The Madden-Julian Oscillation Affects Maize Yields Throughout the Tropics and Subtropics

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Abstract Understanding what causes weather-related stresses that lead to crop failures is a critical step toward stabilizing global food production. While there are many sources of weather-related stresses, the 30–60 days of Madden-Julian Oscillation (MJO) is the dominant source of subseasonal climate variability in the tropics, making it a potential—but as of yet unexplored—source of crop yield anomalies. Here crop models and observational yield statistics are used to assess whether the MJO affects maize yields. We find that the influence of the MJO is widespread; it can increase or reduce maize yields throughout the tropics. In dry, hot environments the MJO can reduce maize yields by reducing precipitation, decreasing soil moisture, and increasing extreme heat, while in wetter, cooler environments—where water stress is less common—MJO-forced decreases in rainfall bring increases in solar radiation that benefits maize yields. These results provide a pathway to develop actionable early warnings using subseasonal forecasts.

1. Introduction

Crop yields in rainfed cropping systems, which account for >75% of cropped areas globally (Portmann et al., 2010), depend not only on seasonal total rainfall and temperature but also on the distribution of that rain and heat within the growing season (Prasad et al., 2008). Exposure to extreme heat, even on the timescale of just hours to days, can significantly damage crop yields (Schlenker & Roberts, 2009), particularly when it occurs during sensitive stages of crop development (Prasad et al., 2008). These extreme events may be relatively short in duration but they often occur with little warning and are spatially widespread enough to affect global-scale food production (Lesk et al., 2016).

Preventing crop failures associated with extreme events requires understanding what causes those conditions in the first place. Climate extremes can have any number of dynamical origins, from interannual variability associated with, for example, the El Niño Southern Oscillation (Anderson et al., 2019; Iizumi et al., 2014) to synoptic weather systems (Ray et al., 2015). Distinguishing between the two is critical when considering how to build a climate-smart food production system. While abiotic stresses arising from weather systems may only be predictable up to a week or two in advance, extreme conditions attributable to predictable modes of variability, like the El Niño Southern Oscillation, may be anticipated and acted upon using seasonal climate forecasts (Goddard & Dilley, 2005). In between the predictable seasonal and weather timescales, however, is a nascent source of climate information for agriculture and food production: the 30–60 days of Madden-Julian Oscillation (MJO).

As the dominant source of subseasonal climate variability in the tropics (Madden & Julian, 1972; Zhang, 2005), the MJO represents a significant opportunity for agricultural climate services. While MJO activity levels vary from year to year, an active MJO organizes tropical atmospheric circulation into regions of enhanced and suppressed convection. Deep convection associated with the MJO often first appears over the Indian Ocean and propagates eastward, reaching the western Pacific about 2 weeks later. The surface expression of the MJO dissipates as it continues east over the cold sea surface temperatures in the eastern Pacific before reforming in the tropical Atlantic. The MJO tends to persist in each of its eight phases for 3–7 days (Pohl & Matthews, 2007), although not all events propagate smoothly through all phases. The effects of a propagating MJO event, therefore, could affect the weather in a given location for anywhere from a few days to a few weeks.

The circumglobal path of the MJO means that it potentially has a far-reaching relevance to global rainfed agriculture. The MJO influences the West African (Berhane et al., 2015; Lavender & Matthews, 2009;
Matthews, 2004; Sossa et al., 2017), Indian (Joseph et al., 2009; Pai et al., 2011), Asian (Lawrence & Webster, 2002), and Australian (Wheeler et al., 2009) monsoons. It affects precipitation in East Africa (Berhane & Zaitchik, 2014; Pohl & Camberlin, 2006a, 2006b), southwest Asia (Barlow et al., 2005; Hoell et al., 2018; Nazemosadat & Ghaedamini, 2010), South Africa (Pohl et al., 2007), South America (Grimm, 2019; Valadão et al., 2017), and southern Mexico (Barlow & Salstein, 2006). But to date, despite progress understanding the often-large impacts of the MJO on rainfall, its physical mechanisms, and improvements to MJO forecasts (Pegion et al., 2019), the impacts of the MJO on agriculture are still largely unknown. Here, for the first time, we analyze whether a single MJO event can affect crop yield statistics and whether the effect of the MJO is detectable in historical crop yields. We focus our analysis on maize because an active MJO has been shown to affect precipitation, soil moisture, and extreme maximum temperatures throughout the tropics in the months prior to harvest (Anderson et al., 2020), which includes the reproductive growth stage when grain crops are particularly sensitive to abiotic stresses (Barnabás et al., 2008; Prasad et al., 2008). Our results provide a pathway to develop actionable early warnings of climate hazards and their impacts using subseasonal forecasts.

2. Materials and Methods

2.1. Data

To identify MJO teleconnections we use daily interpolated station-based temperature data, and daily precipitation and soil moisture products that blend satellite and station data. We use daily soil moisture estimates from the Global Land Evaporation Amsterdam Model (GLEAM) v3.2a (1981–2016), which uses satellite-observed surface (0–10 cm) soil moisture, vegetation optical depth, reanalysis air temperatures, and a multisource precipitation product to derive surface soil moisture values (Martens et al., 2017). Daily precipitation data come from the Climate Hazards group Infrared Precipitation with Stations (CHIRPS; 1981–2016) at 0.25° (Funk et al., 2015). We use values of daily maximum and minimum temperature at 2 m from the Berkeley Earth data set (1981–2016), which is a 1° gridded interpolation-based statistical product (Rohde et al., 2013), and daily solar insolation from the satellite-based NASA-POWER (1983–2013) agroclimatology data set (Stackhouse et al., 2015). To construct weather forcing for the DSSAT crop model we use data from the common period of 1983–2013.

We use observational crop statistics at the national and subnational scale to estimate the effects of the MJO on regional maize yields. Subnational crop statistics were downloaded for India from the Directorate of Economics and Statistics (https://eands.dacnet.nic.in/); for Mexico from the INEGI Information Databank (http://www3.inegi.org.mx/sistemas/biinegi/); for Brazil we use first-season maize only from the Brazilian Companhia Nacional de Abastecimento (CONAB; http://www.conab.gov.br/index.php); data for the rest of Central America, West Africa, and East Africa were only available at a national scale and were downloaded from the Food and Agriculture Organization FAOSTAT database (http://www.fao.org/faostat/en/).

To calculate crop yield anomalies we first remove the long-term trend using a low-pass Gaussian filter with a kernel standard deviation of 3 years, which is similar to a 9-year running mean. Deviations from this “expected yield” are absolute yield anomalies. We calculate percent yield anomalies as the absolute yield anomaly divided by the expected yield for each subnational district. Regional yield anomalies are calculated by using observed harvested areas to calculate regional percent yield anomalies. As a sensitivity experiment, we recalculated the results based on yield anomalies derived from a 5-year running mean but found little difference.

2.2. Daily Climate Anomalies

We estimate the impact of harmful increases in maximum temperature prior to harvest by counting degree days above a critical temperature threshold \((T_c)\), which in this case is 29 °C for maize (Schlenker & Roberts, 2009). Our temperature threshold is chosen to identify detrimental, not necessarily lethal, temperatures (Schlenker & Roberts, 2009; Sánchez et al., 2014). During the 3 months prior to harvest, which is defined for each point using the Sacks et al. (2010) data, the number of “extreme degree days” (EDD) were then calculated as follows:

\[
EDD = \sum_{i=1}^{n} \max(0, T_{max,i} - T_c).
\]
where \( T_{\text{max},i} \) is the maximum temperature on the \( i \)th day of the \( n \) days in the 3-month interval prior to harvest. This 3-month interval does not encompass the entire growing season, even in the tropics, although the fraction of the season that it does cover will vary by location and cultivar. We use an average of daily EDDs across all years to define the climatology of EDDs.

For the non-derived variables of soil moisture and precipitation, we define the climatology using the first three harmonics. Daily anomalies are similarly calculated as departures from this daily climatology and calculated for MJO events during the 3 months prior to harvest.

We test for statistical significance by comparing the distribution of climate anomalies during all days in a particular MJO phase in the 3 months prior to harvest with those that occur in that same 3-month period when the MJO is inactive (RMM amplitude <1). We use a Kolmogorov-Smirnov test as a nonparametric test of whether the distribution of anomalies during neutral days are distinguishable from that of anomalies during each MJO phase at each point. Because points within a region may have a different maize harvest dates, and therefore different numbers of MJO events in Phases 1–8 or neutral, we cannot test regional significance by pooling points in a region together but instead report average point-wise significance in Figure 1.

2.3. MJO Event Identification

To identify MJO teleconnections we use the Wheeler-Hendon Realtime Multivariate MJO (RMM) indices, which measure MJO activity (Wheeler & Hendon, 2004), to create composites of all days (1981–2016) in which the RMM indices have an amplitude of greater than one. We mask out all areas in which there are fewer than 1,000 observations in the climate data set or where maize is not cultivated. Measuring MJO teleconnections is straightforward in Southwest Mexico and Central America, Northeast Brazil, and East Africa, where the MJO influences crop growing conditions is directly related to the eastward propagating convection anomalies. In each of these areas we plot composites of damaging maximum temperatures and soil moisture anomalies by MJO phase in Figure 2 below. MJO teleconnections in West Africa and India, on the other hand, are at least partly the result of Rossby and Kelvin waves that propagate away from the main envelope of deep convection associated with the MJO. In West Africa teleconnections are primarily a response to westward propagating Rossby waves generated by MJO-related convection (Lavender & Matthews, 2009; Matthews, 2004; Vigaud & Giannini, 2019). Over India in the summer, the eastward propagating MJO acquires a northward propagating component that reaches the 10–25N region up to 2 weeks later (Lawrence & Webster, 2002; Wang et al., 2018).

To capture the integrated effect of these teleconnections we plot the cumulative sum of soil moisture and extreme degree-day anomalies during 10-day windows corresponding to the expected timing of teleconnections for each phase: Days 0–10 and 5–15 for West Africa and India, respectively. We choose the timing of the lag based on previous literature demonstrating the time it takes for MJO-forced waves to propagate to our points in West Africa (Lavender & Matthews, 2009; Matthews, 2004; Vigaud & Giannini, 2019) and India (Lawrence & Webster, 2002). For all other regions we show instantaneous teleconnections.

2.4. DSSAT Model Simulation

To simulate MJO teleconnections to maize yields we use the DSSAT crop model (Jones et al., 2003; Jones & Kiniry, 1986; Hoogenboom et al., 2019), run at specific spatial locations. We choose locations that (1) are maize production regions and (2) in which the MJO teleconnections at a single point are representative of the average MJO teleconnection to the entire region as a whole (Figure 3). This ensures continuity between our point-based simulation of yields and regional analysis of climate teleconnections. For each chosen location, we performed a literature review to identify an appropriate cultivar and parameterization for the model (Babel & Turyatunga, 2015; Jagtap et al., 1999; Justino et al., 2013; Royce, 2002). Parameters from regionally relevant field trials were used where available (supporting information Table S1). Where no such data were available, as was the case in Mexico, we relied on expert elicitation from (personal communication with Kai Sonder, Jim Hansen, and Walter Baethgen). We next identify suitable soils in the WISE soils database and calibrate the model planting date based on observational yield statistics. For each location we use three planting dates to simulate variable sowing decisions, and choose two soil profiles to represent different likely soil conditions (Table S1).

We force the DSSAT crop model with observed daily precipitation, incoming solar radiation, and maximum and minimum temperature to create series of baseline crop yield simulations in each location. We next
Figure 1. Average precipitation, soil moisture, and extreme degree-day anomalies during days with an active MJO for each phase (1–8; y-axis) from 15 days before an event occurs to 15 days after an event occurs (x-axis). Values are averaged over each region shown by the boxed area in the top panel, which shows maize growing locations. Propagation of the MJO is indicated by the slope of anomalies in the phase-lag plot. Statistical significance ($p < 0.1$) denoted by stippling.
create a weather forcing ensemble to measure the marginal effect of an MJO event on maize yield anomalies. We use the same MJO events from our composite analysis described in section 2.3 to create the ensemble. For each day in which the MJO was active in a given phase in the 3 months prior to harvest, we select the maximum temperature, minimum temperature, solar radiation, and precipitation for that day and the following 2 weeks to account for propagating waves and persistent teleconnections. To estimate the marginal effect of one MJO event on crop yields, we overwrite 2 weeks of observed weather in the DSSAT forcing file around the reproductive growth stage (as determined by the flowering date in the middle planting date in the DSSAT calibration runs) with the “MJO event weather” and rerun DSSAT with the perturbed weather forcing. For the purposes of generating a large ensemble, each historical MJO event in a particular phase is inserted at the same date, regardless of when it occurred in the observed record. We then repeat this process for all possible combinations of MJO events, years, three planting dates, and two soils to produce an ensemble of size (# events) × (# years) × (# planting dates) × (# soils) for each phase of the MJO. This creates an ensemble of over 300,000 yield anomalies for each region (>40,000 per phase per region). Finally,
Figure 3. Differences between MJO activity in good yield and poor yield years as measured by the normalized, two-dimensional probability density functions of the RMM indices during the months prior to harvest. Subnational or national units included in each region for observational statistics are shown in blue in the top panel. Good yield years are identified as the top-tercile of regional yields, while poor yield years are bottom-tercile years. The difference between the distributions of RMM indices in good yield and poor year yields is statistically significant at the 5% level in all cases.

We calculate the marginal effect of each MJO event by differencing the DSSAT maize yield with the added “MJO event weather” from the DSSAT maize yield forced by observed weather without the added event.

To identify the effect of each MJO phase on maize yields, we use multi-linear regression to regress the MJO phase of each forcing event onto the calculated crop yield anomalies while controlling for the year into which that event was inserted:

\[ \delta Y_{ij} = \Phi_i + Y_{rj}, \]

where \( \delta Y_{ij} \) is the crop yield anomaly in year \( j \) forced by MJO event \( i \), \( Y_{rj} \) is a fixed effect for each year to remove interannual variability, and \( \Phi_i \) is a series of dummy variables corresponding to the phase of the MJO during each event \( i \). In this way we both remove interannual variability and isolate the average expected influence of an individual MJO event on crop yield anomalies.

### 2.5. Effect of the MJO in Observational Crop Statistics

Our regression onto simulated yield anomalies can provide us with an estimate of the potential influence of any single MJO event that begins in a particular phase on maize yields. But it does not tell us whether these effects are present in observational yield statistics. Because we cannot isolate the effect of individual MJO phases in the observational record, as we did with our DSSAT simulations, we instead take a counterfactual approach and ask “do bad yield years and good yield years show a difference in the frequency of events in particular MJO phases?” To answer this question we use both our DSSAT ensemble and observational records.

In our DSSAT ensemble for each location, we identify the highest and lowest 10,000 yield anomalies, which is roughly the top and bottom 2.5% of the distribution, and record the Realtime Multivariate MJO (RMM) index values associated with each MJO event used to produce those yield anomalies in the DSSAT ensemble. We then create two probability density functions of MJO activity in an RMM diagram, one for the events associated with the “good years” and one for the events associated with the “bad years.” The difference of these two distributions indicates the relative frequency of MJO phases that produced good yields and those that lead to bad yields. If there is no difference between the two distributions, then the MJO has no discernible influence. If there is a difference, however, then the relative frequencies can be compared to our climate analysis to check for consistency.

We repeat this process with observational yields by selecting subnational or national units within each region, and aggregating yields into a single regional value. We next identify the high and low terciles of maize yields in the region, and for each year we identify the daily MJO phases and amplitudes during the maize growing season (June–September for India, May–September for Southwest Mexico, May–August for West Africa, April–September for East Africa, and both February–May and September–December for cropping seasons in Northeast Brazil). We again take the difference between the distribution of daily MJO RMM
indices during high and low yield terciles to calculate the difference in MJO activity between good and bad years.

3. Results
3.1. MJO Teleconnections
Dry and hot weather forced by the MJO tends to persist for around 15 days (Figure 1), which is long enough for MJO-related reductions in precipitation to dry out near-surface soil moisture and raise maximum air temperatures (Anderson et al., 2020). Likewise, the MJO may also increase precipitation, wet near-surface soil moisture, and reduce the incidence of extreme maximum air temperatures. Abiotic stresses of this magnitude and duration are sufficient to affect seasonal total maize yields (Schlenker & Roberts, 2009). The temperature-stress pathway is likely to be largest in Northeast Brazil, West Africa, and India where teleconnections to extreme temperatures are strongest.

Using a large ensemble of modeled crop yields, we separate the effect of the MJO from that of both seasonal variability (e.g., the El Niño Southern Oscillation) and random weather. We find that the MJO affects maize yields throughout the tropics but that its influence is stronger in Northeast Brazil and India than in other regions studied (Figure 2). Each MJO event, of which there may be multiple during a given growing season, affects maize yields by $\sim 0.5$–1%. For reference, a year with crop yields 10% below expected yields would be an exceptionally bad harvest, and 15% below expected yields would be disastrous, likely the worst yield in decades. So an effect of 1% from a single MJO event is not in and of itself catastrophic, but it is an appreciable effect particularly if repeated or combined with other influences.

3.2. Regional Dynamics
MJO impacts on Southwest Mexico and Northeast Brazil are phased similarly. Phases 3–6 suppress convection (Figure 1), which, after a few days, dries out the soil and leads to increased maximum air temperatures. 

Despite the similarity of the MJO teleconnections to the climate in these two regions, the effect on maize yields is quite different due to differing growing conditions. Our modeled point in Northeast Brazil is arid and hot, which means that maize is regularly exposed to heat stress and drought. Our point in Southwest Mexico, on the other hand, is relatively wet and cool, such that maize is exposed to less extreme temperatures (Figure 1) and is water-stressed much less often in the DSSAT simulations (Figure S1). Wet, cool conditions in Northeast Brazil during Phases 7–2, therefore, generally increase maize yields, while the hot, dry conditions in Phases 3–6 decrease maize yields (Figure 2). In Southwest Mexico, clear skies bring an increase in solar radiation that tends to improve yields, while increased precipitation decreases solar radiation and leads to lower maize yields on average.

An MJO event being sufficient to affect modeled crop yields does not demonstrate that the effect is necessarily seen in observed yields. After all, the MJO is only one of many factors that affect crop yields in these regions. To test whether the effect of the MJO is present in observational statistics we analyzed whether the frequency or intensity of the MJO during the growing season systematically differs during good and poor harvest years (see section 2).

In Northeast Brazil, years with poor maize yields are associated with increased MJO activity in Phases 2–5 during the growing season, while years with good maize yields are associated with increased MJO activity in Phases 6–1 (Figure 3). The frequency of MJO events in good and bad years based on observational statistics match results based on our DSSAT model ensemble to first order (Figure S2), although there are differences between the two distributions of MJO activity. These results are consistent with our climate analysis for the region, in which dry, hot MJO teleconnections lower maize yields while wet, cool MJO teleconnections improve maize yields (Figure 2).

In Southwestern Mexico the observational ensemble indicates that years with poor maize yields are associated with Phases 7–2 (Figure 3), although the DSSAT ensemble indicates that poor maize yields are associated with MJO Phases 6–8 (Figures 2 and S2). The discrepancy between modeled and observed results may be due to the difference between the area-averaged statistics and the DSSAT point estimate, or it may reflect a discrepancy between the modeled and historical cropping practices in the region. Further research
is needed to more precisely characterize how MJO-related variations in the growing season climate of Southwest Mexico translates into variations in maize yields.

The MJO affects maize yields in West Africa by modifying precipitation via a combination of (1) the direct influence of the convective core of the MJO advecting moisture from the Atlantic (Berhane et al., 2015) and (2) a remote response to MJO activity in the Indian Ocean (Lavender & Matthews, 2009; Matthews, 2004). When the MJO enhances convection in the Indian Ocean and suppresses convection in the West Pacific warm pool (Phases 1–2) it generates an atmospheric equatorial Kelvin wave that travels east and equatorial Rossby waves that travel west, which reach West Africa about a week later, destabilizing the atmospheric column and enhancing rainfall in the region (Lavender & Matthews, 2009; Matthews, 2004). Accordingly, Phases 1 and 2 are characterized by increased precipitation (Figure 1), wet soils, an absence of high temperatures, and above expected maize yields (Figure 2). Phases 3–6 are associated with dry, hot conditions that lower modeled maize yields. Phase four is most damaging to maize yields in West Africa, possibly because as the MJO tends to propagate from Phases 4–8, teleconnections are consistently dry and hot, prolonging the time before rain provides relief to the crop. These results are consistent with good harvests in the observational statistics being associated with an increase in MJO Phases 7–2, while poor harvests are associated with increased activity in MJO Phases 3–6 (Figure 3). Similarly, the good yielding years in the model ensemble are associated with an increase in the frequency of Phases 1 and 2 and a decrease in the frequency of Phases 3 and 4, although the effect of Phases 5–8 are muted in the modeled results as compared to the observational statistics.

In the East African highlands, precipitation anomalies are controlled by the atmospheric stability conditions imposed by the MJO (Berhane & Zaïtchik, 2014; Pohl & Camberlin, 2006a, 2006b). During Phases 2–5 large-scale deep convection is responsible for wet, cool conditions. Similar to Southwest Mexico, however, the growing conditions at our modeled point in Uganda are cool and wet, such that increased precipitation decreases incoming solar radiation and decreases modeled maize yields (Figure 2). These DSSAT results, however, must be interpreted with the understanding that many regions—particularly East Africa—are a complex mosaic of agro-climates and soils, which will result in a non-homogenous crop yield response to a homogenous MJO-forced climate anomaly. In observational crop yield statistics, differences in the frequency of MJO phases in good versus poor yield years are noisy, perhaps due to the lack of available, reliable, subnational crop yield data or due to the complex crop growing environment in the region. While there is reasonable agreement between the modeled maize yields and observed yields, no strong conclusions about observed East African maize yields can be drawn based on Figure 3.

In India, precipitation anomalies are associated with meridionally propagating Rossby waves triggered by the eastward-moving deep-convective anomalies of the MJO (Lawrence & Webster, 2002). Large-scale convective anomalies over the Indian Ocean propagate northward over the course of 1–2 weeks into the 15–25N region (Lawrence & Webster, 2002), where most maize is cultivated in India. Increased deep convection over the Indian ocean in Phases 1–4 leads to increased precipitation 1–2 weeks later, which leads to wet soils and, after a few days, cool air temperatures over the maize growing regions of India (Figure 1). Accordingly, Phases 1–4 lead to increased maize yields in model simulations (Figure 2), and increased MJO activity in Phases 1–4 is associated with years of good maize harvests in both the observational data and model simulations (Figure 3). Phases 5–8, which are associated with suppressed convection over the Indian Ocean, lead to dry, hot conditions (Joseph et al., 2009; Moron et al., 2012; Pai et al., 2011) and below expected maize yields (Figures 2 and 3).

4. Discussion

A historical example of when the MJO likely affected crop yield anomalies was the 2002 monsoon season in India. At the time, the 2002 drought was among the worst in over a century despite seasonal forecasts for normal monsoon rainfall (Bhat, 2006). The drought in July, when the MJO was strongly active in Phases 6–8 (Figure S3), had a large contribution from intraseasonal disturbances (Bhat, 2006; Kripalani et al., 2004), although a developing El Niño likely played a role in the drought as well via cross-timescale interactions (Muñoz et al., 2015). The spatial pattern of maize yield anomalies in 2002 matches well what would be expected from MJO-forced extreme heat in Phases 6–8 (Figure S3). Reduced maize yields in India following MJO activity in Phases 6–8 is furthermore consistent with both our observational and modeled analyses.
(Figures 1–3). The 2002 drought illustrates how intraseasonal forcing may play a role in even the most intense crop failures.

Our results demonstrate that the MJO affects maize yield variations throughout the tropics. The effect is phase dependent and may either improve or reduce yields. In dry, hot environments MJO phases that reduce maize yields do so by reducing precipitation, decreasing soil moisture, and increasing extreme heat while in wetter, cooler environments—where water stress is less common—MJO-forced decreases in rainfall bring an increase in solar radiation that benefits maize yields. These pathways work in the opposite sense as well: MJO phases that bring wet, cool conditions to dry environments improve yields while those that reduce insolation in wet, cloudy environments reduce maize yields. We find that each MJO event affects final maize yields by ~0.5–1% of expected yields, although multiple events may occur in a single season. For reference, the 2002 drought in India led to the worst maize growing season in recent history, with national yields reduced by around 17% compared to the previous year (FAO, 2009). Average MJO reductions in crop yields on the order of 1% per event, therefore, are non-negligible contributions to reductions in crop yields even measured against the most devastating yield losses.

But a number of open questions remain. Our results indicate that one path by which the MJO may affect final crop yields is through an increased frequency of some MJO phases relative to others. It is also possible, however, that a nonlinear crop yield response to excess heat could rectify onto the end-of-season crop yields even when the MJO propagates through both cool phases that improve yields and hot phases that decrease yields. Further research is needed to fully understand the mechanisms by which the MJO affects crop yields.

The ability to attribute crop yield anomalies to the MJO provides a new incentive to glean operational value from our rapidly improving understanding of subseasonal climate. Current forecast models can now forecast the MJO with high skill up to 4 weeks in advance (Vitart, 2017) and—in some of the regions analyzed—subseasonal forecasts of precipitation demonstrate skill at lead times of up to 3 weeks (Pegion et al., 2019). Such forecasts could be used to extend weather forecasts and provide users with a continuum of actionable forecasts from the weather to seasonal timescales. This would represent a significant advance toward an agricultural system that is more prepared for climate shocks. Using subseasonal forecasts to anticipate false starts to the rainy season, for example, could help inform the timing of crop planting to prevent crop failures.

Owing to the effects of the MJO on climate extremes during grain crop growing seasons on virtually every continent (Anderson et al., 2020), there is good reason to believe that the MJO has widespread relevance to global agriculture. Better understanding how the MJO affects crop yields may lead to significant advances in monitoring and predicting food production shortfalls.
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