making process in different sectors, including agriculture. The predictors used in those studies varied from sea surface temperature (SST) observations to single climate model outputs (Alfaro 2007; Alfaro et al. 2018; Esquivel et al. 2018; Maldonado et al. 2018; Fernandes et al. 2020). Traditionally, a baseline is used to compare the skill

of the forecast system and to evaluate whether models can be used as inputs to force crop models (Hansen et al. 2009; Brown et al. 2018). Usually, this baseline is the climatology, i.e., the long-term average of the variable to be forecast (Mason 2016). A given crop model incorporating the climate models should at least provide better forecast-based management strategies than climatology-based strategies (Hansen et al. 2009). This broad generalization assumes that farmers have access to the climatological record of the variables under study and that they are currently applying the climatology-based strategies. In a context of climate service provision to agricultural communities traditionally excluded from mainstream climate information (Pons et al. 2017), where the historical climatology of the variable of interest might not be documented or well understood, the perceived value of the new forecast could be overstated and its overall usefulness for decision-making downgraded in the face of imperfect information. Hence, forecast uncertainty should be explicitly addressed—as transparent as possible—during the climate service provision process, as well as the statistical scores used to measure the forecast attributes (Kusunose and Mahmood 2016).

In this study we developed a model based on the early identification of the climate variable most relevant to farmers in the region; the model was then cross-validated using statistical methods and its output was evaluated against historical coffee yield. We made use of the new seasonal climate forecast system, codeveloped by Guatemala's National Meteorological Institute and the International Research Institute for Climate and Society (IRI), called "NextGen." The system uses a Model Output Statistics (MOS) approach to calibrate a selection of dynamical climate models available from the North American Multi-Model Ensemble project (Kirtman et al. 2014). The results were validated against farmers' perceptions and presented in different graphics, following the users' preference on the transfer and translation methods identified in the early stages of the project. In response to farmers request for statistical charts to communicate the information related to precipitation anomalies, we used relative operating characteristics (ROC) curves and the two-alternative forced-choice (2AFC) score to evaluate the forecasts' discrimination (Mason and Weigel 2009). In particular, the 2AFC metric is relatively easy to interpret and has been recommended to be used to communicate forecasts' quality to nonspecialists (Mason and Weigel 2009).

3. Materials and methods

a. Study site

The Samalá River watershed covers 1500 km² across the departments of Quetzaltenango, Retalhuleu, and Suchitepéquez (Fig. 1). Located between Santiaguito and Santo Tomás volcanoes, it follows the Zunil Fault Zone to the south (Bennati et al. 2011). The volcanic soils in the region have created ideal conditions for agriculture in the region, particularly for coffee plantations (Soto et al. 2015). Annual mean temperature in the region ranges between 10°C at the highest elevation to 28°C,

FIG. 2. Coffee yield as a percentage deviation from average for the period 1989–2009.

with mean annual precipitation within the watershed ranging from 4000 mm, at the top of the watershed, to 1500 mm at the coast (INSIVUMEH 2018). The rainy season spans from May to October and is characterized by a bimodal regime with the first peak in June and the second one in September, with a reduction in precipitation between July and August locally known as the *canícula* or *veranillo* (Magaña et al. 1999; Alfaro 2002; Taylor and Alfaro 2005; Amador 2008; Maldonado et al. 2016; INSIVUMEH 2018; Anderson et al. 2019). The coffee farmers within the Samalá River watershed receive technical assistance from the administrative Region II from ANACAFÉ, which oversees the Suchitepéquez, Retalhuleu, and Sololá; due to geographical characteristics, it also includes the San Miguel Pochuta and El Palmar municipalities belonging to Chimaltenango and Quetzaltenango departments, respectively.

b. Predictand

Coffee productivity data (quintals per hectare) were retrieved from 15 spatially distributed coffee farms across the coffee-growing region of the Samalá watershed, in the southern face of Guatemala's volcanic chain. Instead of a random sampling design, we worked with those coffee farmers willing to participate in the study, which accounted for 26% of the coffee farms within the Samalá River watershed covering up to 900 ha of land planted with coffee (*Coffea arabica*). The average coffee plantation size in the region is 56 ha with a long-term average production of 21 quintals per hectare. Each coffee farm was georeferenced using a Garmin GPS. To capture the most important variables associated with coffee production at the farm level, both the survey and production forms were validated with the farmers by the ANACAFÉ Region II technical office and its extension service agents.

Coffee productivity data were obtained from the farmers' records, ranging from 1989 to 2015. To account for potential technological changes in the historical yield distribution, the productivity data from all of the farmers participating in the study was calculated as $100 \times (\text{production} - \text{trend})/\text{trend}$ to identify the percentage deviation in crop yield for each year from the trend (Raj et al. 2020) (Fig. 2).

In addition, farmers were asked to write down the historical changes in the crop management. Along with the productivity

data, farmers were asked to fill up a chart to capture the area within the farm devoted to coffee plantations per year, timing of shade management (species, density, and pruning months), timing of the pruning of coffee plants and the overall fertilization schemes with no change in the practices over time. Diversification of the coffee production system was only measured through shade diversity. We did not measure any variable associated to the quality of the coffee in the farms. No irrigation schemes were present at any of the coffee farms evaluated in this study. The coffee production system in the region is managed as an agroforestry production scheme with varying shade cover percentages and species ranging from rustic to technified shade (Moguel and Toledo 1999). According to the National Coffee Association's production scale, farmers in the region range from medium to large-scale farmers producing more than 50 quintals per year and 500 quintals per year, respectively. Most of the coffee plants in these farms are *Coffea arabica*, including Bourbon, Catuai, and Caturra varieties. These varieties are planted in an altitudinal gradient from 600 to 2000 m ASL and are harvested from September to March. Flowering of coffee plants in this zone occurs from December to May. The bud formation and fruit development begin in the second week after flowering and ends after 22–24 weeks.

c. Predictor

Successful climate services provision demands the understanding of the users' needs to produce, translate, and transfer information with the potential to become actionable at the farm level. To produce climate information that responds to the demands from the coffee farmers in this region, we divided the assessment of potential candidate predictors into two sections. The first part was devoted to the assessment of farmers' perceptions on the effect of climate on coffee productivity at the farm level. This section included an identification of the climate variables measured and recorded at the farm level and their perceived impact on coffee production. It also included an assessment of the farmers' preferred method for climate information translation and transfer. The second part involved (a) an independent identification of key climate variables (e.g., total rainfall) related to the predictand, based on the recorded coffee

productivity, and (b) a physical analysis of the potential mechanisms and climate drivers involved. These independent processes identified rainfall as a candidate predictor. Since part of the interest is also to produce calibrated seasonal forecasts and most models in the North American Multi-Model Ensemble (NMME; Kirtman et al. 2014) provide precipitation estimates, the analysis presented here focuses on a forecast model of total rainfall at seasonal scales.

1) FARMERS' PERCEPTION ON CLIMATE VARIABILITY

To better understand the coffee farmers' perceptions on local climate variability and its effects on coffee productivity, we administered a 15-question survey directed at assessing the availability of instrumental data at each farm, climate variables measured locally, and their overall usability. The survey included questions related to the farmers' perception associated with changes in precipitation and whether the change was associated with the total amount of rainfall and/or the distribution over time or both. Farmers were asked to report the effects of precipitation on the coffee productivity. In addition, the survey explored observed changes at the farm level attributable to climate variability *via* signs of excessive precipitation at the farm level (fungus in the coffee plants, landslides, etc.), drought, or increases in temperature when instrumental data was not available. Farmers were also asked to identify the level of relevance of having access to precipitation data as well as the best means to make this information available for decision making. One of the questions in the survey was oriented to determine whether the farmers believed that the current climate at the farm level was optimal for coffee production.

2) THE NEXTGEN SEASONAL CLIMATE FORECAST SYSTEM FOR TOTAL RAINFALL

As indicated earlier, the NextGen was codeveloped by INSIVUMEH and the IRI at Columbia University. The present version of the system uses total rainfall from Global Climate Models available *via* the NMME (Kirtman et al. 2014). Prior to NextGen implementation in Guatemala, INSIVUMEH used the previous generation of seasonal climate forecasts that was based on an empirical statistical model using only sea surface temperatures from the tropical Pacific Ocean. NextGen, in turn, is a systematic approach that helps build objective forecasts following international standards (Muñoz et al. 2019b; IRI 2020; WMO 2020), can use multiple observed and dynamical model output predictors, intrinsically enforces calibration *via* a variety of statistical methods, and produces both deterministic and probabilistic forecasts.

The NextGen probabilistic forecasts not only include the more traditional tercile-based predictions, but also the so-called "forecasts in flexible format" (Goddard et al. 2014; WMO 2020), which provides information about probabilities of exceeding—or not—user-defined thresholds. Since total rainfall will be used as a predictor for coffee yield in the Samalá basin, a first step involved assessing the predictive skill of the calibrated, multimodel ensemble to forecast total rainfall itself. Although observed rainfall is not the main

predictand in this study, this step is conducted to identify the best multimodel ensemble configuration to use for coffee, including predictor and predictand domain size, and number of empirical orthogonal functions (EOFs) to keep in the CCA (see, e.g., Tippet and Barnston 2008; Mason and Baddour 2008; WMO 2020) approach used to correct for systematic biases. Since the hypothesis is that total rainfall is a key candidate predictor for coffee yield in the region, if the NextGen forecasts are not skillful predicting that variable, then they cannot be trusted to forecast coffee yield. Hence, a first step consisted in verifying that the models involved were able to represent the main physical processes conducive to rainfall in the region, including the main observed spatio-temporal modes of variability—i.e., the first three to five EOFs, depending on the season of interest. This process was conducted for all NMME models and for all (3 month) seasons for each year during the rainy period from March to October.

Next, precipitation fields from each NMME model were cross-validated using the Climate Hazards Infrared Precipitation with Stations (CHIRPS; Funk et al. 2015) gridded precipitation dataset as "observations," and a leave-5-year-out cross-validation window. CHIRPS span from 1981 to the near present at a 0.05° spatial resolution. This dataset makes use of available meteorological station information as well as satellite-derived information to account for regions where data are scarce. The latest version of the product is explicitly designed for monitoring agricultural drought and hence seemed adequate for the purpose of this study (Funk et al. 2015). The training period for the cross-validation is 1982–2010. The goodness of fit was evaluated for each of the raw (uncalibrated) model outputs using spatially averaged Kendall's tau values. The best models forecasting total rainfall in the region were selected to undergo the pattern-based MOS, and then the multimodel ensemble. A combination of metrics was used to select the best models, requiring that the spatially averaged Kendall's tau values were larger than 0.1, and that the 2AFC (Mason and Weigel 2009) values for tercile-based forecasts were above 0.5—that is, better discrimination than that expected from climatology—for most of the grid boxes in the domain. The final list of models used are presented in Table 1.

The selected MOS method, canonical correlation analysis, builds linear regressions between combinations of EOFs in the predictor and the predictand that maximize the correlation among them, tending to decrease systematic biases in the mean, variance, and spatial distribution of the rainfall field, all as part of the same process (Tippet and Barnston 2008). CCA also implicitly works as a statistical downscaling method (Karamouz et al. 2010), thus producing corrected fields at the same spatial resolution of the predictand field. Hence, in this study CCA produced hindcasts at a resolution of $0.1^\circ \times 0.1^\circ$.

The predictive skill assessment was then repeated independently for each CCA-corrected model, to confirm that the calibration process did not decrease the original predictive skill. The NextGen deterministic ensemble, consisting in this case of a total of 58 members, was obtained via an equally weighted average of the deterministic values of each

TABLE 1. NMME models used in the current study.

Models	Members	Lead times	Reference
GFDL-CM2p5-FLOR-A06	12	0.5–11.5	Vecchi et al. (2014)
GFDL-CM2p5-FLOR-B01	12	0.5–11.5	Vecchi et al. (2014)
NCEP-CFSv2	24	0.5–9.5	Saha et al. (2014)
CanSIPSv2	10	0.5–11.5	Lin et al. (2020)

calibrated model ([Tippett and Barnston 2008](#)). In addition, the ensemble process was also conducted in the “probability space” as follows. Since rainfall in general does not follow a Gaussian distribution, for each model and each grid box the empirical probability density function was first transformed to a Gaussian distribution. The ensemble probability density function was computed for each grid box by averaging the corresponding Gaussian distribution parameters—i.e., mean and variance—across all models (the NextGen standard deviation for each grid box is computed as the square root of the ensemble variance, not as the average of the standard deviations). Last, the predictive skill of the NextGen rainfall forecast system was assessed for all seasons of interest. In addition to Kendall’s tau and the 2AFC for tertile-based forecasts, this final skill assessment also involved the area under the Relative Operating Characteristics curve for above-normal rainfall forecasts—as farmers informed that for coffee yield the above-normal category was the most decisive one—to jointly assess discrimination of the produced probabilistic hindcasts ([Mason 2016](#)).

The seasons of interest for the present study cover the rainy period beginning in March and ending in October. Henceforth, a “lead time” L is introduced to refer to forecasts targeting a particular season but initialized L months in advance. For example, for a target period of March–May (MAM), $L = 1$ refers to forecasts produced at the beginning of February. The skill analysis described earlier was conducted for the April–June (AMJ), May–July (MJJ), June–August (JJA), and September–November (SON) seasons with lead times from $L = 1$ to $L = 4$. All calculations were performed using IRI’s Climate Predictability Tool, version 16.5.5 ([Mason et al. 2020](#)), and its Python interface (PyCPTv1.7; [Muñoz et al. 2019a](#)) to facilitate the mass production of all of the analyses.

3) THE NEXTGEN SEASONAL COFFEE YIELD FORECAST SYSTEM

The design of the NextGen coffee yield forecast system is analogous to the one described for rainfall, although slightly simplified because in this case the predictor is the calibrated total seasonal rainfall forecast field produced by NextGen (14.5°–14.7°N, 91.72°–91.52°W), described in [section 3c\(2\)](#). The predictand is the detrended coffee yield time series, available for the period 1989–2009, a 21-yr subset of the total rainfall hindcasts described in [section 3c\(2\)](#). Hence, the CCA model is simplified to a principal component regression for the case of the Samalá coffee yield NextGen forecast system with the first four EOFs incorporated into the assessment. Following the same procedure described above,

the discrimination between categories was assessed using ROC curves for tercile-based forecasts for each of the seasons discussed in the previous section (below-normal results available up request to the corresponding author). Of particular interest for the study is the JJA season, due to the fraction of precipitation it represents from the total annual precipitation, and the critical phenology stages of coffee plants during this season, as referred by the farmers. Reliability diagrams were computed to evaluate the reliability of the tercile-based probabilistic coffee yield predictions for this particular season.

4. Results

a. Perceived impacts of climate on coffee production

We use descriptive statistics ([Table 2](#)) to provide insights into the coffee growers’ experience with recording instrumental data and perceiving climate variability at the farm level. We also assessed the perceived climate influence on coffee productivity and the current demands for climate information as well as the better means to translate and transfer future climate information. To this respect, 87% of the farmers reported keeping track of instrumental meteorological data and 80% of them considered it useful for decision-making processes at the farm level for coffee management. Similarly, 87% of the farmers reported changes in either the amount or timing of the precipitation in the region, but only 20% of them noticed a change in both. All of the coffee farmers reported that they have experienced excessive precipitation in the region. The majority (93%) of them believe that excessive precipitation has had a negative impact on the coffee productivity while half of them also reported having problems with drought highlighting the importance of precipitation extremes in the region. Independently from the negative impact of excess precipitation to coffee yield reported by most farmers, 60% of the farmers still believe that the current climate at their farm is optimum for coffee production. This contradiction might be related to the ability of farmers to still produce coffee despite having negative effects, or might relate to successfully implemented measures to account for the negative impacts of climate. When it comes to temperature, 67% of the farmers reported noticing changes in temperature and 47% reported negative impacts on coffee plants associated with it. All the farmers in the study reported that precipitation data are critical for decision-making at the farm level ([Table 2](#)). These perceptions on the effects of precipitation on coffee were substantiated with the climate data analysis,

TABLE 2. Descriptive statistics of surveys from coffee farmers in the Samalá area.

Survey question	Response	Percentage
Do you keep meteorological data? If so, since when?	Yes	87
Are these datasets useful for decision-making at the farm level?	Yes	80
Have you noticed changes in precipitation (amount and timing)? When?	Yes	87
Have you noticed changes in the overall precipitation regime?	Yes	20
Do these changes have a positive or negative impact on coffee productivity?	Negative	93
Do you think current climate at your farm is optimum for coffee? If not for what crop?	Yes	60
Have you noticed changes in temperature at your farm? If so, when?	Yes	27
Have you noticed changes associated to temperature changes?	Yes	67
What are the impacts of these changes to your coffee productivity?	Negative	47
When it comes to precipitation, what is worst excess or lack of it to coffee productivity?	Increase	80
Is precipitation data critical to you? How do you want it presented to you?	Yes	100
Have you experienced droughts? When and for how long?	No	60
What were the impacts of droughts to coffee productivity?	None	47
Have you experienced torrential rains? When and for how long?	Yes	100
What were the effects on coffee productivity?	Fruit Drop	47

suggesting a negative impact of above-normal precipitation during the JJA season on coffee yield.

b. Seasonal climate forecast system

The NextGen rainfall evaluation for Guatemala suggests that there is considerable discrimination in the model for most seasons during the rainy period, according to the 2AFC and ROC scores (Figs. 3 and 4). The 2AFC verification results suggest that the NextGen model is more skillful than using climatology as a reference (Mason 2016); areas with a 2AFC score above 50 are considered to have better discrimination skill relative to the climatology (Mason 2016). The approximate study region is highlighted in a black across the different initialization months (from February to May) for the JJA accumulated precipitation season associated with coffee yield. The 2AFC and ROC above-normal areas suggest that the NextGen system can be used to forecast the accumulated rainfall in the country, with particular predictive skill in the southern region of the country, where the Samalá watershed is located. For all lead times considered ($L = 1-4$), the 2AFC scores are higher (2AFC~70%) for the JJA season than for the other seasons (Fig. 3). The ROC for the above-normal tercile in Fig. 4 suggests that there is high discrimination skill for that category in this particular region across all the initializations for the JJA season, suggesting that the model is able to capture when there is a high likelihood of receiving above-average precipitation during the JJA season. In particular, the JJA season initialized in May has slightly better discrimination (~80%) than the JJA initialized in

February (~70%). Our initial assessment on the climate information demands from the coffee farmers in the region was critical to determine the metrics used to evaluate the forecast skill, and to communicate the results to the potential users. For example, the use of ROC curves to assess the model discrimination on above- or below-normal precipitation is easy to interpret and is also recommended for small samples (Mason 2016). It is, however, up to the users to determine whether the information produced by the rainfall NextGen system is of any value at all for decision-making processes at the farm level. This issue is discussed in further sections.

c. NextGen coffee yield model

Our results suggest that, among all the candidate predictors evaluated, the spatially averaged, accumulated precipitation over June–August shows the best predictive skill to forecast coffee yield in farms located within the Samalá watershed. In Fig. 5, we show the retrospective forecasts in comparison with the observed coffee yield in the region for the JJA period, between 1989 and 2009. These results are based on the individual skill assessment for the different seasons for the rainy period as predictors of coffee yield. The model built using JJA accumulated precipitation as a predictor for coffee yield shows a high hit rate against false-alarm rates for multiple probability thresholds in both the above-normal and below-normal coffee yield categories, as shown by the ROC diagram (Fig. 6a). Similarly, the all-categories reliability diagram, corresponding to probabilistic forecasts, suggest almost perfect reliability, despite some of the residuals drafting toward the no

FIG. 3. The 2AFC NextGen initialized 1 Feb, 1 Mar, 1 Apr, and 1 May. The approximate study site has been outlined in black.

skill region for part of the distribution probably due to sampling limitations (Fig. 6b; Mason 2016).

The 2AFC and ROC areas for the above-normal tercile suggest that forecasts at lead times 1–4 for the JJA total precipitation can be used to skillfully predict coffee yield in the basin. In agreement with what farmers indicated, positive precipitation anomalies during the JJA season are associated with decreasing coffee yield in this particular region. This information, in turn, can inform which actions to take at the farm level, months in advance before experiencing the impact of excessive precipitation over the coffee plantations in the Samalá region. The actions derived from a forecast at any lead time need to be placed in the context of socioeconomic constraints for each of the users, and in line with the production

costs associated with each particular farm. This means that while the forecast might suggest above-normal precipitation with associated coffee yield reduction, a farmer in a particular socioeconomic context may decide to apply a certain fertilizer to manage the risk associated with the anomaly in precipitation, while another farmer might decide not to apply fertilizers at all. Both decisions informed by the forecast can be appropriate to each of the circumstances lived by each farmer. Hence, rather than specifically triggering a particular set of actions, the intention of the forecast is to reach the farmers in a timely manner and in the appropriate language and format deemed relevant to them, so that they frame the new information within their own risk management strategies, which in turn might generate an action or prevent it.

FIG. 4. ROC above initialized 1 Feb, 1 Mar, 1 Apr, and 1 May. The approximate study site has been outlined in black.

The use of precipitation as a predictor for coffee yield in this area allowed us to build a forecast model with both high discrimination and reliability (Mason 2016). Predictive skill for coffee yield in the Samalá watershed area is relatively high (e.g., for May, 2AFC = 71.92%). Following the season selection, we produced forecasts at several lead times targeting JJA accumulated precipitation. In this case, forecast lead time 1 ($L = 1$) refers to the seasonal JJA forecast produced at the beginning of May. Lead time 2 ($L = 2$) refers to the JJA forecast produced in April. We assessed the forecast capability up to a lead time of $L = 4$, initialized in February. The earlier lead time of $L = 4$ has the potential to be used by farmers to anticipate coffee yield based on the total amount of precipitation expected in JJA early in the year. According to our survey, the farmers in this location

begin to manage shade in February, which is when precipitation anomalies for JJA associated with coffee yield, can be estimated thanks to the NextGen rainfall forecast system described in this study. With this information, coffee farmers can implement early adaptation strategies to maximize the coffee yield based on the precipitation forecast.

APPLYING THE MODEL FOR DECISION-MAKING PROCESSES ON THE GROUND

In 2009, coffee farmers in the study region experienced an increase of up to 17% above average harvest (PRCC 2016). During this productive year, the region was experiencing the effect of SST anomalies at the beginning of MJJ of +0.4°C and of up to +0.5°C during JJA, as measured by the Oceanic

FIG. 5. Observed (dashed line) and retrospective forecasts (solid line) of coffee yield as a percentage deviation from average for all JJA seasons in the 1989–2009 period. The confidence interval (at 95% level) is shown within the dotted lines.

Niño Index (ONI), which translated into a reduction in precipitation for the JJA season via changes in atmospheric circulation patterns over Central America and more specifically over Guatemala. Previous studies demonstrated the skillful prediction of accumulated precipitation for the May–June rainy season in Central America using SST anomalies from February, March and April as independent predictors (Alfaro et al. 2016; Maldonado et al. 2017). The influence of certain SST modes seems to influence the position of the intertropical convergence zone and strengthening of the trade winds acting as a modulator to the precipitation in the region (Alfaro et al. 2016; Maldonado et al. 2017).

To demonstrate the potential use of the model, we analyzed the retrospective forecast for 2009. The forecast in flexible format for that year (Fig. 7a) allowed us to inspect the probabilities of exceeding any particular coffee yield threshold. For this example, we set the threshold to be 5% (as a percentage of deviation from the average coffee field in the basin for the 1989–2009 period). The flexible format allows for easy interpretation as the dotted line (user defined threshold) intersects with both the probabilities under the climatological values and the probabilities as defined by the forecast. To this respect, the probabilities of collecting a coffee yield that is at least 5% above the historical average are 81.84% whereas the historical probability of getting at least 5% is 39.57%. The probability density functions (Fig. 7b) shows the ability of the model to distinguish between the forecast probability function and the climatological values, suggesting a sharp forecast for the 2009 case. Our model produced not only an accurate categorical (above-average) forecast for the coffee yield in this example, but also the observed value for that year was within the uncertainty envelope of the deterministic forecast (Fig. 5).

5. Discussion and conclusions

The main objective of this study was to evaluate coffee farmers' current and potential use of seasonal rainfall forecasts

at the farm level for decision-making processes associated with coffee productivity. To achieve this, we evaluated the perception of coffee farmers of the association between climate and coffee yield and whether they currently keep records of those variables perceived as relevant to the decision-making processes. We evaluated different potential candidate climate predictors for coffee yield that could bring information relevant to the farmers on the ground. In addition, we asked the farmers about the best transfer and translation methods for climate information provision. Our results suggest that—despite considering critical—farmers' access to climate information is limited. This is in part due to a lack of instrumental data in the study area. Most of the farmers have precipitation gauges but few of them keep historical records. When it comes to temperature, the records are even more scarce. Our analysis suggests a strong agreement between farmers perceptions of climate impacts on coffee yield, and the associations established using statistical analysis. According to our findings, accumulated June–July–August precipitation can be used as a predictor to forecast coffee yield in the study region. At the same time, we evaluated several lead times for the forecast using June–July–August accumulated precipitation. The analysis suggests that the NextGen model for total precipitation for that season has high skill to discriminate above-normal total precipitation with a forecast initialized in February, suggesting that the coffee model can use June–July–August precipitation forecasts to inform farmers on management activities associated with expected coffee yield at the beginning of the year. With this information, coffee farmers can implement early adaptation strategies to maximize the coffee yield, or to avoid losses based on the combination of information from both the precipitation and coffee yield forecast.

Management strategies informed by the NextGen system

The forecast for the June–August accumulated precipitation produced in early February could trigger a set of diverse

FIG. 6. Skill assessment of probabilistic forecasts for the JJA season, initialized in May. (a) ROC curves indicate forecast discrimination for each category (see the color line legend; areas under the ROC curves are indicated in parentheses). (b) Reliability diagram with values of related metrics in the top-left corner of the panel. See the main text for details.

actions at the farm level. For instance, for an above-normal precipitation forecast, the management activities could include budget assessment and allocation for: fertilizer application (both type and timing); adding sand to soil when managing seedlings; fungicides and insecticides selection and their respective adherent; and management of the shade pruning (PRCC 2016). Other set of activities under the same

forecast could include the creation of ventilation between plants to avoid high humidity, having evacuation channels with a 2% slope for water runoff, and application of calcium before fertilizer to help soils retain more nutrients before the precipitation (PRCC 2016).

Although all these activities are important and can be triggered ahead of time by the forecast, shade management in the study area remains the most important adaptation strategy against large positive precipitation anomalies. By using accumulated precipitation as a predictor for coffee yield in the NextGen system, farmers can have this information starting in February–April, when they need to start managing or preparing to manage shade. This information might be particularly helpful during expected excessive rain for the June–August period. During this season, adequate shade pruning is critical because it can have an influence on the flowering, fruit set and photosynthetic activity due to cloud presence. Other measures that can be undertaken by coffee farmers when experiencing increased precipitation with flooding and landslides include soil preservation practices, design and management of coffee shade systems, and avoiding planting crops in high-risk areas (acute slopes and riversides; PRCC 2016).

As part of this research, we shared the results with the technical team at the study site and the experts at the ANACAFÉ headquarters, to validate a set of actions and recommendations that could be implemented by farmers. As an example, Table 3 shows a set of actions that farmers could undertake since February, for the JJA season, given an expected positive precipitation anomaly forecast associated with reduced coffee yield.

According to these set of activities, a precipitation forecast initialized in February associated with expected reduced coffee yield, could help a farmer to evaluate how much of its budget should be appropriated to adjust shade in preparation for an above-normal JJA season. Managing an optimum percentage of shade is key to improve climate resilience at the farm level and early forecasts with high predictive skill could help farmers better prepare for this optimization (Hirons et al. 2018). Given a precipitation forecast initialized in March, the farmers can begin to select a certain type of fungicide that might bring him/her/their the most return to his/her/their investment. If applied in a timely manner, the effects of fungal outbreaks like the coffee leaf rust can be mitigated (Avelino et al. 2015; Lechthaler and Vinogradova 2017). In fact, the discussion with the research center specialists from ANACAFÉ related to fungal activities associated to the above-average precipitation for the JJA period, revealed that the coffee leaf rust fungus incidence follows an exponential outbreak after precipitation anomalies in the region (CEDICAFÉ 2018). The technical advisors from ANACAFÉ indicated that, given a forecast of above-normal precipitation (and hence, lower coffee yield), they might recommend monitoring the coffee farm to identify as early as possible any fungus outbreak. The forecast would allow them to decide if the coffee prices allow for these extra costs of sending technicians to the coffee farms to evaluate the plantation and monitor the presence of pests and infestations. Similarly, the extension service agents from see value in the forecast to estimate weed control strategies, which are

FIG. 7. Forecast in flexible format for 2009, showing (a) probabilities of exceedance of at least 5% above the average coffee yield (vertical dotted line) and (b) the corresponding probability density functions of the 1989–2009 observed average (or “climatology,” in blue) and the 2009 forecast (in red). The fact that the forecast probability density function (in red) is considerably more leptokurtic than the observed average (blue) indicates sharpness in the forecast to distinguish between the probabilities associated with the observed average and the forecast density functions; the ratio of the forecast and observed average probabilities is presented at the bottom in (a).

associated with the amount of total precipitation and constrained by coffee prices.

When it comes to fertilization schemes, an April forecast lead time can help a farmer decide on the type of fertilizer and application technique and to evaluate if it is financially feasible to incorporate a particular type given the economic circumstances at the farm level. This relates to whether the application of the fertilizer should emphasize covering the fertilizer pebbles with soil and/or mixing it with leaf litter to protect it from excessive humidity and to avoid for nutrients to be washed away. The technical advisors in the region agree that a forecast with this skill might even help them make the decision of not applying fertilizers at all if the market prices are low.

A forecast initialized in May for the JJA season, can inform more specific (and potentially more expensive) actions, like preparing terraces and absorption wells, and creating outlets for water overflow to keep plantations from flooding. Also, the May forecast can help farmers to better manage airing between coffee plants allowing for more wind to flow throughout the plantation. The Samalá River watershed experiences one of the highest rates of natural catastrophes in Guatemala associated with hydrologic events (Soto et al. 2015). The information contained in the forecast for total precipitation can also help

coffee farmers manage risks associated with soil erosion, landslides, subsidence, and damage to roads and infrastructure, as indicated by the technical advisors in the region. If these activities are deemed economically viable by a farmer in a risk-management context, the provision of climate services can help the farmer to become more efficient and improve his/her overall welfare (Lechthaler and Vinogradova 2017).

Incrementing the time for decision making can help better prepare to select practices aimed at maximizing their income, especially in a world of low profitability due to high production costs and low market prices. Exploring future combinations of seasonal and subseasonal climate information, for example via an extension of the present NextGen system to produce subseasonal forecasts, could improve the management strategies spectra to inform more specific activities.

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TABLE 3. Lead times for total precipitation for the June–August season, and subsequent potential actions at the farm level.

Lead time of the forecast (month)	Potential activities at farm level given positive anomalies in precipitation
Feb	Adjusting shade percentage to expected precipitation
Mar	Selection of fungicides to treat coffee leaf rust
Apr	Selection of fertilizers and application procedure
May	Preparation of soil conservation strategies

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