Supplementary Text S1

We performed ORYZA v3 model calibration for cultivar F174 using data from 9 field experiments conducted in the localities of Villavicencio (Meta) and Yopal (Casanare) in the years 2013–2015. In each experiment, destructive samples were taken on a bi-weekly basis to measure leaf area index, and leaf, stem, and panicle biomass. Standard agronomic management was followed to avoid nutrient stress, planting density of 130 plants m$^{-2}$, and no irrigation. Five experiments were used for model calibration, and the remaining four were used for model evaluation. In addition to growth, we recorded phenology in all of the experiments.

We performed model calibration by first calculating phenology parameters (development rate in juvenile, photoperiod-sensitive, panicle development, and reproductive phases) using data on emergence, panicle initiation, flowering and physiological maturity dates from the 5 calibration trials. We then calculating growth parameters (specific leaf area, leaf area growth rate, spikelet growth factor, maximum grain weight, fraction of carbohydrates allocated to stems from reserves, carbohydrate partitioning to roots, shoot, leaves and grains, and drought sensitivity) using a genetic algorithm. The genetic algorithm searches the parameter space for a solution that minimizes the Root Mean Square Error (RMSE). The algorithm was run until either when the maximum number of iterations (10,000) was reached, or when the differences between measured and simulated values for the growth variables of interest (i.e. leaf area index, and leaf, stem and panicle biomass) were within the range of measurement deviations.

Model evaluation focused on testing whether the model simulated well phenology, growth and yield dynamics in the 4 evaluation experiments (Fig. S1). The model captures well the growth and development dynamics during the growing season for these experiments. Thus, we use the simulate rice growth in the Orinoquía region.
Figure S1 Simulated growth dynamics for the four evaluation experiments.
Figure S2. Spatial loadings and temporal scores for model using predictor JJA CFSv2 SST (Lead-1) and predictand station-only JJA precipitation. Model consists of 3 CCA modes labeled M1 to M3. Temporal scores are presented in the middle column with corresponding canonical correlations. Spatial loadings of predictor and predictand on the left and right columns respectively. Spatial loadings of Mode 1 are the same as in Fig. 3a and 3b.
Figure S3. Spatial loadings and temporal scores for model using predictor JJA CFSv2 SST (Lead-1) and predictand station-only JJA frequency of wet days. Model consists of 2 CCA modes labeled M1 and M2. Temporal scores are presented in the middle column with corresponding canonical correlations. Spatial loadings of predictor and predictand on the left and right columns respectively. Spatial loadings of Mode 1 are the same as in Fig. 3c and 3d.
Figure S4. Spatial loadings and temporal scores for the model using as predictor Lead-1 JJA CFSv2 vertically integrated meridional moisture flux (VQ) and predictand JJA CHIRPS precipitation. Model consists of 5 CCA modes labeled M1 to M5. Temporal scores are presented in the middle column with corresponding canonical correlations. Spatial loadings of predictor and predictand on the left and right columns respectively. Spatial loadings of Mode 1 are the same as in Fig. 6.