Data description for 'The Madden-Julian Oscillation affects maize yields throughout the tropics and subtropics'

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1. Climate data and statistical data

To identify MJO events 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 1000 observations in the climate dataset or where maize is not cultivated.

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 multi-source precipitation product to derive surface soil moisture values (Martens et al., 2017). Daily precipitation data comes from the Climate Hazards group Infrared Precipitation with Stations (CHIRPS; 1981-2016) at 0.25 degrees (Funk et al., 2015). We use values of daily maximum and minimum temperature at 2m from the Berkeley Earth dataset (1981-2016), which is a one-degree gridded interpolation-based statistical product (Rohde et al., 2013), and daily solar insolation from the satellite-based NASA-POWER (1983-2013) agroclimatology dataset (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 was only available at a national scale and was 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 three years, which is similar to a nine-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 five-year running mean but found little difference.

2. DSSAT model simulation

To simulate MJO teleconnections to maize yields we use the DSSAT crop model (Hoogenboom et al., 2019; J. W. Jones et al., 2003; C. A. Jones, 1986), 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 is representative of the average MJO teleconnection to the entire region as a whole. This ensures continuity between our point-based simulation of yields and regional analysis of climate teleconnections in the main paper. For each chosen location, we performed a literature review to identify an appropriate cultivar and parameterization for the model (Jagtap et al., 1999; Justino et al., 2013; Babel & Turyatunga, 2015; Royce, 2002). Parameters from regionally-relevant field trials were used where available (Table S1). Where no such data was 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 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 the previous section to create the ensemble. For each day in which the MJO was active in a given phase in the three months prior to harvest, we select the maximum temperature, minimum temperature, solar radiation and precipitation for that day and the following two weeks to account for propagating waves and persistent teleconnections. To estimate the marginal effect of one MJO event on crop yields, we overwrite two 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 re-run 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)x(# years)x(# planting dates)x(# 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) that we use in our analysis.

Region	Lat, Lon	Cultivar	P1	P2	P5	G1	G2	PHNT	WISE soils	Planting dates	Calibration yield data to determine planting date	Relevant references
Northeast Brazil	9.5 S, 40.4 W	AG7000	319	0.5	880	695	5.2	42.3	WsBR062(SL), PHBR083 (SCL)	December 15, December 30, January 15	Brazilian Companhia Nacional de Abastecimento (CONAB; http://www.conab.gov.br/index.php)	Justino et al. (2013)
India	22 N, 75 E	PC005 2750-2800 GDD	260	0.75	850	800	8.5	49	WI_FRIN091 (SCL), WI_LVIN116 (SL)	June 15, June 22, June 30	Directorate of Economics and Statistics (https://eands.dacnet.nic.in/)	Hoogenboom (2019)
Uganda	2 N, 32 E	MH-16	270	0.28	800	400	6.5	50	WI_ACUG011 (C), WI_GLUG006 (SCL)	March 1, March 15, March 30	Food and Agriculture Organization FAO- STAT database (http://www.fao.org/faostat/en/)	Babel et al. (2015)
West Africa	10 N, 4.5 E	MEDIUM SEASON (Medium duration variety)	350	0.3	730	882.1	9.66	40	WI_LXNG007 (SL), 0000001 (SL) (from Jagtap et al 1999)	April 15, May 1, May 15,	Food and Agriculture Organization FAO- STAT database (http://www.fao.org/faostat/en/)	Jagtap et al. (1999)
Southwest Mexico	17.5 N, 100 W	ACROSS 8328BN C6	310	0.6	980	550	8	45	WI_FLGT005 (C), WI_PLMX016 (LS)	May 1, May 8, May 15	INEGI Information Databank (http://www3.inegi.org.mx/sistemas/biinegi/)	Royce (2002)

Table S1. DSSAT simulation model coefficients. Data, references, and coefficients used in the DSSAT crop model for each modeled point

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