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Simulating rice and maize yield potential in the humid tropical environment of Indonesia

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ABSTRACT

Little is known about the yield potential of modern rice and, particularly, maize cultivars in the tropical humid environment of Indonesia where farmers can grow 2–3 consecutive crops on the same piece of land per year. This study provides a first step to fill this knowledge gap by using two crop simulation models to estimate yield potential for rice and maize based on experiments conducted across multiple site-years and measured weather and soil data. Data collected from well-managed irrigated experiments, with observed yields ranging from 7.8 to 10 Mg ha^{-1} (rice) and 12 to 14.4 Mg ha^{-1} (maize), were used to calibrate phenology and growth coefficients for both a rice (OryzaV3) and maize crop model (Hybrid Maize). The calibration was performed for commercial, high-yielding irrigated rice and maize cultivars. Subsequently, calibrated models were evaluated on their ability to simulate yield potential using an independent database available from variety (irrigated rice) and fertilizer (irrigated and rainfed maize) trials conducted at multiple site-years across major rice and maize producing areas in Indonesia. Calibrated coefficients for rice were robust at reproducing observed leaf area, aboveground biomass, and biomass partitioning to different plant organs. In the case of maize, close agreement between simulated and observed yields suggests that the generic growth model coefficients originally derived for temperate maize performed well at simulating yield potential of modern tropical maize hybrids. The two models reproduced with acceptable performance the maximum observed yields across variety and fertilizer trials, except for rainfed maize grown in a region with very heavy clay soils. Across site-years, yield potential for irrigated rice and maize averaged 9.1 and 11.6 Mg ha^{-1}, respectively, while rainfed maize averaged 11.5 Mg ha^{-1}. Comparison between simulated yields and average national rice and maize yields (5.2 and 5 Mg ha^{-1}, respectively) suggested that room exists to further increase average farmer yields in rice and maize-based crop systems. Our study also highlighted the high yield potential of modern maize hybrids grown in intensive crop sequences in the humid tropics (> 10 Mg ha^{-1}). The two models evaluated here can be used to benchmark productivity in rice and maize crop systems in the humid tropical environments of South East Asia and fine tune current management practices and inputs application.

1. Introduction

Yield potential (Yp) is defined as the yield of a well-adapted crop cultivar with non-limiting water and nutrients, and with biotic stresses effectively controlled (Evans, 1993). Water-limited yield potential (Yw) is similar to Yp but it also accounts for the influence of water supply amount and distribution during the growing season and soil properties influencing the crop water balance, such as rootable soil depth, available-water holding capacity, and terrain slope (Cassman et al., 2003; van Ittersum et al., 2013). Robust estimates of Yp and Yw are needed to assess potential extra food production, set realistic yield goals and associated water and nutrient requirements, and identify opportunities for improving yield and input-use efficiency. Crop simulation models provide a robust approach for estimating Yp and Yw (van Ittersum et al., 2013). These models rely on weather, soil, and management data to simulate the influence of genotype, environment, and

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management practices on crop growth, development, and yield (Grassini et al., 2015; Rotter et al., 2015).

Multiple rice and/or maize crops are often grown on the same piece of land within a 12-month period in the humid tropical environment of South East Asia (Pasuquin et al., 2014). For example, up to three crops per year can be grown in irrigated and favorable rainfed environments of Indonesia. Due to a combination of high cropping intensity and large arable land, Indonesia is the third and fifth largest rice and maize producing country in the globe, respectively (FAOSTAT, 2017). Still, Indonesia has imported substantial amounts of maize and rice grain during recent decades. At the same time, there has been massive cropland conversion for industrial and residential uses (d'Amour et al., 2017). Hence, it is crucial for Indonesia, as well as other countries in South East Asia, to understand what the extra crop production potential is on existing cropland and identify those factors that constrain on-farm yields. Few studies have attempted to estimate rice and, in particular, maize Yp and Yw in Indonesia using crop simulation models (Boling et al., 2004, 2007, 2008; Timsina et al., 2011; Laborte et al., 2012; Pasuquin et al., 2014; Stuart et al., 2016). These previous attempts suffered from limitations and/or sources of uncertainty. First, most of these studies have focused at estimating Yp (or Yw) using models that were calibrated for individual site-years; hence, it is unknown how robust these models are at estimating Yp (or Yw) across Indonesia's wide range of environments and cropping systems. Second, previous studies have relied on coarse-scale gridded and/or generated weather data, which can lead to important biases in simulated Yp and Yw (van Wart et al., 2013, 2015). Finally, many of these studies have used generic model coefficients derived from outdated cultivars that are not representative of modern high-yielding cultivars and/or from experiments that did not reach near-optimal conditions for crop growth, which may have led to an underestimation of Yp (or Yw). For example, Boling et al. (2004, 2007, 2008) reported Yp of *ca.* 4.5 Mg ha^{-1} for irrigated rice in Central Java. We note that this estimate of Yp is lower than current average farmer yield in the same region (*ca.* 5 Mg ha^{-1}) and the Yp of *ca.* 9-10 Mg ha^{-1} expected for irrigated rice in South East Asia (Kropff et al., 1996; Peng et al., 1999).

Robust calibration and evaluation of crop models requires experimental data from crops grown under near-optimal conditions that allow expression of Yp (irrigated) and Yw (rainfed crops), including crop variables (yield, phenology, *etc.*) and weather, soil, and management data needed to simulate site-year specific conditions. However, it is difficult to ensure near-optimal growing conditions, even in controlled experimental plots, due to the multitude of factors influencing crop growth and the difficulties in removing every single limiting factor across space and time (Cassman et al., 2003). These limiting factors include (i) incidence of insect pests and pathogens, which are especially problematic in the humid tropics, (ii) insufficient supply of water (in the case of irrigated crops) and plant nutrients, and (iii) sub-optimal management in relation with transplanting, sowing date, plant density, *etc.* (Lu et al., 2007; Laborte et al., 2012; GRiSP, 2013; Buresh et al., 2015; Castex et al., 2018; Stuart et al., 2016). Likewise, it is difficult to access high-quality measured weather and soil data in many regions of the world, which is needed to conduct site-specific simulations of Yp and Yw (Grassini et al., 2015). Due to lack of data, many studies have relied on coarse-scale or poor quality weather and soil data for model calibration and evaluation, which, as mentioned previously, can seriously distort resulting Yp and Yw estimates (Van Wart et al., 2013, 2015). We are not aware of any explicit effort to calibrate and evaluate crop models for modern high-yielding rice and maize cultivars in Indonesia using data collected from well-managed experiments coupled with high-quality on-site weather and soil data.

The present study made a first step towards a better estimation of Yp and Yw in intensive rice- and maize-based cropping systems in tropical humid environments using high-quality experimental data from modern high-yield cultivars and measured weather data and soil properties. Our objective was to calibrate two crop models (ORYZA and Hybrid Maize) for modern rice and maize cultivars and to evaluate the calibrated models on their ability to estimate yield potential for major rice-maize cropping systems in Indonesia.

2. Materials and methods

2.1. ORYZA and Hybrid Maize models

ORYZA is a crop model that simulates rice growth and development (Kropff et al., 1993; Bouman et al., 2001; Li et al., 2017). Briefly, the model simulates CO_2 assimilation and respiration on a daily basis. Daily net carbon assimilation is estimated by difference and allocated to roots, stems, leaves, and panicles, with partitioning coefficients dependent upon developmental stage. For simulating Yp, ORYZA assumes no limitations by water and nutrients and an absence of insect pests, weeds, and diseases. ORYZA has been used to simulate Yp across major rice producing areas in the world (*e.g.*, Espe et al., 2016; Guilpart et al., 2017a,b; Stuart et al., 2016; Yuan et al., 2017). The latest version of ORYZA (ORYZA V3) has been released recently, with an improved capability to simulate rice growth and yield across a wide range of environments (Li et al., 2017). ORYZA requires calibration of six coefficients to account for cultivar differences in phenology: development rates for juvenile (DVRJ), photoperiod-sensitive (DVRI), panicle development (DVRP), and reproductive phases (DVRR), photoperiod sensitivity, and maximum optimum photoperiod. Another set of coefficients related to dry matter partitioning at different crop stages also requires calibration. Consequently, calibrating ORYZA for a given variety requires detailed experimental data (dates of heading, anthesis, and physiological maturity, leaf area index [LAI], and dry matter production and partitioning), management practices (plant density and dates of sowing and transplanting), and daily weather data, including solar radiation and maximum (T_{max}) and minimum temperature (T_{min}).

'Hybrid Maize' simulates maize growth and development for rainfed and irrigated conditions (Yang et al., 2004, 2017). Hybrid Maize is similar in structure to ORYZA, but only requires a single genotype-specific input parameter: growing-degree days (GDD) from crop emergence until the crop reaches physiological maturity. All other parameters governing photosynthesis, respiration, leaf area expansion, light interception, biomass partitioning, and grain filling are considered to be stable across modern maize hybrids. For estimating Yw in rainfed crops, Hybrid Maize accounts for water supply amount and distribution as well as soil properties influencing crop water availability such as soil texture, soil depth, and field slope. The model has been satisfactorily evaluated on its ability to reproduce observed yields in well-managed experiments that portrayed a wide range of rainfed and irrigated environments, with yield ranging from near crop failure to 18 Mg ha^{-1} (Grassini et al., 2009; Yang et al., 2017). Hybrid Maize has been used across many countries with diverse climate and soils to estimate Yp, Yw, and yield gaps,[2] determine yield goals to estimate nutrient requirements, and evaluate management options (Witt et al., 2006; Timsina et al., 2010, 2011; Grassini et al., 2011; Setiyono et al., 2011; Chen et al., 2011, 2013; Meng et al., 2013; Schulthess et al., 2013; van Ittersum et al., 2016). However, an explicit evaluation of Hybrid Maize's ability to reproduce Yp and Yw of maize in the humid tropics is lacking.

2.2. Databases for model calibration and evaluation

2.2.1. Rice experimental data

Two sources of experimental data were used for rice: (i) high-yield (HY) experiments conducted by the Indonesian Center for Rice Research (ICRR) and (ii) ICRR's multi-location cultivar evaluation

[2] Yield gap is defined as the difference between Yp for irrigated crops (or Yw for rainfed crops) and average farmer yield (van Ittersum et al., 2013).

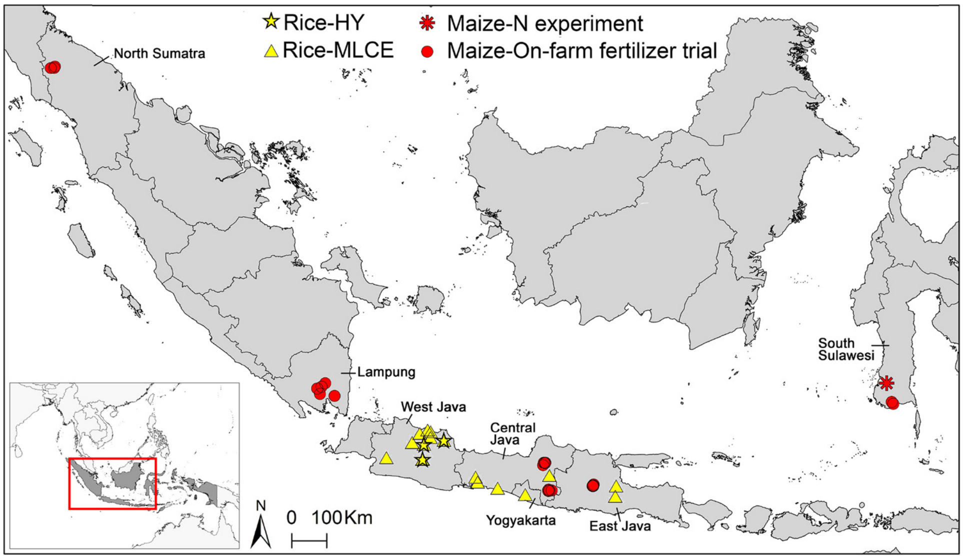

Fig. 1. Location of rice (yellow) and maize (red) experiments used for model calibration (rice high-yield [HY] and maize-nitrogen [N] experiments; stars) and evaluation (rice multi-location cultivar evaluation [MLCE; triangles] and on-farm maize fertilizer trials; circles). Inset shows location of Indonesia within South East Asia. Province boundaries and names are shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 1
Description of databases used in this study, including location of experiments (province), year, nearby weather station, water regime (and season), and dominant crop sequence and soil textures.

Experiment[a]	Province	Year	Weather station	Water regime (season)[b]	Crop sequence[c]	Soil texture[d]	*n*[e]
Rice-HY	West Java	2016	Jatiwangi, Darmaga, Bandung	Irrigated (DS)	[L] rice-**rice**	n.r.	3
Rice-MLCE	Central Java & Yogyakarta	2011, 2013, 2014	Cilacap, Sragen*, Banjarnegara, Yogyakarta	Irrigated (DS)	[L] rice-rice-**rice**	n.r.	5
	East Java	2010, 2013	Perak II, Karang Ploso	Irrigated (WS)	[L] **rice**-rice-maize [L] **rice**-rice-rice	n.r.	2
	West Java	2011-2016	Citeko, Sukamandi, Darmaga, Bandung, Jatiwangi	Irrigated (DS & WS)	[L] **rice-rice(-rice)**	n.r.	14
Maize-N experiment	South Sulawesi	2005, 2006, 2008, 2009	Maros	Irrigated (DS)	[L] rice-**maize**	n.r.	4
Maize-On-farm fertilizer trial	Central Java	2004, 2005	Jakenan, Yogyakarta	Irrigated (DS), rainfed (WS)	[L] rice-rice-**maize** [U] **maize**-maize (-maize)	Clay	19
	East Java	2004	Karang Ploso	Irrigated (DS)	[L] rice-rice-**maize**	n.r.	5
	Lampung	2005-2007	Kota Bumi	Rainfed (WS)	[U] **maize**-maize	Clay	12
	North Sumatra	2004, 2006	Parapat	Rainfed (DS & WS)	[U] **maize-maize**	Clay loam	16
	South Sulawesi	2005, 2006	Jeneponto*	Rainfed (WS)	[U] **maize**-maize	Silty clay loam	7

[a] HY: high-yield experiments; MLCE: multi-location cultivar evaluation trial.
[b] DS: dry season; WS: wet season.
[c] Letters in brackets indicated ecosystem: lowland [L] or upland [U]. Simulated crop cycle is shown in bold; parenthetic third crop appears on a relatively small fraction of the crop area.
[d] Not reported (n.r.) because soil data are not needed for simulation of yield potential for irrigated crops.
[e] Number of site-year-seasons per province.
* Gridded NASA POWER weather data used for model simulations.

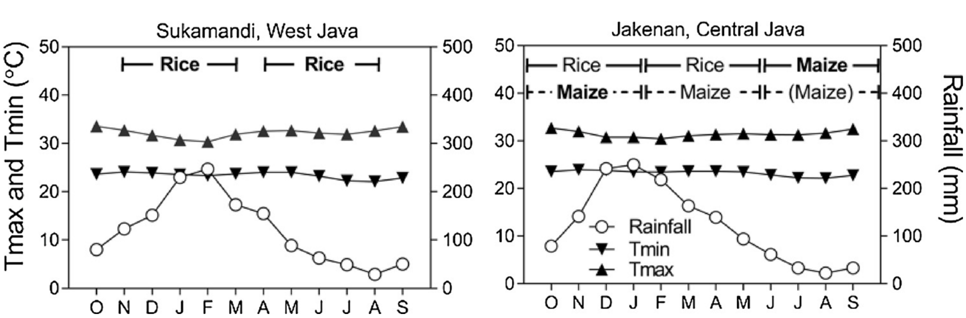

Fig. 2. Annual patterns of monthly average maximum (Tmax) and minimum temperature (Tmin) and total precipitation for two locations in Java: Sukamandi (West Java; 6.25°S, 107.16°E) and Jakenan (Central Java; 6.78°S, 111.20°E). Dominant lowland irrigated (solid) and upland rainfed crop sequences (dashed lines) are shown for each site and simulated crop cycles are indicated in bold. Parenthetic third crop appears on a relatively small fraction of the crop area.

(MLCE) trial (Fig. 1, Table 1). Experiments were located at 17 sites across Java Island; the latter accounts for 46% of rice area in Indonesia (https://www.bps.go.id). In all cases, rice seedlings were transplanted *ca.* 21 days after sowing (DAS), with 2–3 seedlings per hill. Fields received adequate water supply, with water depth maintained at *ca.* 5 cm during the entire crop season. Rice yields were determined from a sample (size: 6.25-12 m^2) collected from the center of each plot at harvest maturity. Reported yields correspond to paddy rice adjusted to 14% grain moisture content. Annual patterns of temperature and precipitation are shown for two representative locations in Java (Fig. 2).

The HY experiments were conducted at three sites in west Java: Subang (6.624°S; 107.746°E), Indramayu (-6.518°S, 108.291°E), and Bandung (-7.011°S, 107.746°E). Experiments were conducted during the dry season (April–September) in 2016 (Fig. 1). Experiments followed a randomized complete block design with four replicates (plot size: 30 m^2) and included two plant density treatments (16 and 21 hills m^{-2}). The same variety (Inpari 32) was grown across experiments. Inpari 32 is a new high-yielding inbred variety (parental lines: Ciherang and IRBB64), which is becoming one of the predominant varieties across major producing rice areas in Indonesia, replacing old varieties such as Ciherang, Dodokan, and Silugonggo. Periodic applications of pesticides and manual weeding kept crops free of weeds, diseases, and insect pests during the entire growing season. Total applied fertilizer was 126 (nitrogen [N]), 11 (phosphorous [P]), and 25 (potassium [K]) kg ha^{-1}, with fertilizer amounts determined based on soil tests and estimated requirements to achieve yields near Yp at each site. N fertilizer was split in three applications (*ca.* 7, 24, and 42 days after transplanting [DAT]). Destructive plant samples were taken at early vegetative (7 DAT), 10% flowering (67 DAT), and physiological maturity (112 DAT) stages to determine leaf area and dry matter per plant organ (stems, leaves, and panicles).

The MLCE trials were conducted in 13 irrigated farmer fields over seven years (2010–2016), including both wet (October to March) and dry (April to September) seasons, representing a total of 24 site-year-season combinations (Table 1). These trials followed a complete randomized design, with three replicates (plot size: 20 m^2). Same plant density was used across experiments (16 hills m^{-2}). The goal of these trials was to evaluate performance of commercially available rice inbred varieties, including new (Inpari 10, 13, 18, 23, 28, and 33) and old varieties (Ciherang, Dodokan, and Silugonggo). Cultivars varied across site-year-seasons, but there were at least 3 varieties per trial. Crops were not necessarily managed with an aim to reach Yp; instead, fertilizer amounts and management practices were guided by local recommendations. Total applied fertilizer ranged from 115 to 140 (N), 7 to 16 (P), and 25 to 50 (K) kg ha^{-1} across site-year-seasons.

2.2.2. Maize experimental data

Data on maize yield and phenology (dates of silking and physiological maturity) were available from on-farm (NPK) fertilizer trials conducted for hybrid maize across 5 major producing regions in Indonesia during 2004–2007 (Table 1, Fig. 1). In each region, on-farm experiments were conducted in at least five farmer fields, totaling 59 site-year combinations. Additionally, we used data from a replicated N fertilizer experiment conducted during the dry season in 2005, 2006, 2008 and 2009 at the Indonesian Cereal Research Institute at Maros, South Sulawesi. Hybrids varied across experiments but represented commercially available modern hybrids grown across Indonesia, including Pioneer 21, Pioneer 12, Bisi 2, and Bima 1. Soil and agronomic data were collected for each field and treatment. Experiments were scouted every 11–13 days to determine phenological stage. Grain yield was determined from 1 to 2 samples taken from the center of each plot after physiological maturity. All yields reported here correspond to grain yield (without cob) at 15.5% grain moisture content. Detailed description of these experiments can be found elsewhere (Witt et al., 2006; Pasuquin et al., 2012, 2014).

On-farm fertilizer trials included the following treatment plots: (i) omission plots to which no fertilizer N, P, or K were applied, (ii) fully (NPK) fertilized plot that received 150–200 kg N ha^{-1}, 35–52 kg P ha^{-1}, and 75–100 kg K ha^{-1}, (iii) a site-specific nutrient management (SSNM) treatment, and (iv) a farmer fertilizer practice (FFP) treatment, in which farmers made all decisions in regards with crop and fertilizer management practices without interference from researchers. Treatment plots were managed to ameliorate incidence of other yield-limiting factors, which included changes in plant density, manure or lime application, and better control of weed, insect pests, and diseases. Fields were rainfed or irrigated depending on the dominant water regime at each location. Experiments conducted in South Sulawesi during 2005, 2006, 2008, and 2009 followed a split plot design, with four replicates. Main plots correspond to different N fertilizer amounts (0, 75, 150, and 225 kg N ha^{-1}) and subplots to different combinations of number and timing of splits dressings. Experiment conducted during 2006 had also two plant populations (7.3 and 6.6 m^{-2}). Large rates (kg ha^{-1}) of fertilizer P (17) and K fertilizer (90–125) were applied to ensure that P and K were not limiting. Plots were irrigated as necessary to maintain adequate soil moisture during the entire crop season and crops were kept free of weed, diseases, and insect pests.

2.3. Approach to calibrate and evaluate crop models in Indonesia

We followed two steps for calibrating and evaluating ORYZA and Hybrid Maize in Indonesia: (i) calibration of phenological (Hybrid Maize and ORYZA) and growth-related (ORYZA) parameters, and (ii) evaluation of calibrated models by comparison of simulated yields *versus* highest observed yields in variety and fertilizer trials. We calibrated model parameters for Inpari 32 (rice) and Pioneer 21 (maize) because these two cultivars were included in the majority of site-years included in the database. These are commercial, broadly adapted cultivars, with good pest resistance and 90–130 days growth duration, and widely grown across all major rice and maize producing areas in Indonesia. We did not attempt to calibrate coefficients for hybrid rice as current adoption is still very low (< 1% of harvested rice area in Indonesia). Model simulations assumed non-water limited conditions for simulation of Yp for irrigated rice and maize, while water limitation was accounted for in the simulation of Yw for rainfed maize, irrespective if crops were grown during the dry or wet seasons. Yp is expected to be higher in the dry *versus* wet season due to higher solar radiation levels, while Yw is typically higher during the wet season as a result of abundant in-season precipitation. In all cases, simulations assumed no nutrient limitations and no yield reductions due to biotic factors such as insect pests, weeds, and diseases.

2.3.1. Model calibration

In the case of rice, we used data from the high-density treatment in the HY experiments (yield range: 7.8-10 Mg ha^{-1}) to calibrate phenological and growth-related coefficients for Inpari 32. In the case of Hybrid Maize, it only requires calibration of GDD from emergence to physiological maturity. We used data from the treatment that received the largest N fertilizer application (*ca.* 225 kg N^{-1}) in the N-fertilizer experiment (yield range: 12-14.4 Mg ha^{-1}) to derive the GDD for Pioneer 21 and also to evaluate the robustness of Hybrid Maize generic growth coefficients at simulating the observed yields. In both (HY and N-fertilizer) experiments, crops were maintained fully irrigated during the entire crop season and received management practices that were conducive for expression of Yp.

For ORYZA, we calibrated the model on ‘experiment’ mode in order to reproduce the observed values. Two optimization programs (DRATES and PARAM) were used for calibrating model ORYZA coefficients related with phenology and crop growth (Li et al., 2017). Subsequently, the AutoCalibration tool was iterated *ca.* 7000 times to minimize deviation between simulated outputs and observed values and derive the final values for the coefficients. Following previous studies on rice modelling (Bouman et al., 2001; Li et al., 2016; Yuan et al., 2017), default values derived from IR64 and IR72 cultivars were used for the two parameters associated with photoperiod influence on phenology (photoperiod sensitivity [0 h^{-1}] and maximum optimum photoperiod [11.5 h]). Measured and observed values of total dry matter (WAGT), panicle weight (WSO), stem weight (WST), leaf weight (WLVG), and LAI were compared to evaluate the robustness of the calibrated growth-related coefficients for ORYZA. In the case of maize, GDDs were calculated as the sum of daily mean temperature (after subtracting a base temperature of 8°C) between reported dates of sowing to physiological maturity for each experiment.

Agreement between simulated and observed variables was assessed with the coefficient of determination (r^2), root mean square error (RMSE), and normalized RMSE (RMSE$_n$):

$$RMSE = [(\sum (S-O)^2/n)]^{0.5} \quad (1)$$

$$RMSE_n = [(\sum (S-O)^2/n)]^{0.5}/M_{mean} \quad (2)$$

$$r^2 = \left(\frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}}\right)^2 \quad (3)$$

where S (or y) and O (or x) are the simulated and observed values, respectively, and n is the number of paired values. Small RMSEn and high r^2 indicate good agreement between simulated and observed values. Following Gaydon et al. (2017), RMSE was also compared with the observed standard deviation, as estimated from the replicates of each treatment in each experiment, to assess the degree of agreement between observed and simulated values relative to experimental data uncertainty.

2.3.2. Model evaluation

The second step (*i.e.*, model evaluation) consisted of comparing simulated *versus* observed yields to evaluate model ability to reproduce Yp (maize and rice) and Yw (maize). We used the MLCE rice trials (range: 3.6-9.1 Mg ha^{-1}) and on-farm maize trials (range: 0.5-13.7 Mg ha^{-1}) to evaluate ORYZA and Hybrid Maize using the calibrated coefficients. We also included the low-density treatments from the (rice) HY experiments and the other treatments included in the N-fertilizer experiment to the evaluation dataset (these treatments were not used for model calibration so they can be treated as independent from the calibration dataset). All together, these experiments portrayed the range of climate, soils, and cropping systems in Indonesia.

We acknowledge that the maize and rice databases used for the evaluation included experiments that were not designed to eliminate all yield-limiting factors. Hence, it was expected that a well-calibrated model would predict Yp (or Yw) values greater than observed yields in most cases, consistent with previous studies attempting to quantify Yp or Yw for other crops (Cassman, 1999; Lobell et al., 2009). Still, it can be expected that simulated Yp (or Yw) will be less than observed yields at some sites due to sampling variability and measurement error in both yield and weather data, though these cases should be a minority for a model that simulate Yp (or Yw) well. To benchmark the performance of our calibrated models at reproducing Yp and Yw, we selected the treatment with highest yield at each site-year-season experiment. The assumption was that some of these highest yields would approach Yp (or Yw) for that environment. Other previous modeling studies have followed a similar approach to evaluate crop model performance in absence of experimental data from crops that were explicitly managed to reach Yp or Yw (*e.g.*, Hoffmann et al., 2014; Espe et al., 2016; Rattalino Edreira et al., 2017). Finally, we used phenology data from the on-farm fertilizer trials to evaluate the degree to which GDD derived for Pioneer 21 were robust at predicting phenology across other sites, years, seasons, and hybrids.

2.3.3. Sources of weather, soil, and management data and initial conditions for simulations

For both model calibration and evaluation, we used reported dates of sowing (or transplanting) and plant density, and site-specific soil type (for Yw simulations) and daily weather data, including solar radiation, T_{max}, T_{min}, humidity, wind speed, and precipitation. For the MLCE trial, Yp was simulated using the coefficients calibrated for Inpari 32; in the case of the on-farm maize trial, we used the reported dates of sowing and physiological maturity. Measured daily weather data from nearest meteorological station to each experimental site were retrieved from the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG; http://www.bmkg.go.id/) (Table 1). Quality control and filling and/or correction of the weather data was performed based on correlations between the target station and one to three adjacent weather stations following the methodology described by van Wart et al. (2013) and references cited therein. Number of corrected and/or filled data was always lower than < 3% for all variables. We used data from a total of 14 meteorological stations. No nearby weather station was available for the experimental sites near Sragen (Central Java) and Jeneponto (South Sulawesi); hence, we used gridded weather data from the Prediction of Worldwide Energy Resource dataset from the National Aeronautics and Space Administration (NASA-POWER; NASA, 2012). Pedo-transfer functions for tropical soils were used to derive the upper and lower soil water retention limits for simulation of Yw for rainfed maize based on the soil texture reported at each site (Hodnett and Tomasella, 2002; Rustanto et al., 2017). Given the lack of information on soil rootable depth, we assumed a 1.5 m soil depth for all site-years, which would be the typical maize rootable depth in a soil without chemical and physical constrains to root growth (Dardanelli et al., 1997; Tolk et al., 2016; Ordóñez et al., 2018). Sensitivity analysis for maize indicated that Yw would be slightly (7%) smaller if a shallow soil depth (1 m) would have been chosen for the simulations. In rainfed sites, the soil water balance was initiated near harvest time of the preceding crop using a fixed soil water content, which was obtained from expert opinion and/or simulation of water balance for the previous crop.

Table 2
Calibrated coefficients for Inpari 32 (rice) and Pioneer 21 (maize) based on data collected from high-yield rice and maize experiments.

Coefficient	Value
Rice	
Development rate during juvenile stage (DVRJ; °C d^{-1})	0.0008753
Development rate during photoperiod-sensitive stage (DVRI; °C d^{-1})	0.0007576
Development rate during panicle development stage (DVRP; °C d^{-1})	0.0007787
Development rate during reproductive stage (DVRR °C d^{-1})	0.0015390
Fraction total dry matter partitioned to the shoot (FSHTB)[a]	0.6067476; 0.7414253; 1.0000000; 1.0000000
Fraction shoot dry matter partitioned to the leaves (FLVTB)[a]	0.6802744; 0.4227301; 0.0000000; 0.0000000
Fraction shoot dry matter partitioned to the stems (FSTTB)[a]	0.3197256; 0.5532699; 0.0000000; 0.0000000
Fraction shoot dry matter partitioned to the panicles (FSOTB)[a]	0.0000000; 0.0240000; 1.0000000; 1.0000000
Maize	
Growing-degree days (GDD)[b]	1821 (± 11)

[a] Partitioning factors associated with four crop stages (in this order): emergence, panicle initiation, grain filling, and physiological maturity.

[b] Average GDD (in °C day; T_b = 8 °C) and standard error (± s.e.) for the period between emergence and physiological maturity.

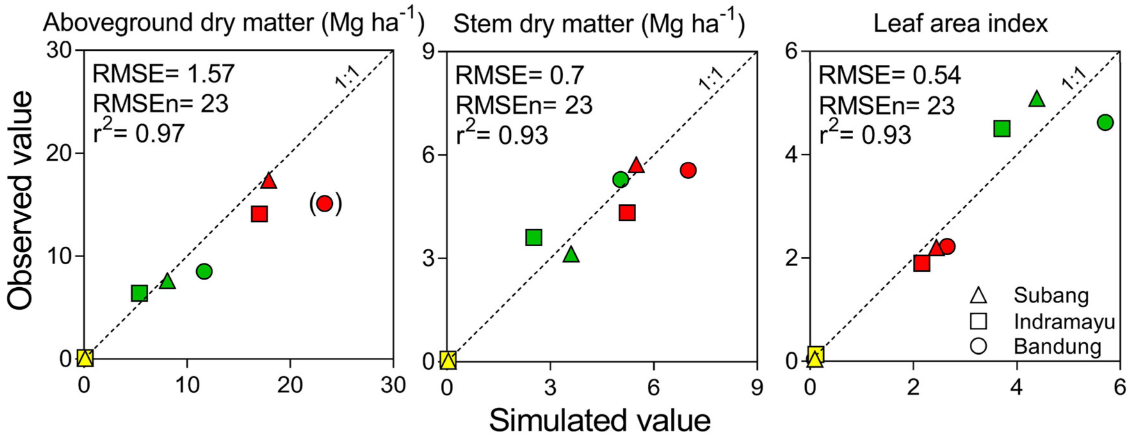

Fig. 3. Comparison between observed and simulated rice total aboveground dry matter (left), stem dry matter (center), and leaf area index (right) at early vegetative (yellow), flowering (green), and physiological maturity stage (red). Coefficient of determination (r^2), root mean square error (RMSE), and normalized root mean square error (RMSEn, in %) are shown (encircled data point in left panel was excluded for their calculation because of water stress during grain filling at this site). Dashed diagonal line indicates x = y. Data were collected from high-yield irrigated experiments conducted at three sites (Subang, Indramayu, and Bandung). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

3. Results

3.1. Derivation of model coefficients using data from high-yielding experiments

Calibrated coefficients for the rice (Inpari 32) and maize (Pioneer 21) cultivars are shown in Table 2. These coefficients were estimated using data from high-yield rice and maize experiments that were likely to approach near-optimal growing conditions that allow expression of Yp (and Yw).

Fig. 3 shows a comparison between observed total aboveground dry matter, stem weight, and LAI at different crop stages (early vegetative, flowering, and physiological maturity) against simulated values using the calibrated coefficients. In general, there was reasonably good agreement between simulated and observed values for all parameters without a detectable bias across locations and crop stages (RMSEn = 23%; $r^2 > 0.93$, after exclusion of one observation). RMSE values for aboveground biomass (1.6 Mg ha^{-1}), stem dry matter (0.7 Mg ha^{-1}), and leaf area index (0.5) was similar to their average observed experimental standard deviation (1.1 Mg ha^{-1}, 0.6 Mg ha^{-1}, and 0.2, respectively). An exception was the overestimation in total aboveground dry matter at maturity at the site located at high elevation (Bandung). Water supply was limiting during grain filling at that site leading to crop water stress, which explains the discrepancy between simulated and observed values at late reproductive stages. Overall, the calibrated coefficients were robust at reproducing crop growth and partitioning for this high-yielding rice variety.

In the case of maize, GDD derived for Pioneer 21 from the N fertilizer experiment (1821°Cd; 95th confidence interval: 1799 to 1843°Cd) was similar to those derived for the same hybrid based using the data from the on-farm fertilizer trials (average: 1786°Cd; confidence interval: 1657 to 1915°Cd). *T*-test indicated that the difference between GDDs derived from the two databases did not deviate significantly from the null hypothesis of zero ($p = 0.64$). That finding implicitly shows that the model was robust at reproducing observed dates of silking and physiological maturity in the evaluation database. Across site-years (including all experiments), coefficient of variation for GDD for Pioneer 21 was 13%, indicating that GDD were stable irrespective of the biophysical environment. Analysis of on-farm maize trials indicated that Bisi 2, another widespread maize hybrid in Indonesia, had similar, though slightly less (5%), GDD to Pioneer 21. To summarize, the GDD derived from the two trials indicate that our estimate of GDD for Pioneer 21 can be considered as representative for commercial maize hybrids in Indonesia and stable across site-years.

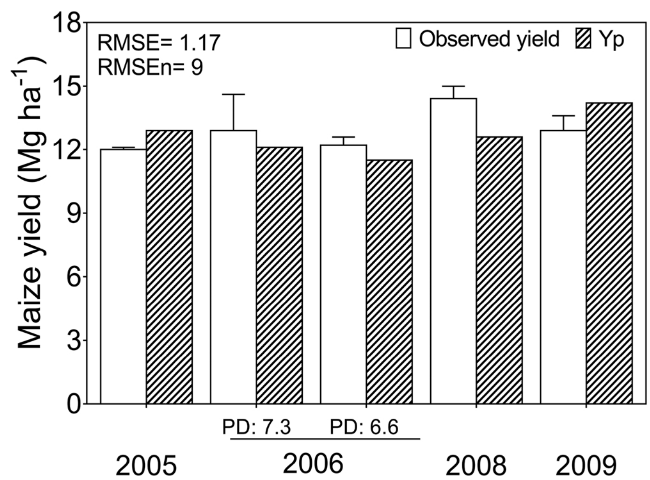

Fig. 4. Observed yield and simulated yield potential (Yp) for maize grown in irrigated experiments at Maros (South Sulawesi) during four crop seasons. Experiment in 2006 included two different plant densities (PD; 7.3 and 6.6 m^{-2}). Bars indicate standard errors. Root mean square error (RMSE) and normalized root mean square error ($RMSE_n$, in %) are shown.

The treatments that received large NPK fertilizer amounts in the irrigated N-fertilizer experiment provided a near-stress free environment where it was possible to evaluate the performance of the generic growth parameters in Hybrid Maize. As mentioned previously, these coefficients had originally been derived for temperate hybrids but never validated for tropical maize. Fig. 4 shows the observed yields and associated simulated Yp using site-specific weather and reported dates of sowing and physiological maturity. Observed maize yields were very high, ranging from 11.2 to 15.3 Mg ha^{-1} across years (excluding the low density treatment), with very low inter-annual CV (7%). Remarkably, Hybrid Maize reproduced very well the high yields measured in those experiments and response to plant density, with RMSE of 1.2 Mg ha^{-1} (9% of observed mean), which was, in turn, similar to observed standard deviation in these experiments (average: 1.4 Mg ha^{-1}, equivalent to 11% of the observed mean). Confidence intervals ranged from 12.2 to 13.7 Mg ha^{-1} and 12.1 to 13.5 Mg ha^{-1} for observed and simulated yields, respectively, with paired *t*-test indicating that the difference between observed and simulated yields did not deviate significantly from zero ($p = 0.75$). Observed yields were within ± 10% of Yp in all cases but one (15% higher in 2008). This analysis indicates

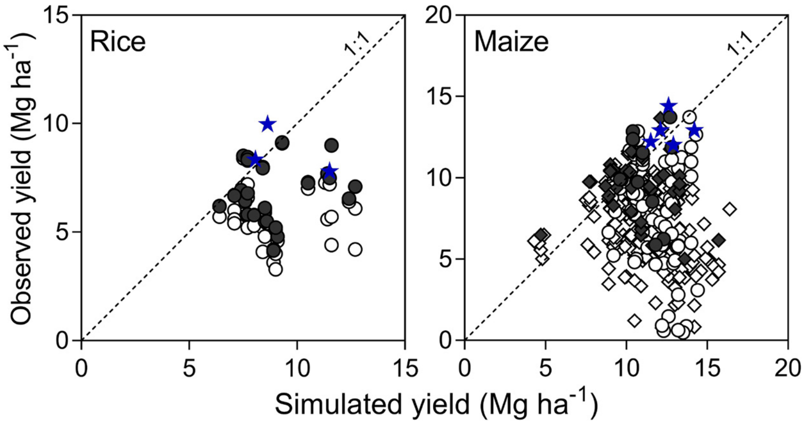

Fig. 5. Model evaluation for rice and maize in Indonesia. Each datapoint represents a site-year-season-cultivar-treatment combination, including rainfed (diamonds) and irrigated (circles) crops. The evaluation database includes the rice MLCE and maize on-farm fertilizer trials and also the treatments from the rice HY and maize N-fertilizer experiments that were not used for model calibration (n_{total}: 24 and 291 for rice and maize, respectively). The highest yields at each site-year-season are shown (solid symbols). Note that data used for model calibration (best treatments in the rice HY and maize N-fertilizer trials) are shown for comparison purposes (stars) but not used to compute the values shown in Table 3. Dashed diagonal line indicates x = y.

that the generic growth coefficients in Hybrid Maize seem adequate to reproduce Yp of modern high-yield maize hybrids in Indonesia and, more broadly, in the tropical humid environments.

3.2. Evaluation of model performance across a wide range of environments and crop systems

There was large variation in observed yields across site-year-treatments included in the evaluation dataset (Fig. 5). Observed irrigated rice yield averaged 6.1 Mg ha^{-1}, ranging from 3.3 to 9.1 Mg ha^{-1}. Average irrigated and rainfed maize yield was 8.1 and 7.5 Mg ha^{-1}, respectively, ranging from 0.8 to 13 Mg ha^{-1} (rainfed) and 0.5 to 13.7 Mg ha^{-1} (irrigated). Large variation in observed yield was expected due to differences in weather, soil type, and management across site-year-treatments. Likewise, many of these experiments may have experienced nutrient and water deficiencies, incidence of biotic adversities, and other yield-reducing factors such as lodging, submergence, *etc.* Indeed, most of the variation in observed maize yields, for a given level of simulated yield potential, is attributed to differences in nutrient fertilizer application across treatments.

Examination of observed and simulated yields indicates that, despite the fact that many of these experiments and/or treatments were not managed to achieve Yp (or Yw), 41% and 39% of the rice and maize observations, respectively, were above 80% of the simulated Yp (or Yw) (Fig. 5). Indeed, the simulated yields matched reasonably well the range of maximum observed yields in both crops. These findings suggest that crops in some site-year-seasons-treatments approached their Yp and Yw as determined by climate and soil type. There were some cases with observed yield slightly higher than simulated yields, which we attributed to measurement error in both yield and weather data, but we note that only 1% of observed yields exceeded simulated Yp (or Yw) by more than 10%.

Average simulated Yp for rice was 9.1 Mg ha^{-1}, ranging from 6.4 to 12.7 Mg ha^{-1} across site-years included for the model evaluation (Table 3). Average Yp and Yw for irrigated and rainfed maize were 11.6 and 11.5 Mg ha^{-1}, respectively, ranging from 8.9 to 14.4 Mg ha^{-1} (Yp) and 4.3 to 16.4 Mg ha^{-1} (Yw). Similarity in irrigated and rainfed maize simulated yields was not surprising as their corresponding experiments coincided with the dry and wet seasons, respectively (Fig. 2), except for one rainfed maize trial conducted during the dry season in North Sumatra. As expected, variation in Yp across site-year was smaller than for Yw as indicated by their CVs (12% *versus* 19%). The range of highest observed yields, expressed as percentage of their respective Yp (or Yw for rainfed crops), indicated that, in most cases, the yield achieved by the best treatments was comparable to the simulated Yp (or Yw) for at least one site. An exception was the case of rainfed maize in Central Java where highest observed yields were all well below their corresponding Yw (33–49% of Yw). Rainfed experiments in this province were located in areas with heavy clay soils (*ca.* 80% clay content, with vertic properties which may suggest (i) model inability to reproduce root dynamics and water balance for this type of soil and/or (ii) difficulties to ensure near-optimal growing conditions over time and space to overcome unfavorable soil conditions. Likewise, one site in North Sumatra experienced severe drought and observed yield was clearly above Yw (% of Yw = 140). We note, however, that the underestimation is relatively small in absolute terms (1.5 Mg ha^{-1}) and this deviation could be attributed to differences in precipitation between the weather station and experimental site.

4. Discussion

This study presented a first assessment of yield potential for intensive rice-maize cropping systems in the humid tropical environment of South East Asia. Two crop models were used to simulate Yp (or Yw)

Table 3
Average simulated yield potential (Yp) or water-limited yield potential (Yw) and highest observed yields. The latter is also shown as percentage of Yp and Yw for irrigated (I) and rainfed (R) crops, respectively. Parenthetic values indicate range across site-years.

Province	Water regime	Simulated Yp or Yw (Mg ha^{-1})	Average highest yields (Mg ha^{-1})[a]	% of Yp (or Yw)[a]
Rice				
Central Java & Yogyakarta	I	8.5 (7.4-11.6)	7.8 (6.4-9.0)	93 (77-114)
East Java	I	9.6 (7.7-11.5)	7.3 (6.8-7.5)	77 (65-88)
West Java	I	9.2 (6.4-12.7)	6.7 (4.2-9.1)	73 (47-110)
Maize				
Central Java	I	13.3 (12.5-14.0)	9.0 (5.8-13.7)	67 (44-99)
	R	14.0 (12.0-15.7)	6.0 (5.0-6.8)	44 (33-49)
East Java	I	10.4 (9.2-11.0)	11.1 (9.4-12.8)	105 (91-120)
Lampung	R	11.8 (9.0-14.1)	9.0 (6.5-11.8)	77 (62-98)
North Sumatra	R	9.6 (4.3-12.4)	10.1 (6.2-11.6)	108 (82-144)
South Sulawesi	R	12.8 (12.3-13.2)	7.6 (4.0-9.6)	59 (33-74)

[a] Average of highest observed yield across site-years per province.

using coefficients derived for two commercial high-yielding rice and maize cultivars based on experimental data and measured weather and soil data from well-managed experiments in Indonesia where observed yields approached the Yp (or Yw) as determined by the climate (and soil) at each site. These coefficients were robust at portraying the maximum yields observed in on-farm trials conducted across multiple sites, years, seasons, cultivars, and water regimes for dominant rice-maize cropping systems. In contrast to other models that require a large number of cultivar-specific coefficients (*e.g.*, Jones et al., 2003), Hybrid Maize only required calibration of cultivar-specific GDDs. Along these lines, an interesting finding from this study was that growth-related coefficients derived for temperate maize in the original calibration of Hybrid Maize were robust for simulating Yp in irrigated, well-managed experiments in the tropical environment of Indonesia. Similarly, Yang et al (2017) found the model coefficients to work well at reproducing observed yields in USA, across a wide range of water supply that lead to a range of yields from near crop failure up to 18 Mg ha^{-1}. Altogether, these findings support the contention made by Yang et al. (2004) that the model can provide reliable estimates of Yp across a wide range of environments, without need of calibrating site- and cultivar-specific coefficients, except for GDDs, which are needed to account for differences in phenology among hybrids.

Our study provided a first insight about the range of Yp (or Yw) across major rice and maize crop systems in Indonesia. Comparison between our average rice Yp (9.1 Mg ha^{-1}) and maize Yw (11.5 Mg ha^{-1}) against respective average farmer yields in Indonesia based on FAOSTAT national statistics for the 2012–2016 interval (5.2 and 5 Mg ha^{-1} for rice and maize, respectively) suggests that there is still room for increasing annual productivity in rice- and maize-based cropping systems in Indonesia, and more broadly, in South East Asia. The range in simulated Yp for rice in our study (*ca.* 8-11 Mg ha^{-1}) was consistent with previous simulations of rice Yp in the tropics (*e.g.*, Kropff et al., 1996), including estimates at two specific locations in Indonesia (Laborte et al., 2012; Stuart et al., 2016). In contrast, our simulated Yp for rice was clearly higher than those reported by Boling et al. (2004, 2007, 2008) for Central Java (range: 4-6 Mg ha^{-1}). We note that observed yields and aboveground dry matter at maturity used in our calibration are much higher than those reported in these previous studies using ORYZA, with observed yields ranging from 1 to 6 Mg ha^{-1} (Boling et al., 2004). Such a discrepancy in simulated Yp may suggest that those previous studies for rice in Indonesia were based on experimental data collected from crops that were not explicitly managed to reach Yp. Changes in Yp over time are unlikely to explain differences in Yp between our study and previous ones given the lack of increase in Yp for rice varieties released after the onset of the Green Revolution in South East Asia (Peng et al., 1999). In the case of maize, despite evidence of high yields (10-15 Mg ha^{-1}) in irrigated (or favorable rainfed) subtropical and tropical environments based on field observations (Betran et al., 2003; Pasuquin et al., 2012, 2014; Worku et al., 2016) and simulation (Timsina et al., 2010; van Ittersum et al., 2017), previous efforts in calibrating and evaluating maize simulation models for these environments were based on experiments that did not exceed 10 Mg ha^{-1} (*e.g.*, Carberry et al., 1989) and, in most cases, were below 5 Mg ha^{-1} (*e.g.*, Soler et al., 2007; Gaiser et al., 2010; Bassu et al., 2014; Kadiyala et al., 2015). As far as we know, this is the first study reporting a maize model evaluation for the humid tropics using experimental yields > 10 Mg ha^{-1}. A global assessment of crop models on their ability to simulate Yp and Yw in the humid tropics based on data from crops that were explicitly managed to achieve near-optimal conditions is lacking. We believe such an evaluation should receive priority given the massive expansion in global maize harvested area (*ca.* 50 million ha) during the last 15-y period (2002–2016) period, with 40% of this area increase occurring in tropical and subtropical regions located in Southeast and South Asia, Sub-Saharan Africa, and South America (http://www.fao.org/faostat/en/#data/QC).

South East Asia has diverse cropping systems where multiple rice and/or maize crops are grown in the same piece of land during one year depending upon climate, soils, and access to irrigation. Different (lowland and upland) ecosystems, water regimes (irrigated and rainfed), and crop sequences typically co-exist within the same geographic region. Previous assessments of yield gaps for South East Asia have focused on individual crops, usually at one or few locations (*e.g.*, Laborte et al., 2012; Stuart et al., 2016; Pasuquin et al., 2014). At the other extreme of the spectrum, global studies aiming at estimating Yp (or Yw) and yield gaps have relied on gridded weather data and coarse assumptions about the crop-system context leading to unrealistic estimates of Yp, Yw, and yield gaps (*e.g.*, Fischer et al., 2002; Nelson et al., 2010). The models evaluated in the present study, together with available weather, soil, and agronomic databases, can be used for estimating Yp (or Yw) in rice- and maize-bases agro-ecosystems in South East Asia, not only for individual crops but also at the crop-system level (Guilpart et al., 2017a,b; Silva et al., 2017). Likewise, these models can be used for *ex-ante* assessment of food security for different scenarios of climate change and land conversion, to evaluate opportunities to close yield gaps and/or improving resource-use efficiencies through fine-tuning of current crop practices, such as sowing date and cultivar maturity, and better estimation of yield goals and their variability to inform fertilizer recommendations (*e.g.*, Witt et al., 1999; Setiyono et al., 2011; Pasuquin et al., 2012, 2014).

5. Conclusions

Our study provides robust estimates of yield potential for modern high-yield rice and maize cultivars in the humid environment of Indonesia based on high-quality experimental data from modern high-yield cultivars from multiple site-years and measured weather and soil properties. This study clearly advances current knowledge from previous published studies, which were based on one or few site-years and relied mostly on coarse gridded weather and soil data, generic model parameters, and/or experiments that were not explicitly managed to achieve near-optimal conditions for crop growth and yield. Findings confirmed the expected yield potential for modern rice varieties reported elsewhere in South East Asia (Peng et al., 1999), with our simulated rice yield potential remarkably higher than that reported for Indonesia based on experimental data and crop modeling (Boling et al., 2004). Finally, our study indicates a high-yield potential for maize in irrigated conditions and favorable rainfed environments. It also suggests that there is still room for increasing productivity in intensive rice-maize based crop systems in South East Asia, though a more rigorous analysis per region and cropping systems is needed to understand where the largest yield gaps are and their underlying causes.

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