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Targeting management practices for rice yield gains in stress-prone environments of Myanmar

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A R T I C L E I N F O

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A B S T R A C T

Rice in Myanmar is grown in diverse environments, including inland dry zone and salt-affected coastal deltas. This study evaluated management options that could improve productivity and reduce risks of rice crop in stress-prone areas of the country. We selected four sites from two regions in the central dry zone (Wundwin) and the Ayeyarwady delta (Labutta, Bogale and Mawlamyinegyun). We used experimental and survey datasets on farmers' practices and rice yields from 2012 to 2014 to run the ORYZA model to simulate the climatic yield potential (YP; yield without stress) and the attainable yield under rainfed conditions (YW; yield limited by water), saline conditions (YS; yield limited by salinity), and under conditions of current farmers' practices (YF; yield in farmers' practices). Simulated yield responses to different management practices showed spatial variability within and among the selected sites. YP ranged from 5.4 to 11.1 t ha^{-1}, YW ranged from 0.5 to 7.5 t ha^{-1}, and YF ranged from 2.2 to 4.2 t ha^{-1}. In salt-affected areas, average YS ranged from less than 0.1 t ha^{-1} to 5.6 t ha^{-1}. Yield gains with the choice of an improved variety and adjusted sowing date were estimated at up to 53% above YF. Changing the time of sowing and using improved rice varieties provided the greatest yield gains in salt-affected and drought-prone areas where YF was the least. In areas where YF was greater, the improvement of nitrogen management provided larger benefits than in areas with lower YF. We conclude that an integrated approach using remote-sensing technologies, crop modeling, and a geographic information system is valuable for targeting the best management options to close the yield gap in unfavorable rice environments in Asia.

Abbreviations: CHIRPS, climate hazards group InfraRed precipitation with station data; DAS, days after sowing; DEM, digital elevation model; DVRI, developmental rate during the photoperiod sensitive phase; DVRJ, developmental rate during juvenile phase; DVRP, developmental rate during panicle development phase; DVRR, developmental rate during reproductive phase; FLVTB, fraction of total above ground biomass to leaves; FSHT, fraction of total biomass partitioning to the shoot; FSOTB, fraction of total above ground biomass organ storage; FSTB, fraction of total above ground biomass to stem; GIS, geographic information system; ISRIC, international soil reference and information centre; MDV, high-yielding variety with medium to long duration; MODIS, moderate resolution imaging spectro-radiometer; SDV, high-yielding variety with short growth duration; SOC, soil organic carbon content; SON, soil organic nitrogen content; TRMM, Tropical Rainfall Measuring Mission; YF, rice yield with current farmers' practices; YP, climatic yield potential under non-limited irrigated system; YS, maximum attainable yield under salinity stress using river and canal water as the source of irrigation; YW, maximum attainable yield under rainfed conditions

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1. Introduction

Global agri-food systems have to produce more food with less land, labor, and water to meet the demand of the growing population (Foley et al., 2011). This demand is challenging for rice farmers in rained rice environments who tend to have low levels of household food and nutrition security. Change in climate patterns and salinity are the main constraints in these environments and mainly in tropical coastal deltas where rice is the major crop grown. Innovative approaches and practices for rice crop are then required to ensure the necessary productivity increases to meet the population food and nutrition demand (Rumanti et al., 2018).

Rice is grown on 7.28 million ha in Myanmar and it occupies about two-thirds of the arable land (MoAI, 2014). Rice area increased by about 20%, from 1994 to 2014, while production increased by about 31% (FAOSTAT, 2015). The dry zone in central Myanmar has 22% of the national rice area and the Ayeyarwady delta has 24% of the national rice area. These are the two zones that contribute most to the national rice production (JICA, 2010; DoA, 2015). Farmers in the dry zone with no or limited access to irrigation water produce rice in the wet season (June to November) and pulses or oilseeds in the dry season (December to May). In the delta, rice is subject to flooding in the wet season and is affected by salinity in the dry season. The considerable variability in these agro-environments requires crop management that adapts to each location. Furthermore, decision making on crop management would be better guided with accurate predictions of rainfall and salinity in these environments to reduce risks.

Rice farmers in the delta and the dry zone use low rates of fertilizer compared to favorable lowland areas in Myanmar. In stress-prone areas, shifting the cropping calendar, improving fertilizer management, and using stress-tolerant or short-duration rice varieties may offer opportunities to reduce risks and raise productivity. Although such management options are limited in number, improved stress-tolerant rice varieties have been recently released for drought-, salinity-, and flood-prone fields (Manzanilla et al., 2016). Use of short-duration varieties can reduce risks of crop loss by avoiding periods of expected stress, and allowing for intensification and diversification (Dalgliesh et al., 2016). Adjusting planting dates can be an adaptive strategy for abiotic stresses (Tun Oo et al., 2017; Wassmann et al., 2009).

Dissemination of options for cropping systems adaptation and technologies can be facilitated by developing “recommendations domains” as spatially explicit areas with similar potential and constraints, and within which options and technologies are expected to be appropriate (Rubiano et al., 2016). These geographic areas are likely to have similar biophysical and socio economic characteristics. Determination of these domains requires information on the biophysical environments that indicates their potential and actual yield (Silva et al., 2017; Stuart et al., 2016). Establishing potential yields would be the first step toward targeting available technologies for improve productivity and reduce risks in unfavorable areas (Robertson et al., 2008). Further, recommendation domains can provide a reference for impact assessments of technology adoption and reduce the need for detailed site characterization to establish priority for better decision making and in technologies targeting (Williams et al., 2008). Remote-sensing has recently facilitated the mapping of cropping patterns and of areas affected by salinity, drought, and flood in rice growing areas. These maps provide accurate information on the spatial and temporal distribution of land use and abiotic stresses (Laborte et al., 2017; Nelson et al., 2015; Xiao et al., 2006), and have also supported analyses of the spatial and temporal variability of crop productivity (Wassmann et al., 2009). Similarly as in breeding materials evaluation, delineation of target population of environments can also guide the choice of suitable varieties for particular environments as an adaptive strategy to address climate variability (Chenu et al., 2011, 2013; Li et al., 2016).

Our study, for the first time in tropical Asia, aimed to test an integrated approach of using remote-sensing, crop simulation model and a geographic information system (GIS) to identify the spatial distribution of the opportunities and risks associated with use of particular crop management practices in unfavorable rice environments. This information provides opportunities to create a framework to describe the performance of technologies in diverse environments in a way that is not usually feasible with conventional multi-location experiments. We applied this approach to establish spatially explicit benchmarks of rice productivity and the potential gains with adaptive management options in the Ayeyarwady delta and the dry zone in Myanmar. The objectives of this study were to identify the spatio-temporal variability in rice yield potential in these two contrasting and major rice growing areas of the country, to quantify any yield losses due to abiotic stresses such as drought and salinity, and to estimate any yield gains by adopting management options that may mitigate risks of drought and salinity. The options evaluated were rice sowing dates, nutrient management regimes, and the choice of varieties. Research priorities and future work on site-specific crop management in stress-prone areas by this integrated approach were also discussed.

2. Materials and methods

2.1. The study sites

This study focused on the Ayeyarwady delta and the dry zone in Myanmar, where we selected four townships (Labutta, Bogale, Mawlamyinegyun, and Wundwin). The cropping patterns in these regions are driven by the onset of monsoon, with early rains expected in mid-May (Htway and Matsumoto, 2011). The delta (Ayeyarwady, Yangon, and Bago regions) has average total annual rainfall of 3300 mm (Fig. 1) with July and August being the wettest months, while the dry zone (Magway, Mandalay, and Sagaing regions) has a mean total annual rainfall of 823 mm with September and October being the wettest months. In the delta, the risk of salinity varies by location but has an important dynamic that limits crop production in the dry season. Salinity levels rise due to decreased river flows in April (Mu et al., 2015). Labutta and Bogale are located in the salt-affected lower delta and the townships include about 148,000 and 126,000 ha of rice, respectively, while Mawlamyinegyun is less affected by salinity and has about 90,000 ha of rice. In Wundwin, in the dry zone, irrigation water scarcity is the major bottleneck for cropping systems where rice is grown on 40,000 ha.

2.1.1. Environmental data to characterize the study sites

Open-source datasets for climate and soils were used to characterize the four study sites.

2.1.1.1. Weather data. Rainfall data in mm d^{-1} were derived from the Tropical Rainfall Measuring Mission (TRMM, NASA, 2015a) database that provides daily rainfall data from 50 °N and 50 °S in raster grid format with 0.25-degree (~28 km) resolution. Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS, Funk et al., 2015) were used to provide daily rainfall values in mm d^{-1} on a 0.05-degree grid from 2000 to 2015 spanning 50 °S-50 °N (and all longitudes). Temperature maximum and minimum in degrees Celsius were derived from the Global Surface Summary of the Day (GSOD, NOAA, 2015) database covering years 2000–2015. The data were interpolated using the digital elevation model (DEM) as a covariate in a thin-plate-spline algorithm to match the spatial resolution of the rainfall data at 0.05 °. Climatic variables of solar radiation (watts m^{-2}), wind speed ($m\ s^{-1}$), and relative humidity (%) were derived from the NASA-POWER database covering years 2000–2015 (NASA, 2015b).

2.1.1.2. Soil data and river salinity. Soil data were derived from the International Soil Reference and Information Centre (International Soil Reference and Information Centre ISRIC, 2015) with spatial resolution of 250 m and 1-km grids; the data included texture (percent clay and

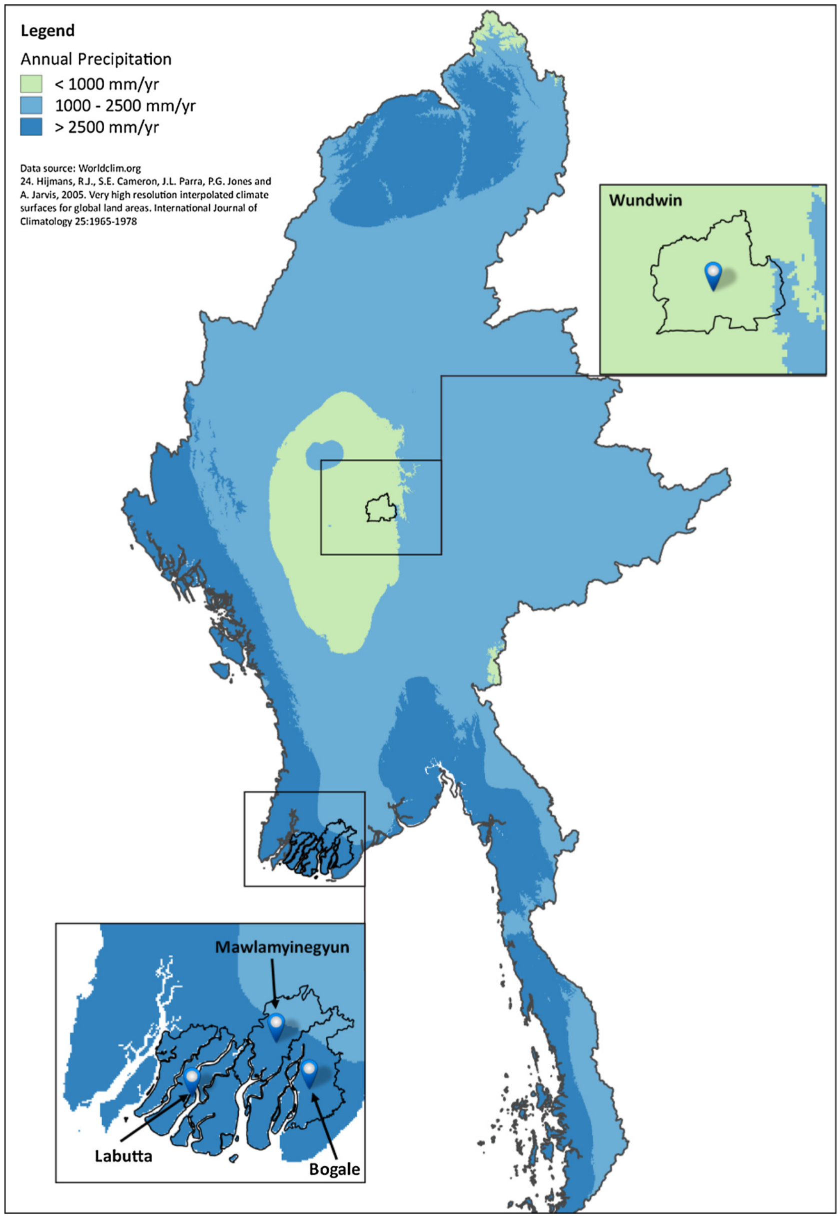

Fig. 1. Study sites, distribution of total annual rainfall, and agro-climatic zones in Myanmar. The dry zone has total annual rainfall of less than 1000 mm, the delta zone is the southern area with total rainfall of more than 1000 mm. Total annual rainfall presented is the average from 2000 to 2014.

Table 1
Soil characteristics for the four study sites. Values presented are mean of 3 soil layers from 0 to 10, 10–20 and 20–50 cm, extracted from ISRC soil database. Values in bracket are coefficient of variation in percentage within considered grids in each township at 0.5^0x 0.5^0 resolution.

Sites	Clay content (%)	Sand content (%)	Bulk density (g/cm3)	Soil organic carbon content (%)
Bogale	27.65	35.74	1.29	2.41
	(8)	(10)	(4)	(130)
Labutta	26.55	37.90	1.29	1.28
	(8)	(9)	(2)	(85)
Mawlamyinegyun	27.24	37.10	1.32	1.53
	(7)	(6)	(2)	(61)
Wundwin	30.99	39.05	1.42	1.04
	(15)	(15)	(3)	(43)

sand), bulk density, hydraulic conductivity, and volumetric water content. Mean values of each pixel from the soil map were aggregated at 0.05 ° to match the spatial resolution of the weather data. The three sites in the delta had similar soil type and were classified as sandy loam with clay content of 27% and sand content of 36% to 38% in the first topsoil layer (0–20 cm) (Table 1). Soil bulk density of these sites ranged between 1.29 to 1.32 kg m^{-3}. In the dry zone, the soil in Wundwin is classified as sandy clay and consisted 31% clay and 39% sand with a bulk density greater than 1.42 kg m^{-3}. Soil organic carbon content within townships ranged from 1.03% to 2.41% among the townships (Table 1).

Coastal salinity was mapped using the electrical conductivity of river water monitored (dS m^{-1}) from 2012 to 2014. Regression interpolation methods were applied to derive data showing the level and seasonality of salinity. Mean values of each pixel from the salinity map were aggregated at 0.05 ° to match the spatial resolution of the weather data. These data were used to simulate rice yields under saline conditions and assuming irrigation from the river. In Labutta, salinity occurs from March to May during the dry season, with a peak of 16 dS m^{-1} at which time it is unsuitable for irrigation of rice (LIFT, 2015, Supplementary Fig. 4). A similar pattern was observed in Bogale but with a lower level (up to 8 dS m^{-1}), with a peak from February to March. Salinity was less pronounced in Mawlamyinegyun, with a maximum below 8 dS m^{-1} in April (LIFT, 2015, Supplementary Fig. 4).

2.1.1.3. Rice-growing areas and ecosystem classification. The rice extent map for Asia (Xiao et al., 2006) was used to determine the rice areas in Myanmar. The rice extent map shows the spatial distribution of rice based on temporal analysis (2000–2012) of MOD09A1 data from the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra and Aqua satellites using previously published paddy mapping algorithm (Xiao et al., 2006; LIFT, 2015).

Time-series analyses of the normalized difference vegetation index derived from the MODIS sensor MOD13Q1 16-days 250-m spatial resolution were conducted and spectral matching techniques applied to detect cropping patterns (intensity = single or double cropping; pattern = rice in monsoon followed by pulses in the dry season or rice in monsoon followed by another rice crop) and rice ecosystems (irrigated or rainfed) in Ayeyarwady Division. A cropping system map was then derived and used to define the seasonality of rice crops. The map of the irrigated areas was used to provide details on where rice could be grown during the wet (monsoon) and dry seasons for the whole of Myanmar. We assumed that rainfed rice could be grown only during the wet season while irrigated rice could be grown twice a year (monsoon and dry season) with the dry-season rice being limited by the availability of water and salinity levels.

2.2. The modeling framework

Simulation modeling was used to integrate several data sources at different resolutions and this followed five steps comprising: (1) characterization of the productivity and risks in the current rice-based cropping systems, (2) calibration and validation of crop model, (3) scenario simulations of rice yield, (4) mapping of outputs from simulation, and (5) description of spatial variation of yields and productivity to define recommendation domains for technologies (Fig. 2). As access to primary data to describe the spatial variability within the study sites was limited, secondary data on salinity, soil, and weather were used as inputs to the model for each location of the surveyed farmers and townships in the study (Table 1). Information generated from the data integration was projected at a standard resolution to evaluate the spatial variability of the constraints and the productivity of rice crops in the study sites.

2.2.1. The model

The rice crop model ORYZA v3 (Li et al., 2017; Bouman et al., 2001) was used to simulate rice yield with current farmers' practices (YF) and different production scenarios in i) the non-limited irrigated system (YP), ii) rainfed system (YW), iii) improved nitrogen management, iv) varietal growth duration. ORYZA v3 has been extensively tested in simulating rice crop growth and yield across the world's different rice ecosystems and production systems with current to expected climatic conditions (Li et al., 2013, 2017). The model considers interactions between genotype, environment, and management, and is a powerful tool to explore scenarios with combinations of variety and management in various environments (Yadav et al., 2011; Li et al., 2013; Silva et al., 2017). Before the simulation exercises, the model's ability to simulate the conditions of rice production within the study sites was evaluated using field experiments and survey data. Rice yield with current farmers' practices (YF) of three sites in the delta was simulated by considering the current water and nitrogen management by the farmers. To capture the variability of varieties used, we considered simulations for the different crop growth durations reported.

2.2.1.1. ORYZA model parameterization and calibration. The parameters for the ORYZA model were estimated based on data from field experiments in 2014–2015 in Yezin (19°50′8″N, 96°16′41″E) with three rice varieties: (1) a variety with medium to long growth duration (MDV) cv. IRRI154, (2) a variety with shorter duration (SDV) cv. IRRI138, and (3) a popular variety of farmers with relatively medium duration (FV) cv. Shwe Thwe Yin. These varieties are used as references in field trials of the regional varietal improvement program. The field experiments were managed to minimize yield losses due to pests and diseases. Nitrogen application

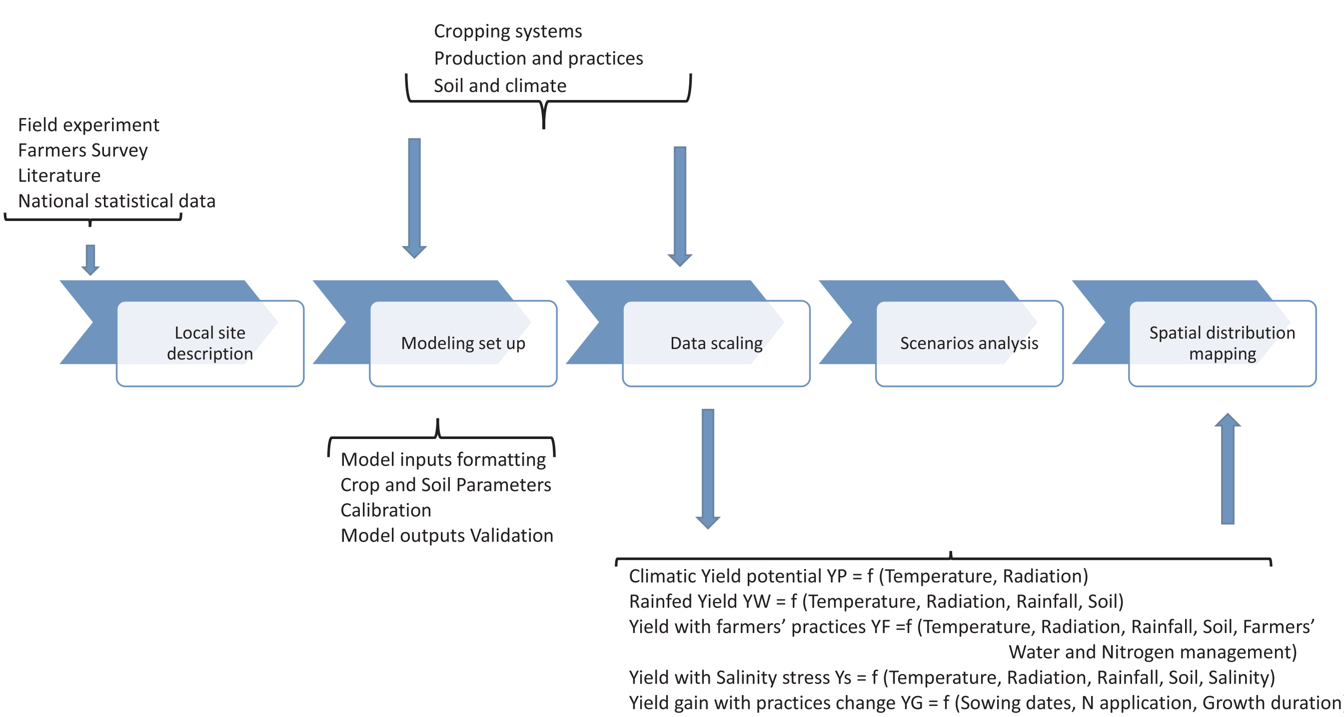

Fig. 2. Methodological framework in rice yield simulation and mapping.

followed the standard "national" recommendations (Supplementary Table 2). Rice seedlings were transplanted from a nursery to the field at 25 days after sowing (DAS) in 2015 and at 27 DAS in 2014. The field was fully irrigated and a flood water depth of 2 to 5 cm was maintained in the field. Radiation, temperature, relative humidity, and wind speed and direction were recorded every 15 min near the experimental field using an automate weather station (Davis Instruments, USA).

Calibration for crop parameters of the ORYZA model was carried out using the auto-calibration tool of the model (IRRI, 2015). The parameters for phenology (developmental rate during vegetative stage (DVRJ, DVRI) and reproductive stage (DVRP, DVRR)) and biomass partitioning to the shoot (FSHT), fraction of total above ground biomass to leaves, stem and organ storage (FLVTB, FSTB, FSOTB) for the three varieties were derived from the field experiments using flowering date, physiological maturity date, total aboveground biomass and grain yield at harvest. Due to the limited available data, standard crop parameters, for instance, for stress responses and leaf growth, were for rice variety IR64 (IRRI, 2015).

2.2.1.2. ORYZA model validation. Validation of the ORYZA model simulations for the current practices at the study sites used rice yield statistics and yields reported from the farmers' household survey data (Supplementary Tables 3,4, and 5). The average yields of the three rice varieties under the farmers' practices (sowing dates, fertilizer and water management) was assumed to be representative of the actual rice yields at the case studies sites (Supplementary Table 1 and Supplementary Figs. 1 and 2). Farmers' practices used in simulations were those determined from the survey data from 2012 to 2014 in Labutta, Bogale, and Mawlamyinegyun (Supplementary Tables 3,4, and 5) with rice varieties of different growth duration and a range of fertilizer management from low to high rates of application. Sample households with complete information from the survey were selected randomly to capture the variation in practices at each study site. The practices were then grouped to capture a range of nitrogen inputs. Information on farmers' practices in Wundwin was not available in the survey, therefore to validate the model outputs, we used the practices used in the experimental trials with the three varieties. YF and yield gain were also analyzed only for the three sites in the delta.

Soil and weather data for the sites surveyed were collected from the secondary sources as described in Environmental data (section 2.1). Soil bulk density, soil texture, soil organic carbon (SOC) content, and soil organic nitrogen (SON) content were estimated while other parameters including percolation rate and soil nitrogen recovery required in the PADDY soil file of ORYZA were maintained at the standard values as defined for paddy fields.

2.2.2. Scenario simulations

Long-term simulations over 15 years (2000–2014) were used to evaluate rice productivity for the study sites/country. Productivity was evaluated using climatic yield potential (YP), maximum attainable yield under the rainfed conditions (YW), yield of crops with farmers' practices (farmer yield, YF), and yield under salinity stress using river water as the source of irrigation (YS). YP was simulated with no limitations of water, nutrients, and pests and diseases. YP variability was assumed to be a function of variety, temperature, and radiation. Attainable yield under rainfed conditions (YW) was simulated for the same climatic conditions as YP but used rainfall as the only source of water. Variability in YW is driven by rainfall, temperature, radiation and soil type. The difference between YP and YW represents the potential yield gain from using supplemental irrigation, with no limitations of nutrient supply and with control of pests and diseases. In the study sites, supplemental irrigation may be fresh water from river and irrigation canal that requires pumping and or irrigation inlet management to access the field.

To consider the effect of salinity, the modified version of ORYZA (Radanielson et al., 2018) was used to simulate yield under saline conditions (YS). YS was simulated for the three townships in the delta. Salinity data were not available for all 15 years of the long-term simulation, and hence yield under salinity (YS) was simulated for 2012 to 2014. Potential yield loss due to salinity was evaluated against YP for the same period.

2.2.2.1. Variety, crop calendar, and cropping pattern scenarios. Rice growth duration was considered using standard values for the crop growth duration of the three varieties check as: short duration as for SDV (90–95 days), relatively medium to long duration as the MDV (110–115 days), and medium duration as for FV (98–110 days). To define optimum dates for dry-season rice, grown from November to May, and for monsoon wet-season rice, from June to October, simulations were conducted for sowing dates at 15-day intervals over these periods (Supplementary Table 6); the outputs were aggregated and averaged to estimate monthly mean yield values.

Farmers' practice for nitrogen applications in Bogale were classified as three rates, low ($<=30$ kg ha^{-1}), medium (greater than 30 kg ha^{-1} and lower than 80 kg ha^{-1}), and high (>80 kg ha^{-1}, Supplementary Table 3). These rates were used for simulations with the different growth duration of the varieties reported from the farmers' survey in each of the townships. In Mawlamyinegyun, farmers' practices were also classified into three nitrogen application rates (Supplementary Table 5). In Labutta, farm management options were considered using the local variety with nitrogen application rates classified into no application and low and medium rates (Supplementary Table 4).

2.2.3. Model outputs analysis and spatial distribution of productivity mapping

Statistical analyses of the simulation outputs were used to describe the spatial variability of rice yields between the sites. Analysis of variance was performed using R software (R Development Core Team, 2018). Factors tested were sowing dates (interval of 15 days), varieties, and nitrogen management for each grid of the combination of soil and climatic conditions (replication). For each site, average yield was computed as the mean of the simulated yields over the 15-year period. For the dry season, the optimum sowing "window" was defined as the sowing dates that gave the maximum average YP over the 15 years, assuming no limitation of water supply. For the wet season, the optimum sowing window was defined as the sowing dates with the greatest YW of 50% of probability of exceedance and a maximum of 10% probability of crop failure.

Maps of YP, YW, YS and yield gain were overlaid to take into account the spatial and temporal variability of climatic conditions, soil characteristics, and river salinity dynamics over the rice-growing areas and at the study sites. YP was simulated nationally using weather data resolution at 0.25° (~ 28 km). At the township level, YP, YW, YS, and YF were simulated using weather, soil, and salinity data at 0.05-degree resolution. Computation of yield gain and risk was undertaken at the same resolution to allow evaluation of the variability of constraints and potentials within the townships.

Yield gains were estimated as the percentage difference between YF (simulated yield with current farmers' practices) and yield with improved practices. Yield gains were expressed in percentage of the YF. The changes in practices included date of sowing from current to the optimum (calendar), varieties with different crop growth duration (variety), nitrogen application from the lowest rate to the highest rate (fertilizer), and supplemental irrigation water from only rainfed to fully irrigated water access (water).

Risks of drought and salinity stress were quantified using the ratio between YW and YS to YP, respectively. The severity of the stress was evaluated with the yield losses with the stress as compared to YP. The risk of the stress is defined by the probability of the yield loss related to the stress being higher than 50%.

The map of rice area extent was used to *mask* the map of simulation outputs (yield and yield gain). The projection of the gridded simulated yield at the sub-national level presented distinct boundaries or shapes that were "smoothed" using spatial interpolation based on the critical points available for the grid of interest. We considered critical points the centroids defined as the center of the shapes or the center of the pixels of the low-resolution raster inputs. Values of the different variables (actual yield, variety, calendar, and nitrogen) at the centroids were then extracted from the initial outputs. Using the *Krig* function of the fields package in R (R Development Core Team, 2018; Nychka et al., 2017), a modelled redistribution of the simulation outputs was created based on the data at the centroids. The modeled data were then used as an input to the interpolate function from the raster package in R (Hijmans, 2017) to make a smoothed version of the initial simulation data.

3. Results

3.1. Rice cropping systems in Myanmar and actual productivity

Rice yields collected in our survey were within the range of yields reported for the Ayeyarwady region (DoA, 2015, Supplementary Table 7). In Labutta, the average actual yield was 3.2 ± 0.4 t ha^{-1}, while in Mawlamyinegyun it was 4.3 ± 1.0 t ha^{-1} and in Bogale it was 3.9 ± 0.7 t ha^{-1} (Supplementary Table 3,4,5).

3.2. Variability in yield potential (YP) for fully irrigated systems in the delta and in the dry zone

Simulations of YP show differences in yields across the country, between wet- and dry-season rice crops, and among sites, rice varieties, and dates of sowing (Fig. 3).

3.2.1. Wet-season crops

For wet-season rice crops sown from May to August, the average YP is 5.1 t ha^{-1}, with large variability (CV 64%) mainly due to differences in radiation and temperature. The greatest yield was from rice sown in July with MDV (long-duration) which gave 6.3 t ha^{-1}. The least yield was from SDV (short-duration) sown in August (5.4 t ha^{-1}). In general, variation in YP among dates of sowing suggests the optimum sowing dates for rice in the wet season are May in the dry zone and late July to early August in the delta (Fig. 3a, Table 2). Sowing windows with highest YP were however different within the sites of study.

3.2.2. Dry-season crops

Dry-season rice crops sown from November to February present an average YP of 9.1 t ha^{-1} (CV 22%) with the greatest yields with crops sown in November, regardless of varieties.

In the dry zone, YP varied from 3.5 to 11.9 t ha^{-1} (Table 2; Pakkoku, Nyaung U Yamethin and Wundwin). SDV gave greater yields when sown in late November across sites compared with sowing in early January. The MDV sown from late December to early January was vulnerable to high-temperature stress in some sites (e.g Pakkoku, Supplementary Fig. 3).

In the delta, average YP varied from 3.5 to 11.8 t ha^{-1} and the highest yields resulted from crops sown in early November (Table 2). The MDV gave higher yields when sown in late October/early November in the delta compared with yields with FV sown in December. The distribution of YP suggests that, in Bogale and Labutta, rice yields would decline if the crops were sown in January.

3.3. Variability in climatic yield potential in rainfed systems YW at the four sites

The optimum sowing period for rainfed rice in the wet-season (June to November) was in June both in the dry zone and the delta. Crops sown in August were predicted to have a high risk of crop failure at all the sites. The MDV presented the highest yield (YW of 7.6 t ha^{-1}) for rice sown in June in Wundwin and when sown in August it was simulated as well with the maximum YW (4.3 t ha^{-1}) compared to the other varieties. MDV gave 41% higher yield than the FV and 52% higher than the SDV. Rice sown in June was predicted to have greater risk of high-temperature stress in Wundwin than at the three sites in the delta.

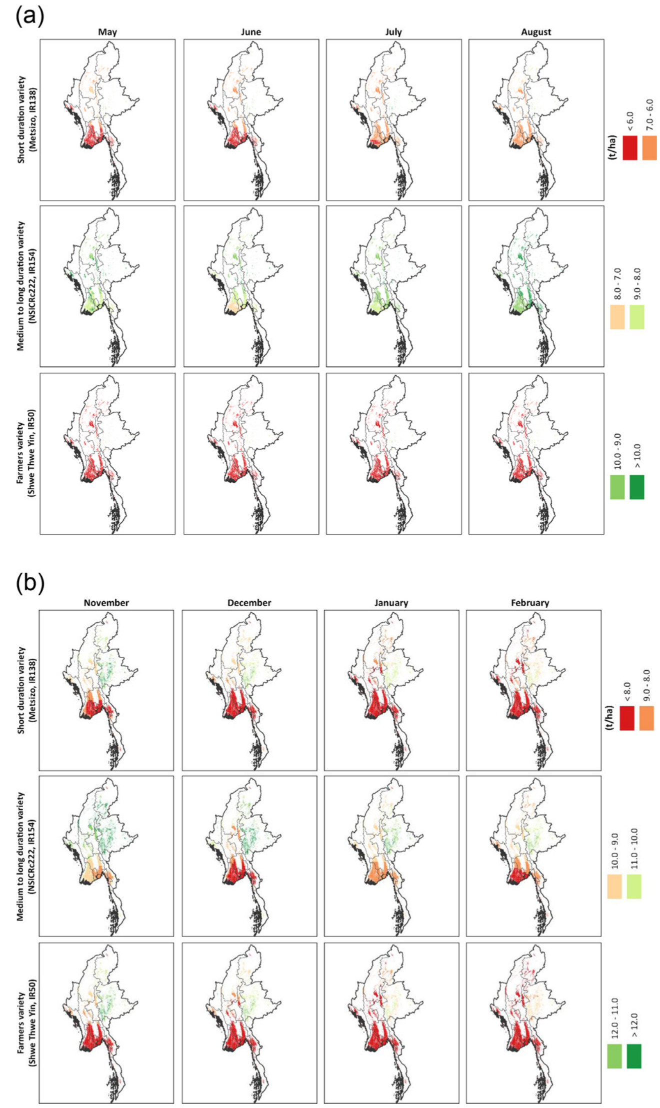

Fig. 3. (a) Simulated yield potential (YP) of wet-season rice crops in current rice-growing areas in Myanmar for the short duration variety (IR138, Mestizo), the medium to long duration variety (NSIC Rc222, IR154), and the farmers variety with medium duration (Shwe Thwe Yin, IR50). (b) Simulated yield potential (YP) of dry-season rice crops in current rice-growing areas in Myanmar for the short duration variety (IR138, Mestizo), the medium to long duration variety (NSIC Rc222, IR154), and the farmers variety with medium duration (Shwe Thwe Yin, IR50).

In Bogale, YW for the MDV sown in June was 6.1 t ha^{-1}, compared to a YP of 6.7 t ha^{-1}, it had 10% yield reduction (Table 3). The FV had a mean yield of 4.7 t ha^{-1} at the same level as for SDV. The lowest YW (0.5 t ha^{-1}) predicted among the sites was for the MDV in Bogale sown in August while the same variety sown in August but with adequate irrigation had a predicted yield YP of 8.5 t ha^{-1} (Fig. 3) suggesting that SDV is likely to yield better than MDV and the current FV in high risk conditions as in Bogale.

Rice yields with SDV in rainfed conditions, were greater in Labutta and Mawlamyinegyun than in Bogale with average YW of 5.1 t ha^{-1} for rice sown from May to July. Likewise, with the MDV, YW was 6.4 t ha^{-1} in Labutta and 6.3 t ha^{-1} in Mawlamyinegyun compared to the

Table 2
Yield potential for three varieties and different sowing dates for selected townships in the Ayeyarwady Delta and Central Dry Zone. Average yield potential (t ha^{-1}) ± standard deviation of simulated yields at 15-day intervals of sowing per month for the period 2000–2014 for the rice-growing areas of the study sites at 0.25° × 0.25° resolution. SDV, short-duration variety (90–95 days); MDV, medium- to long-duration variety (110–115 days); FV, farmers' variety with medium duration (98–110 days).

Varieties	Sites	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SDV	Bogale	5.8 ± 0.2	6.8 ± 0.1	6.0 ± 0.1	5.3 ± 0.1	4.9 ± 0.1	5.2 ± 0.1	5.9 ± 0.1	6.5 ± 0.0	7.2 ± 0.0	7.9 ± 0.0	8.1 ± 0.1	7.2 ± 0.3
	Labutta	6.0 ± 0.2	6.9 ± 0.1	6.5 ± 0.1	5.4 ± 0.1	4.9 ± 0.1	5.2 ± 0.1	5.9 ± 0.1	6.5 ± 0.0	7.1 ± 0.0	7.8 ± 0.0	8.2 ± 0.1	7.5 ± 0.3
	Mawlamyinegyun	5.7 ± 0.1	6.8 ± 0.0	6.0 ± 0.0	5.3 ± 0.0	4.9 ± 0.0	5.1 ± 0.0	5.9 ± 0.0	6.4 ± 0.0	7.1 ± 0.0	7.9 ± 0.0	8.1 ± 0.1	6.9 ± 0.2
MDV	Bogale	7.5 ± 0.2	8.0 ± 0.1	6.9 ± 0.1	6.2 ± 0.1	6.3 ± 0.1	6.7 ± 0.1	7.9 ± 0.1	8.5 ± 0.1	9.3 ± 0.1	10.1 ± 0.0	10.1 ± 0.1	8.1 ± 0.3
	Labutta	7.7 ± 0.2	8.1 ± 0.1	7.0 ± 0.1	6.3 ± 0.2	6.3 ± 0.2	6.7 ± 0.1	7.9 ± 0.1	8.5 ± 0.1	9.3 ± 0.1	10.0 ± 0.0	10.2 ± 0.1	8.5 ± 0.3
	Mawlamyinegyun	7.4 ± 0.1	7.9 ± 0.1	6.9 ± 0.0	6.1 ± 0.1	6.2 ± 0.1	6.7 ± 0.0	7.8 ± 0.1	8.4 ± 0.1	9.2 ± 0.0	10.1 ± 0.0	10.0 ± 0.1	7.9 ± 0.2
FV	Bogale	5.2 ± 0.1	5.6 ± 0.1	5.0 ± 0.1	4.2 ± 0.0	3.6 ± 0.1	3.6 ± 0.0	4.2 ± 0.1	4.9 ± 0.1	5.7 ± 0.0	6.5 ± 0.0	7.3 ± 0.0	6.7 ± 0.2
	Labutta	5.3 ± 0.1	5.7 ± 0.1	5.1 ± 0.1	4.2 ± 0.1	3.6 ± 0.1	3.6 ± 0.1	4.2 ± 0.1	4.9 ± 0.1	5.7 ± 0.0	6.5 ± 0.0	7.3 ± 0.0	6.9 ± 0.1
	Mawlamyinegyun	5.0 ± 0.1	5.6 ± 0.1	5.0 ± 0.0	4.1 ± 0.0	3.5 ± 0.0	3.6 ± 0.0	4.1 ± 0.0	4.9 ± 0.0	5.6 ± 0.0	6.5 ± 0.0	7.3 ± 0.0	6.8 ± 0.2
Ayeyarwady Delta zone		6.2 ± 0.1	6.8 ± 0.1	6.0 ± 0.1	5.2 ± 0.1	4.9 ± 0.1	5.2 ± 0.1	5.9 ± 0.1	6.6 ± 0.0	7.4 ± 0.0	8.1 ± 0.0	8.5 ± 0.1	7.3 ± 0.2
SDV	Pakkoku	7.4 ± 2.0	7.7 ± 1.6	8.0 ± 0.4	7.5 ± 0.3	7.1 ± 0.4	6.8 ± 0.5	6.7 ± 0.3	6.8 ± 0.4	8.0 ± 0.5	8.9 ± 0.2	9.5 ± 0.3	9.3 ± 1.1
	NyaungU	7.2 ± 2.0	7.7 ± 1.4	7.9 ± 0.4	7.4 ± 0.3	7.1 ± 0.4	6.8 ± 0.5	6.7 ± 0.3	6.8 ± 0.4	7.9 ± 0.5	8.9 ± 0.2	9.5 ± 0.3	9.2 ± 1.1
	Yamethin	7.4 ± 2.0	8.5 ± 1.1	8.4 ± 0.4	7.9 ± 0.3	7.6 ± 0.4	7.3 ± 0.5	7.1 ± 0.4	7.2 ± 0.4	8.1 ± 0.5	9.2 ± 0.3	9.7 ± 0.4	9.3 ± 1.3
	Wundwin	7.4 ± 0.2	8.0 ± 0.2	8.4 ± 0.1	7.9 ± 0.1	7.5 ± 0.1	7.2 ± 0.1	6.9 ± 0.1	7.1 ± 0.1	8.2 ± 0.1	9.2 ± 0.1	9.7 ± 0.1	9.3 ± 0.1
MDV	Pakkoku	8.6 ± 2.1	9.2 ± 1.8	9.2 ± 0.5	8.7 ± 0.4	8.5 ± 0.4	8.3 ± 0.6	8.3 ± 0.4	8.8 ± 0.4	10.2 ± 0.6	11.3 ± 0.4	11.6 ± 0.7	9.2 ± 2.4
	NyaungU	8.6 ± 2.0	9.2 ± 1.5	9.1 ± 0.5	8.5 ± 0.4	8.4 ± 0.5	8.3 ± 0.6	8.3 ± 0.4	8.8 ± 0.5	10.2 ± 0.6	11.3 ± 0.3	11.5 ± 0.7	9.4 ± 2.5
	Yamethin	8.9 ± 1.9	10.1 ± 1.1	9.7 ± 0.5	9.1 ± 0.3	8.9 ± 0.4	8.8 ± 0.5	8.7 ± 0.4	9.1 ± 0.5	10.2 ± 0.7	11.5 ± 0.4	11.8 ± 0.7	9.5 ± 2.6
	Wundwin	8.9 ± 0.4	9.7 ± 0.2	9.7 ± 0.1	9.1 ± 0.1	8.8 ± 0.1	8.7 ± 0.1	8.5 ± 0.1	9.0 ± 0.1	10.3 ± 0.1	11.5 ± 0.1	11.8 ± 0.2	9.2 ± 0.3
FV	Pakkoku	6.0 ± 1.9	6.8 ± 1.6	6.7 ± 0.8	6.3 ± 0.4	5.6 ± 0.4	5.3 ± 0.4	5.2 ± 0.4	5.4 ± 0.3	6.3 ± 0.4	7.8 ± 0.5	8.8 ± 0.4	8.5 ± 1.1
	NyaungU	5.9 ± 1.8	6.9 ± 1.6	6.7 ± 0.7	6.1 ± 0.4	5.5 ± 0.4	5.2 ± 0.5	5.2 ± 0.4	5.3 ± 0.3	6.2 ± 0.4	7.7 ± 0.5	8.7 ± 0.4	8.4 ± 1.1
	Yamethin	6.1 ± 1.9	7.2 ± 1.5	7.4 ± 0.5	6.7 ± 0.3	6.1 ± 0.4	5.7 ± 0.4	5.6 ± 0.4	5.7 ± 0.3	6.5 ± 0.5	7.9 ± 0.5	8.9 ± 0.5	8.6 ± 1.2
	Wundwin	6.0 ± 0.3	6.9 ± 0.2	7.2 ± 0.2	6.7 ± 0.1	6.1 ± 0.1	5.6 ± 0.1	5.4 ± 0.1	5.8 ± 0.1	6.5 ± 0.1	8.0 ± 0.1	9.1 ± 0.2	8.6 ± 0.2
Central dry zone		7.4 ± 1.5	8.2 ± 1.2	8.2 ± 0.4	7.6 ± 0.3	7.3 ± 0.3	7.0 ± 0.4	6.9 ± 0.3	7.1 ± 0.3	8.2 ± 0.4	9.5 ± 0.3	10.1 ± 0.4	9.0 ± 1.2

Table 3
Rainfed rice yields (YW) for three varieties and different sowing dates at four study sites. Yields (t ha^{-1}) presented are monthly averages ± standard deviation of simulated yields with sowing at 15-day intervals for the period 2000–2014 during the wet season from May to August for rice-growing areas in the townships at 0.05° x 0.05° resolution. SDV, short-duration variety (90–95 days); MDV, medium- to long-duration variety (110–115 days); FV, farmers` variety (98–110 days).

Varieties	Sites	May	June	July	August
SDV	Bogale	3.1 ± 0.5	4.7 ± 0.4	3.5 ± 0.2	0.6 ± 0.1
	Labutta	4.9 ± 0.1	5.1 ± 0.1	5.3 ± 0.1	1.1 ± 0.1
	Mawlamyinegyun	4.9 ± 0.0	5.0 ± 0.1	5.2 ± 0.1	1.0 ± 0.1
	Wundwin	3.2 ± 0.2	3.4 ± 0.2	3.0 ± 0.3	2.2 ± 0.4
MDV	Bogale	4.0 ± 0.6	6.1 ± 0.5	3.9 ± 0.3	0.5 ± 0.1
	Labutta	6.4 ± 0.1	6.7 ± 0.1	6.1 ± 0.2	0.9 ± 0.1
	Mawlamyinegyun	6.3 ± 0.1	6.6 ± 0.1	5.9 ± 0.2	0.9 ± 0.1
	Wundwin	6.5 ± 0.5	7.6 ± 0.2	6.7 ± 0.6	4.3 ± 1.0
FV	Bogale	3.1 ± 1.0	4.7 ± 1.4	3.5 ± 0.5	0.7 ± 0.3
	Labutta	3.5 ± 0.1	3.6 ± 0.1	4.2 ± 0.1	1.7 ± 0.2
	Mawlamyinegyun	3.5 ± 0.0	3.5 ± 0.0	4.2 ± 0.0	1.7 ± 0.2
	Wundwin	2.3 ± 0.2	2.3 ± 0.2	2.6 ± 0.3	1.7 ± 0.2

average YW in Bogale of 4.6 t ha^{-1}. In contrast, the FV in Labutta and Mawlamyinegyun was predicted to have similar yields as in Bogale (3.7 t ha^{-1}). The crops with MDV yielded then 79% more than with the FV sown in the same period for Labutta and Mawlamyingyun (Table 3). In Bogale, this level of yield gain was only simulated for June sowing.

3.4. Yield variability in saline conditions in the delta

YS presents temporal and spatial variability as a reflection of the occurrence and severity of salinity among the sites and seasons (Supplementary Fig. 4, 5).

In Labutta, salt-affected areas cover about 58% of the rice areas, with yield losses greater than 90% in the dry season. Only 29% of the rice-growing areas in the dry season presented YS greater than 2 t ha^{-1}. In the wet season, 38% of the rice area in Labutta was also affected by salinity with average YS ranging from 2.0 to 5.6 t ha^{-1}. June-sown crops were simulated with the lowest yield losses (Table 4, wet season sowing in Supplementary Fig. 5).

In Bogale, simulations indicate that crops failed on almost 5% of the rice area during the dry-season crop and only 35% of the areas affected presented YS greater than 2 t ha^{-1} (dry season sowing in Supplementary Fig. 5). The highest average yield losses were simulated up to 75% for crops sown in January while crops sown in November were predicted to have losses of 49% on average (Table 4). This suggests that early sowing of dry-season rice in these areas reduced the risks of salinity affecting crop growth (Table 4). The severity of salinity decreases with the onset of the wet season, with only 2% of the area having crop failure (YS < 0.1 t ha^{-1}), and about 44% of the rice areas present yields higher than 2 t ha^{-1} (2.0-5.4 t ha^{-1}). May and June are favorable for sowing rainfed crops in Bogale when the probability of high salinity is low. In that case, crops sown in May and June gave average YS of 1.7 and 2.2 t ha^{-1}. It is worth noting that YW was at similar levels as YP for May and June sowing for the majority of the areas in Bogale, indicating the low occurrence of drought during the season thus less need of irrigation.

Table 4
Effects of salinity (YS) at different sowing dates in three study sites in Ayeyarwady. Yield (t ha^{-1}) presented is an average of simulated yields at every 15 days interval of sowing per month for the period 2012–2014 for the rice growing areas within the township at 0.05^{0}x0.05^0 resolution. Yloss is the ratio of the difference between YS and YP to YP.

	Bogale (t ha^{-1})		Labutta (t ha^{-1})		Mawlamyinegyun (t ha^{-1})	
DATE	YS	Yloss	YS	Yloss	YS	Yloss
Jan	1.60	0.75	0.53	0.92	2.42	0.62
Feb	2.14	0.69	0.32	0.95	3.28	0.52
Mar	1.87	0.69	0.28	0.95	3.39	0.44
april	1.84	0.65	0.36	0.93	2.52	0.52
may	1.77	0.66	0.79	0.84	2.00	0.60
june	2.21	0.61	1.05	0.80	2.35	0.55
july	2.49	0.52	1.31	0.78	3.15	0.47
aug	2.19	0.63	1.59	0.76	4.31	0.35
sept	2.41	0.64	2.09	0.72	6.68	0.09
oct	3.12	0.58	1.33	0.84	7.97	0.02
nov	4.14	0.49	0.34	0.96	7.92	0.08
Dec	2.41	0.68	0.08	0.99	6.52	0.14

In Mawlamyinegyun, salinity was less severe than in Bogale and in Labutta. In the dry season, rice sown in November was not affected by salinity, with an average yield of 7.9 t ha^{-1}(YS, Table 4). For crops sown in November and December, salinity did not reach a high level and yield reductions ranged only from 7% to 14%. The maximum simulated potential yield loss was 61% of YP for crops sown in January (Table 4). In saline-prone areas, crops sown in May were more affected by salinity, with average yield simulated of 2.0 t ha^{-1} or a yield loss of 60% compared with YP, showing that June is the optimum sowing date for wet-season crops.

In summary, the temporal and spatial variability in salinity level expressed as the variability in yield reduction due to salinity were less in Mawlamyinegyun than in Labutta and Bogale. In salt-affected areas, sowing wet-season rice in August to October minimized the effects of salinity in Labutta and Bogale but presented a higher risk of crop failure due to drought. With access to irrigation water, wet-season rice sown in August may benefit from a reduced risk of salinity and as a result have greater YP in salt-affected areas. This option would likely be feasible when only one rice crop per year was grown as the delay in the establishment of a second crop in the dry season to January and February would reduce YP of the second crop.

3.5. Effects of combining variety with optimal management of nitrogen, sowing date, and supplemental irrigation

In Bogale, increasing nitrogen application from low to medium rates is predicted to give yield increases of 14%. With high N rates, the yield increase was 16% (Fig. 4, Table 5) compared with the low rate of application. Using short or medium to long-duration varieties (SDV and MDV) was predicted to give a yield gain of 8% to 12% compared with the use of FV. In areas where two rice crops are grown, sowing the dry-season crop in November or December in Bogale, rather than the farmers' practices (i.e., sowing in January), gave 51% to 55% greater yields (Fig. 4, Table 5). Areas with the least actual yields (illustrated in red in Fig. 4) were predicted to show the greatest yield gains by shifting the cropping calendar (up to 55% yield increase) and by increasing nitrogen application (up to 15.8%, illustrated in green in Fig. 4). At sites with greatest farmers' yields, moderate yield gains were simulated with changes in practices of nitrogen management, shifting the cropping calendar, and variety change (illustrated in yellow in Fig. 4).

Particularly in Bogale, an earlier sowing date of the wet-season rice from the current practice of June to May did not present a significant change in yield. When sowing was delayed to July, however, an average yield gain of about 20% was apparent compared with the current June sowing. Access to irrigation water was a key determinant for this gain as under rainfed system July and May sowing presented risk of yield loss due to drought (Table 3). Combining changes in sowing date with increased nitrogen use in the wet season was predicted to increase yield by 63% for crops sown early in May and by 153% for crops sown in July. The use of a medium-duration rice variety (MDV) sown in May permits early sowing of the subsequent dry-season rice in November or in December. The occurrence of salinity at the end of April and in early May, however, might limit the feasibility of this second crop in salt affected areas. A recommendation for July sowing of wet season rice

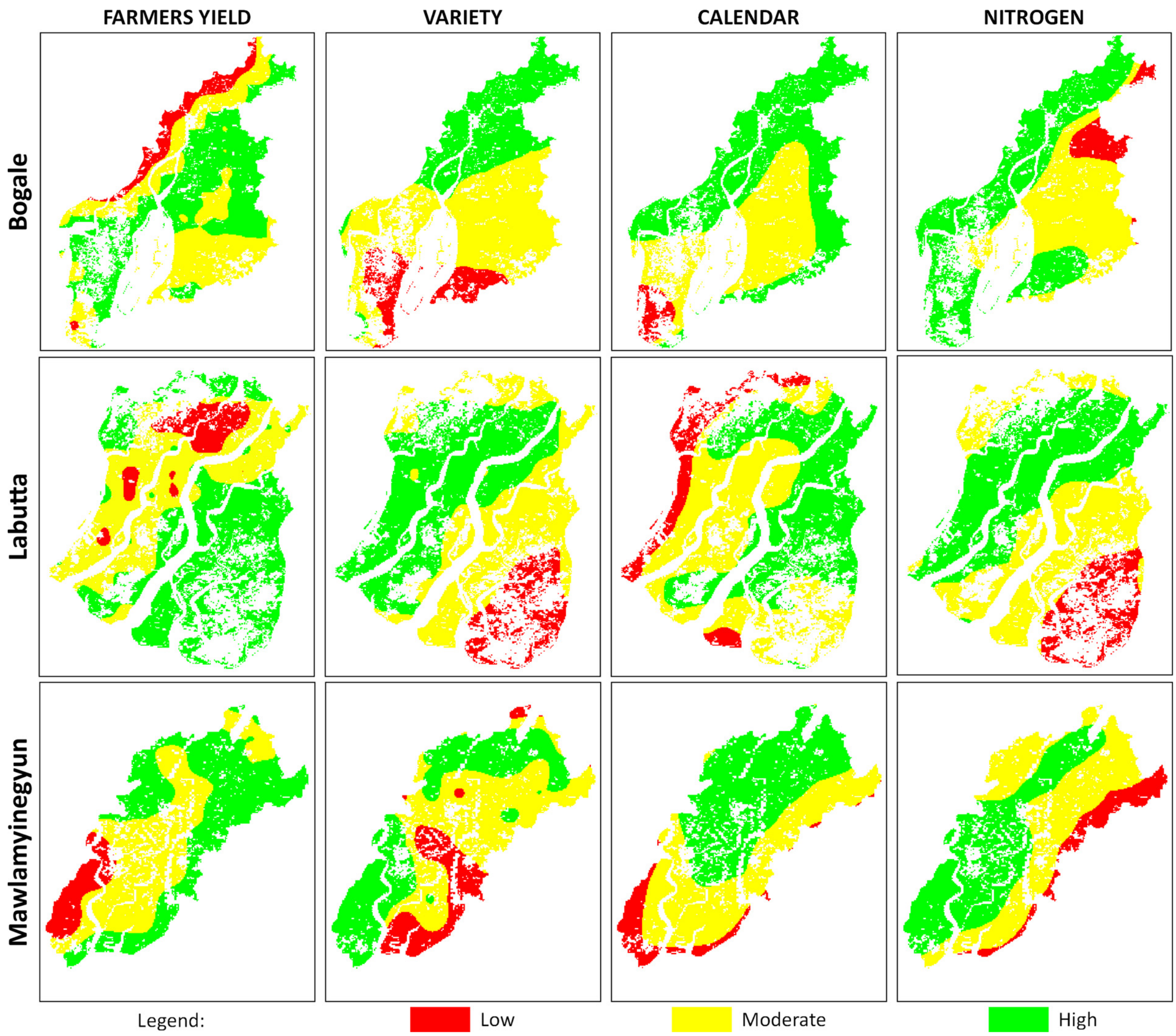

Fig. 4. Farmers' yields (YF) in the wet season (kg ha^{-1}) for current rice-growing areas in Bogale, Labutta, and Mawlamyinegyun with the simulated yield gains as % of YF after using improved fertilizer management (Fertilizer), shifting cropping calendar (Calendar), and change in crop duration (Variety). Low indicates areas in the bottom 10 percentile of the YF and productivity gain by practices change; high indicates areas in upper 10 percentile of the productivity gain while moderate are areas representing the average rest in the distribution. Average values are referenced in Table 5.

may be appropriate for short-duration varieties (SDV) in areas with irrigation water access providing drainage infrastructure and the weather allow the crop to be established once the monsoon has begun. Sowing of a second rice crop in November and December enables medium-duration rice varieties to be grown in the dry season.

In Labutta, the farmers' practice of June sowing gave the highest yield, and sowing either earlier or later resulted in yield decreases. Combining early sowing in May with a medium rate of nitrogen application was predicted to give yield gains of up to 69% in some areas compared with sowing in June with low input use. Early sowing of wet-season rice provides greater flexibility for the establishment of a second crop, and high nitrogen rates for May-sown crops were predicted to raise yields, with a range from 14% to 184% compared to YF and depending on location (Fig. 4). YP in Labutta suggests that sowing in November would give the highest yields for dry-season rice (Fig. 3, Table 2); changing the variety from FV to SDV would increase yields by 13%, and by 45% by changing to MDV. Rising salinity levels in rivers from November to May, however, limit the possibilities for irrigation of

Table 5
Grain yield (t ha^{-1}) and yield gains for three sites in the delta during the monsoon wet season: YP = climatic yield potential under fully irrigated conditions, YW = climatic yield potential under complete rainfed conditions, and YF = farmers` yield with existing current practices. Values presented are the average ± standard deviation of the 15 years of simulations (2000–2014) and the 15-day interval of sowing dates for each month within the sowing window of the wet-season crop from May to August for the rice-growing areas at 0.05° x 0.05° resolution.

	Grain Yield (t ha^{-1})			Yield gain (%)		
Sites	YP	YW	YF	Nitrogen management	Variety	Crop calendar
Bogale	7.1 ± 1.1	3.3 ± 0.2	5.9 ± 0.4	14.9 ± 0.9	10.1 ± 1.9	35.9 ± 21.8
Labutta	7.1 ± 1.2	3.6 ± 0.1	3.8 ± 1.2	30.4 ± 12.2	64.8 ± 22.5	−11.0 ± 10.9
Mawlamyinegyun	7.0 ± 1.1	3.5 ± 0.0	2.6 ± 0.2	26.9 ± 12.0	23.6 ± 3.3	18.94 ± 13.8

dry-season rice in Labutta. Early sowing in May for a wet-season crop would also require access to fresh irrigation water to flush the salt from the soil together with the use of a rice variety with a tolerance of up to 8 dS m^{-1} to secure yields up to a maximum of 50% of YP. In Labutta, the greatest impact on productivity was likely with improved stress tolerant varieties combined with improved nitrogen management.

In Mawlamyinegyun, using a SDV rather than the farmers' variety (FV) is predicted to give yield gains of 9% and using a MDV would raise yields by 27%. In Mawlamyinegyun, double cropping of rice is commonly practiced by farmers. Sowing of dry-season rice in November was predicted to give average yield gains of 30% compared with the current practice of January, while sowing in December would give yield gains of 26%. Increasing nitrogen application rates from low input to medium input would result in average yield increases of 36% and up to 43% might be achieved with high N input. Beyond the low nitrogen application rate of 23 kg ha^{-1}, as commonly practiced by farmers, increased applications are predicted to give a yield increase of 12 kg grain per kg of nitrogen applied. Using a short-duration variety (SDV) sown in December, with high nitrogen input, was predicted to increase yields by up to 131% compared with the use of a FV sown in January with low nitrogen input. Rainfed rice yields (YW) in the wet season crop sown in July in Mawlamyinegyun presented a potential yield with FV of 4.2 t ha^{-1}, while a MDV sown in June is predicted to give an average yield of 6.6 t ha^{-1}. The FV sown in June will result in 15% less yield (3.5 t ha^{-1}) than the July sowing. Sites simulated to have less yield (YF) in Mawlamyinegyun were predicted to benefit the most from the adoption of varieties such as MDV and SDV combined with improved nitrogen management (Fig. 4).

4. Discussion

4.1. Adding value to conventional agronomy research by using GIS and crop simulation models

This study serves as a proof of concept on how the integration of different research tools (survey data, remote sensing, crop modeling, and GIS) can be used to assess combinations of crop management options to provide recommendations at landscape scale in stress-prone environments. The study aimed also to provide firsthand information on the yield potential of rice-growing areas in Myanmar and to quantify yield gains from combinations of technologies (varieties) and crop management options (sowing dates and nitrogen management) to enable better targeting their dissemination in the main rice bowl of the country (Fig. 4). The reported results provide useful information on how options can be combined and could guide site-specific recommendations. The use of remote sensing coupled with crop modeling has been validated in different applications such as yield gap analysis (Lobell, 2013; van Ittersum et al., 2013), yield loss estimates after damage, and regional production assessments (Nelson et al., 2015; Boschetti et al., 2017). Similarly, the use of survey data coupled with modeling can provide robust estimates for yield gaps and for the identification of key constraints to productivity (Affholder et al., 2012; Stuart et al., 2016). Those applications used *ex post* assessments and were relevant for impact assessments of development initiatives. Our study, however, is a novel *ex ante* assessment that integrates survey data, remote sensing, and experimental field stations, and focused mainly on rainfed and salt-affected areas. We used historical data covering more than 15 years, as suggested by van Ittersum et al. (2013), in order to compensate for the low resolution of the available data for weather. The distribution of YP combined with information on rainfall distribution was used to define areas with similar potential and constraints as agro-ecological zones relevant to two main rice growing regions of the country. The use of further data on crop management options (sowing dates, nitrogen, and water regimes) and varieties permitted the identification of potential areas for intensification and as recommendation domains in the delta. Scenario analyses used the robust rice crop model ORYZA to strengthen the targeting and delineation of these rice-growing areas with potential, and risk assessments related to drought and salinity (Li et al., 2017; Radanielson et al., 2018). Extending simulations in a similar approach would be relevant to account for "flash" flooding, which recently has been one of the major constraints for wet-season rice in Myanmar, and which is expected to increase in future climates (IPCC, 2014).

4.2. Variability in yield potential and use of the approach as a guide for the dry zone

The rice-growing areas in Myanmar have a large production potential with YP greater than 12 t ha^{-1} but with large coefficient of variation due to the varying climatic conditions among seasons and the duration of varieties (Fig. 3). Yield data from the national statistics and the household survey indicate there is a range of yield gaps up to 2.2 t ha^{-1} given an achievable "agronomic" yield of 5.3 t ha^{-1} as estimated as 75% of YP after van Ittersum et al. (2013). This also suggests that actual farm yields in rainfed areas could be improved by about 78% on average through a combination of different varieties and crop management.

In fully irrigated areas in the upper delta (Bago), rice yield gaps were estimated to be 37% (Stuart et al., 2016). The best farmers' yield by Stuart et al. (2016) was equivalent to YP of a rice crop sown in July in Bago (8.2 t ha^{-1}). Actual yields in the official statistics for Bago are 3.9 t ha^{-1} under favorable conditions and 3.1 t ha^{-1} in less favorable environments (DoA, 2015).

The quantification of YP for wet- and dry-season rice throughout the country was consistent with the expected productivity in Myanmar. YP and YW are indicators only for what could be expected with intensified rice cropping systems. These do, however, allow assessments of the potential return on investments such as the infrastructure to permit irrigation as may be planned for the dry zone. Such quantification permits a reference that can be used in an analysis of the trade-offs required to achieve regional food self-sufficiency by expansion and/or intensification of rice-based cropping systems. Furthermore, in marginal areas in the dry zone, the information on potential gains from management interventions in rice became for the first time available from this study.

4.3. Rainfed rice yields in the deltas: validation with what has been reported

Information on the spatial variability of rainfed rice yields contributes to the characterization of the rice-growing environments in the delta and can support the design of technology combinations (varieties, nitrogen management, and cropping calendar) to improve productivity. Simulated rice yields reveal a baseline for recommendations on crop management that can be used to target technologies at levels of resolution of field, region, or nation. Elsewhere, changing sowing date is one of the main strategies to address environmental constraints to crop productivity and minimize risks in rainfed environments (Timsina et al., 2008; Dalgliesh et al., 2016). In Myanmar, rainfed rice is commonly sown in the nursery in July and transplanted in August. Our results suggest that rainfed rice in the Ayeyarwady Delta has a potential average yield (YW) of 3.4 t ha^{-1} which is 17% to 47% less than the potential yield (YP). This yield range is consistent with that reported from national statistics (DoA, 2015). Scenario simulations suggest that a shift to an earlier sowing date could give yield gains of up to 35% which is a greater yield gain than farmers could expect by increasing fertilizer application which was indicated increase yields by 14% to 30%. These yield gains with improved fertilizer were consistent with those reported (of about 25%) from rainfed rice in other delta regions, such as the Mekong (Mamun et al., 2016) and Bangladesh (Sarangi et al., 2016). Similarly, in the coastal areas (e.g. Labutta), the risks of salinity for wet-season rice could be mitigated by changing sowing dates. Similar recommendations were proposed for the delta region in

Bangladesh where early sowing resulted in higher yield and allowed timely establishment of a dry-season crop to escape salinity (Mondal et al., 2015; Ahmed et al., 2014). The possibilities for dry-season rice in salt-affected areas are conditioned by the availability of fresh irrigation water and the use of rice varieties with tolerance of more than $8\,dS\,m^{-1}$.

4.4. Application for technology development and recommendations

These modeling activities were based on three "check" varieties used in Myanmar as references for the breeding program for salt-tolerant varieties. These varieties may not be representative of the most recently developed varieties from breeding programs. But they are representative of the range of varieties available for farmers. The scenario analyses enabled orientation of different research and development initiatives in rice growing areas and allow targets to be set as reasonable objectives. The approach in our study assumed that opportunities exist for farmers to access sufficient inputs for production. In particular, increasing nitrogen application is expected to increase farm yield. Extensive soil surveys and experimentation are costly, and as such the maps of potential yield gains can narrow down the need for surveys and detailed observations. Adjusting sowing dates was simulated with potential yield increases of up of 35% (Table 5). In this way, supporting farmers' decisions on the selection of an appropriate sowing date may significantly affect farm productivity. Similarly, information on reasonable expectations for a particular variety under stress and non-stress conditions would help guide evaluation and dissemination of varieties. The use of "target population of environments" in plant breeding has a similar objective for a given environment and provides information that farmers and extension agents can use to assist in their decision making (Li et al., 2013; Chenu et al., 2011). On-farm studies in the coastal delta (Mawlamyinegyun) reported yield gains of 17% to 34% through the use of an improved rice variety and improved management compared with farmers' practices using a local variety (LIFT, 2015). The simulations in our study (i.e., 19% to 27%, Table 5) were consistent with this range of values and this supports a conclusion that the use of the integrated GIS-modeling approach provides reliable information from which to evaluate technologies and options.

In summary, this study predicted that rice yield can be improved with appropriate combinations of the available technical options for farmers. Potential gains vary according to site and the associated risks of drought, high temperature, and salinity. Spatial variability in the simulated yield gains by the adoption of improved management permits the identification of sites with low, medium, and high potential (Fig. 4). On average, 1 kg of additional nitrogen applied resulted in a grain yield increase of 12.8 kg in Mawlamyinegyun, 13.3 kg in Labutta, and 15.4 kg in Bogale. Early sowing resulted in different yield responses, ranging from -14% to 205%. The use of improved varieties medium to long duration (MDV) and short duration variety (SDV) was predicted to result in a consistent positive response, with yield increases from 6% to 32%. These are firsthand hypotheses aiming to improve the productivity of rice-based cropping systems in the delta, which need to be validated prior to recommendations for improved practices.

4.5. Limitations of the present study

Yield gap analyses to date, using experimental fields and modeling, have mostly focused on favorable environments where farmers have access to fresh water for irrigation (Lobell et al., 2010; Schulthess et al., 2013; Hochman et al., 2013; Stuart et al., 2016), which are widely unavailable in less favorable lands. The rice growing areas in the dry zone and in the delta in Myanmar present gradients of potential productivity and risks in time and space. A static approach of comparing farmers with high to low yields may thus be limited as the levels of environmental constraints encountered by the farmers present spatio-temporal variability. This study used available data from different sources including field experiments, survey data and secondary data. This forced us to put valuable hypotheses in the simulation of YP and the potential impact of improved management. The translation of these hypotheses into actionable information requires caution due to the strong assumptions on how representative is the data that was used to parameterize the model, simulate the study sites and define combinations of scenarios simulated by the model to evaluate the expected yield gains. Model validation against the national statistics may also have limitations due the uncertainties associated to the data collection and processing.

However, these results can however considered as a first "milestone" in the construction of more faithful representation of the rice growing areas in Myanmar that will be possible as more data becomes available and further research can provide further data and greater insights. In future research, the structure of irrigation canals in salt-affected areas should be considered for better assessment of salinity risk. The improvement of the soil salinity models by using the hydrological models of river salinity would also be required to validate the impact of salinity in the delta. The rice maps in the study dated back to 2012 and we overlaid the outputs of simulation using data up to 2015; these should be revisited with further data. Similarly in the mapping of YF, it would have been useful to have evaluated the impact of improved management on rice yields at regional level, in addition to what we attempted at farm level. Further similar work could be conducted for the dry zones and in major unfavorable rice growing areas in tropical areas and this required joint efforts in data collection, sharing and interoperability for use in different research such impact assessment, spatial analysis and modeling.

5. Conclusions

Assessment of productivity and yield gaps and scenario analysis in the major rice-growing areas in Myanmar were performed using a new research framework coupling GIS, remote-sensing technologies and crop modeling. The potential productivity and risks were quantified for the inland dry zone and the coastal delta prone to drought and salinity stresses. Among the crop management options, adjusting the cropping calendar by changing the sowing date presented the greatest advantage in terms of yield gain, followed by the choice of improved varieties. The yield gains with these options varied within and between regions. Information on the spatial distribution of yield variability should be useful to develop site-specific crop management recommendations for farmers, particularly in relation to constraining and changing environments.

Declaration of Competing Interest

The authors do not have potential conflict of interest in conducting and reporting the works presented in this manuscript.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.fcr.2019.107631.

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