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Yield gap analysis of US rice production systems shows opportunities for improvement

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ABSTRACT

Many assessments of crop yield gaps based on comparisons to actual yields suggest grain yields in highly intensified agricultural systems are at or near the maximum yield attainable. However, these estimates can be biased in situations where yields are below full yield potential. Rice yields in the US continue to increase annually, suggesting that rice yields are not near the potential. In the interest of directing future efforts towards areas where improvement is most easily achieved, we estimated yield potential and yield gaps in US rice production systems, which are amongst the highest yielding rice systems globally. Zones around fourteen reference weather stations were created, and represented 87% of total US rice harvested area. Rice yield potential was estimated over a period of 13–15 years within each zone using the ORYZA(v3) crop model. Yield potential ranged from 11.5 to 14.5 Mg ha^{-1}, while actual yields varied from 7.4 to 9.6 Mg ha^{-1}, or 58–76% of yield potential. Assuming farmers could exploit up to 85% of yield potential, yield gaps ranged from 1.1 to 3.5 Mg ha^{-1}. Yield gaps were smallest in northern California and the western rice area of Texas, and largest in the southern rice area of California, southern Louisiana, and northern Arkansas/southern Missouri. Areas with larger yield gaps exhibited greater annual yield increases over the study period (35.7 kg ha^{-1} year^{-1} per Mg yield gap). Adoption of optimum management and hybrid rice varieties over the study period may explain annual yield increases, and may provide a means to further increase production via expanded adoption of current technologies.

1. Introduction

The quantification of crop yield potential (the yield possible without constraints from water, nutrients, pest and disease pressure), the attainable yield (the proportion of yield potential attainable by farmers given economic optimization), and the corresponding yield gap (the difference between attainable yield and actual yields) is crucial to meeting the challenge of increasing food, fuel, and fiber production to meet the demands of a growing world population (Lobell et al., 2009; Grassini et al., 2013; Fischer, 2015). Focusing research and policy on areas where improvement is easiest cannot occur without understanding the current state of yield gaps. Recent papers (Licker et al., 2010; Foley et al., 2011; Mueller et al., 2012) suggest several highly intensified agricultural systems have achieved actual yields equivalent to nearly 100% of attainable yield for most staple crops. However, many of these same systems continue to experience yield increases in the last decade, calling into question both the accuracy and suitability of

Abbreviations: CA, California; TX, Texas; AR, Arkansas; MO, Missouri; MS, Mississippi; LA, Louisiana.

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the methodology used by these earlier estimates. For example, US rice yields averaged 7.8 Mg ha^{-1} in the time period 2009–2011 (US Department of Agriculture - National Agricultural Statistics Service, 2016), yet these papers estimated US rice attainable yield at 7.43 Mg ha^{-1}. Average US rice yields have continued to rise; from 2012 to 2015 US average yields were 8.5 Mg ha^{-1} (US Department of Agriculture - National Agricultural Statistics Service, 2016). This inaccuracy could be caused by the method used to estimate attainable yield, namely taking the 95% quantile of actual yields as attainable yield. This method has distinct disadvantages; because yield potential is not estimated, in systems where actual yields are well below yield potential, estimated attainable yield may be lower than the true potential.

These inaccurate estimates of crop yield gaps can confound efforts to focus research on where improvements are easiest. Despite comparatively low domestic rice production and consumption, the US is the 4th largest exporter of rice onto the global market (Childs, 2016). This is due in part to the fact that US rice production systems are highly intensified and are amongst the highest yielding rice systems globally (FAOSTAT, 2015). Changing demographics and population growth are expected to increase US domestic consumption (Westcott and Hansen, 2016), while land suitable for production is increasingly constrained by urbanization (Godfray et al., 2010; Foley et al., 2011). Additionally, warming temperatures driven by global climate change are projected to decrease yields (Peng et al., 2004). To maintain its position in the global market, the US must increase production per unit area despite these factors. Failure to do so will threaten food security in areas that rely on rice imports. If US rice production is currently achieving 100% of attainable yield (i.e., the maximum yield given physical and economic limits), research efforts should focus on increasing yield potential through breeding new rice varieties with greater inherent yield potential (e.g., Denison, 2015; Dingkuhn et al., 2015; Sheehy and Mitchell, 2015). If, however, there are some areas not at 100% of yield potential, the challenge can be partially addressed by management. Under this scenario, increasing genetic yield potential should be combined with efforts to realize the current yield potential through optimum management and broader adoption of current yield-increasing technology.

Thus, it is important to revisit yield gaps in US rice production systems using alternate methods to estimate yield potential. Here, rather than estimating yield potential via quantiles of achieved yields (e.g., Licker et al., 2010; Foley et al., 2011; Mueller et al., 2012), yield potential was estimated using simulations from a mechanistic crop model and up-scaled according to the Global Yield Gap Atlas (GYGA) protocol (van Wart et al., 2013; van Bussel et al., 2015). The strengths and weakness of this approach have been well discussed by other authors (Fischer, 2015; van Ittersum et al., 2013; van Wart et al., 2013; van Bussel et al., 2015). This study sought to (1) quantify rice yield gaps in all major areas of US rice production, (2) explore spatial and temporal variation in yields and yield gaps, (3) identify potential environmental constraints to increasing yields, (4) explore potential ways to increase yields using existing varieties (i.e., without new genetic improvements).

2. Methods

2.1. Climate zones

Yield potential and yield gaps were calculated within 14 zones following previously developed protocols (van Wart et al., 2013; van Bussel et al., 2015). Agro-climatic zones were identified that captured major differences in global agricultural production areas based on accumulated heat units, aridity index, and temperature seasonality. From these agro-climatic zones, six were identified that each included greater than 5% of total US rice harvested area per the MapSPAM raster layer of rice area (You et al., 2016). Additionally, two zones, each with less than 5% US harvested area (both in TX), were added to ensure coverage of all relevant US rice production areas. These eight agro-climatic zones include 92% of US rice production area. For each agro-climatic zone, one or more weather stations were selected after consultation with rice researchers within each state to ensure representation of rice production areas (e.g., not located in city centers, airports, etc.). From this list of weather stations, 14 reference weather stations (RWS) were chosen. Surrounding each RWS, a 100 km zone was created and clipped by agro-climatic zone boundaries. This ensured each RWS was surrounded by a corresponding buffer zone that consisted of a single agro-climatic zone. In cases where two buffer zones overlapped within the same climatic zone, the buffer zones were separated such that the border between buffer zones was equidistant to each RWS. These final 14 zones represent 87% of all US rice harvested area (Fig. 1).

2.2. Weather data

Data for each RWS was collected and quality controlled per the previously developed protocol (van Wart et al., 2013; van Bussel et al., 2015) (see Table S1 for locations of RWS and sources of data). For each RWS, weather data were collected from 1999 to 2014 (except LA, which had data starting from 2001). Solar radiation data for all sites was retrieved from the NASA-POWER Agro-climatic database (National Aeronautics and Space Administration, 2016), since few RWS collected these data. Data were checked for extreme or missing values (T_{min}, T_{max}, vapor pressure, wind speed, and precipitation), which were imputed using linear interpolation. In cases where greater than 10 consecutive days of data were missing, corresponding values from the NASA-POWER Agro-climatic database (National Aeronautics and Space Administration, 2016) were used after correction (see Grassini et al., 2015 for more information on this method). This correction adjusts NASA-POWER data to be closer to locally observed values by estimating the bias between the two sources of data over a historical period. In all cases, missing or questionable data constituted less than 5% of annual measurements.

2.3. Estimation of yield potential

Yield potential was estimated using the ORYZA(v3) crop model (Bouman et al., 2001). This model was chosen due to its wide-scale adoption and existing body of work validating it for various rice cropping systems (https://sites.google.com/a/irri.org/oryza2000/publications). Calibration and validation of this model to simulate US rice yield potential for representative high-yielding varieties typical of the types planted in the study area (M-206, a pure-line *japonica* type for CA, and Clearfield XL745, an herbicide-resistant hybrid type for the Southern US) is described in Espe et al. (2016). In order to minimize the influence of variation between simulations, yield potential was simulated for each zone over a 13 (LA sites) or 15 year span and then averaged to estimate the long-run yield potential for each zone.

For each zone, simulations began on the average date when 50% of a region had reached emergence (hereafter emergence date) (Fig. 2). The average emergence date was estimated from average planting dates for each zone (as reported by rice researchers in each state) and the historical relationship between planting dates and emergence dates for each state (US Department of Agriculture - National Agricultural Statistics Service, 2016). For CA, emergence was assumed to be the day after planting since CA growers pregerminate rice seed prior to aerial planting into a field with standing water. Sensitivity analyses were conducted to assess the impact of

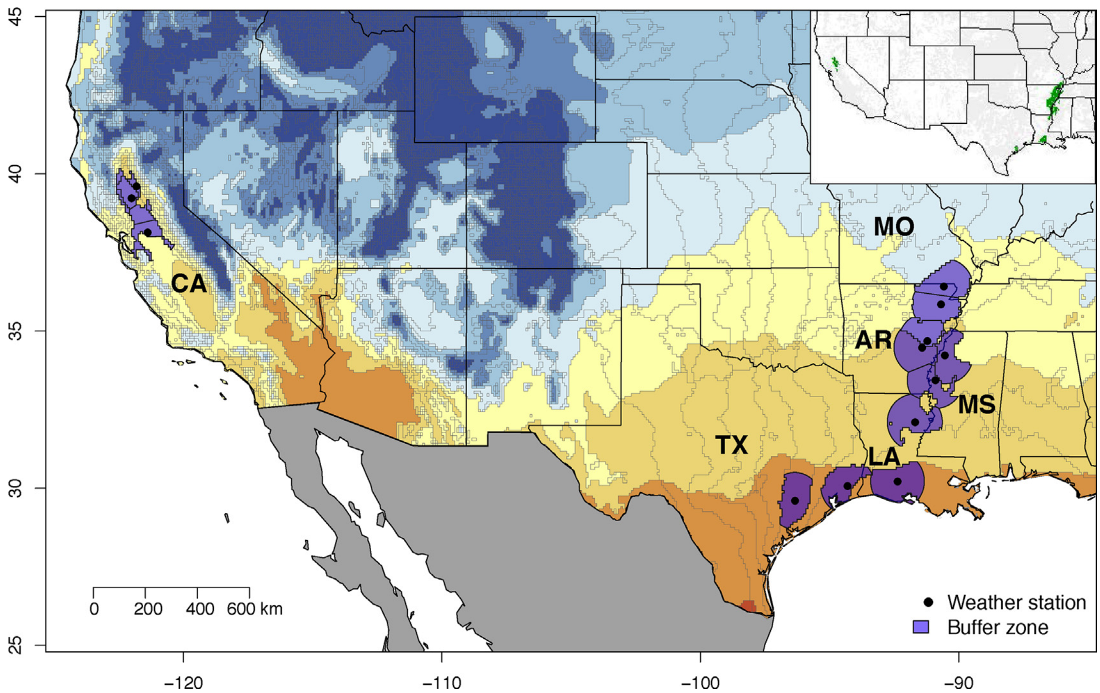

Fig. 1. Map of reference weather stations and associated zones. Agro-climatic zones are shown as background, shaded by similarity. Of all US rice harvested area, 92% was contained within 8 agro-climatic zones and 87% was contained within the 14 zones. Six US states are represented; California (CA), Missouri (MO), Arkansas (AR), Mississippi (MS), Louisiana (LA), and Texas (TX). Inset: Distribution of rice harvested area in the Continental US.

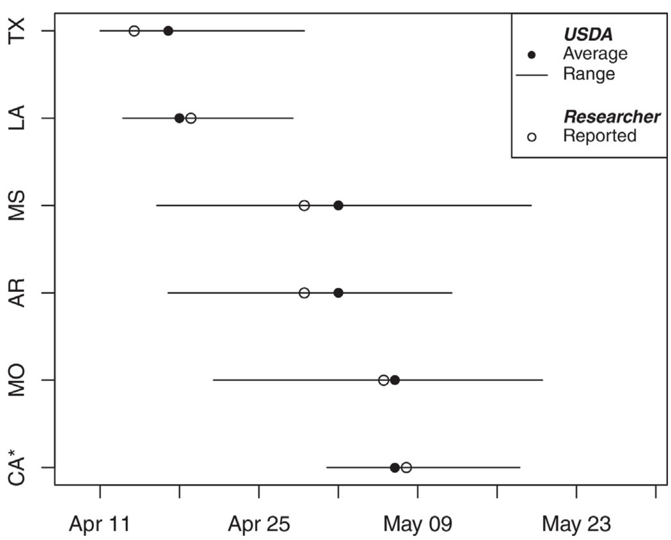

Fig. 2. Average and year-to-year variation of reported dates when 50% of planted rice area in each US state reaches emergence as reported by the USDA-National Agricultural Statistics Service, along with the average dates as estimated from reports by rice researchers in each state for the purposes of estimating rice yield potential. For California (*), the date of planting is presented since growers pre-germinate seed prior to planting.

using the average (single date) rather than a symmetric distribution of emergence dates (multiple dates) centered at the average, but there were only slight differences observed (absolute difference of less than 0.25 Mg ha^{-1}; results not presented). To further investigate sensitivity of estimated yield potential to variation in planting date, yield potential was simulated for 7 d earlier and later than the reported average. In all cases, yield potential was simulated for a single (main) crop per year. In areas of the Southern US, harvesting from second crops (i.e., ratoon crops) is possible, but simulation of this system is not supported by the ORYZA model and as such not included in these analyses. Annual simulated yield potentials were averaged by zone to estimate yield potentials. Individual simulation results were quality controlled by visual inspection for unrealistic results or failed simulations prior to averaging.

2.4. Actual yields

Data from the USDA-NASS database (US Department of Agriculture - National Agricultural Statistics Service, 2016) were used to determine actual yields within each zone. Since zones were constructed without regard for state or county boundaries, county-level data were retrieved and aggregated to obtain estimates for each zone. In order to do this, the zone average yield was calculated as a weighted average of county estimates, where weights were determined by the proportion of a zone's harvested area within each county.

$$Y_k = \sum_{j=1}^{n} \left(\mu_j * \frac{a_j}{a_k} \right) \tag{1}$$

where Y_k is the average yield for zone k, μ_j is the average reported yield for county j, n is the number of counties with harvested acres in zone k, a_j is the harvested area of county j in zone k, and a_k is the total harvested area in zone k. Yield data were retrieved from 1999 to 2014. To minimize potential confounding effects of yield trends over time, only the most recent reported data (2010–2014) were used in the calculation of yield gaps, while the full 15 years of data were used for all other analyses. Zone estimates of actual yields were calculated by year and then averaged across years to get the average zone yield.

2.5. Yield gaps

There is considerable uncertainty regarding what portion of yield potential is attainable by farmers, though most sources agree it is between 70 and 85% of yield potential (Lobell et al., 2009;

Fischer, 2015). Studies have shown that in highly intensified cropping systems, farmers are able to attain 85% of yield potential (Grassini et al., 2011). Therefore, this 85% limit can be taken as representing the average upper limit of the exploitable yield gap (i.e., the highest average yield increase that can be expected given current varieties and technology), though the true limit may be lower. This is in contrast to other methods (e.g., Mueller et al., 2012) where 100% is assumed to be attainable by farmers.

2.6. Data manipulation, analysis, and visualization

Data were processed using the R statistics program (R Core Team, 2015). Spatial aggregation and visualization were accomplished using the following packages for R: 'raster' (Hijmans, 2015), 'sp' (Bivand et al., 2013; Pebesma and Bivand, 2005), 'rgeos' (Bivand and Rundel, 2016), 'rgdal' (Bivand et al., 2015), 'RColorBrewer'(Neuwirth, 2014), 'maps' (Becker et al., 2016), 'mapproj' (McIlroy et al., 2015), and 'maptools' (Bivand and Lewin-Koh, 2016). Data analyses and regressions utilized the *stan_glm()* function in the 'rstanarm' package (Gabry and Goodrich, 2016), an interface to the Stan probabilistic programming language (Stan Development Team, 2016). All regressions followed standard recommendations and used weakly informative normal priors to regulate estimates (Gelman et al., 2013). In cases where effects were estimated at the state or zone level, multi-level models were utilized (Gelman and Hill, 2007), with states and zones representing two levels of hierarchy in the effects. Model assumptions and fit were assessed using diagnostic statistics and posterior predictive checks. Credible intervals were calculated as the 95% quantile of the posterior distributions. All data, model files, and R code are publicly available through the Open Science Framework (https://osf.io/gkwjx/; Espe, 2016).

3. Results

3.1. Yield potential

Simulated yield potential ranged from 11.5 to 14.5 Mg ha^{-1}. The lowest simulated yield potential was in the southern US (eastern TX and LA) while the highest yield potential was in CA, followed by the western rice production area of TX (Fig. 3a and e). In general, yield potential increased going South to North (Southern US) and North to South (CA).

3.2. Actual yields

Actual yields ranged from 7.4 to 9.6 Mg ha^{-1}, with lowest yields occurring in eastern TX and LA, and highest yields occurring in northern CA and the western area of TX (Fig. 3b and f). Actual yields generally showed similar trends as yield potential. However, zones with the lowest actual yields and thereby largest estimated yield gaps (Fig. 3d and h) tended to have the highest rates of yield growth over time, with the exception of the southern rice area of CA (Figs. 4 and 5; Table 1).

Expressed as a percentage of estimated yield potential, current yields for all zones are below 76% of estimated yield potential (Fig. 3c and g). The lowest actual yields are in LA, Upper and Lower AR (61–64% of yield potential), while the highest are in northern CA (73–76% of yield potential) and the western TX rice area (70–73% of yield potential). In the middle region of AR, southern rice area of CA, and eastern TX actual yields are between 64 and 70% of yield potential.

Annual yield increases over the period of 1999–2014 ranged from 48 to 135 kg ha^{-1} increase per year (Figs. 4 and S1). The greatest rates of increase were seen in areas where actual yields were furthest from the yield potential (LA and AR) and smallest in areas where actual yields were closer to yield potential (Fig. 4). Emergence dates have shifted to earlier in the season in some, though not all, of these same areas (Fig. S2). The ORYZA model estimated a yield advantage to earlier emergence dates for all locations (Fig. S3).

3.3. Yield gaps

The estimated exploitable yield gap was the greatest in the southern rice area of CA, southern LA, and the eastern TX rice area, followed by the Mississippi River Valley (AR, MS, and MO) (Fig. 3d and h). The lowest exploitable yield gap occurred in northern CA and the western rice area of TX. Annual yield increases were correlated with the estimated yield gap, as areas with larger yield gaps also experienced the greatest rate of yield increase from 1999 to 2014 (Fig. 5, Table 1). For every Mg ha^{-1} increase in exploitable yield gap, there was an estimated 35.7 kg ha^{-1} year^{-1} increase in the rate of yield improvement, though there was high uncertainty in this estimate, as reflected in a relatively wide credible interval (Table 1).

4. Discussion

4.1. Yields and yield gaps in the US

Contrary to previous reports (Licker et al., 2010; Foley et al., 2011; Mueller et al., 2012), estimates from this analysis suggest that current rice yields in the US have not achieved 100% of attainable yield and there is opportunity for increased yields. This discrepancy is caused by the above studies not estimating yield potential and by an implicit assumption in the quantile method that 100% of attainable yield has been realized in some locations and therefore the top recorded yields can be assumed to represent attainable yield. van Ittersum et al. (2013) assert that this assumption is unreasonable in situations where best management practices are not in use. Based on this present study, this assumption is questionable even in highly intensified cropping systems because even in these systems current yields might not reflect the physiological limits. Here, yield potential was estimated between 11.5 and 14.5 Mg ha^{-1}, greater than those previous estimates but still lower than the theoretical maximum possible with an idealized plant type (Sheehy and Mitchell, 2015). For reference, yield potential estimated for CA is similar to the winning yields from rice yield contests (14.2 Mg ha^{-1}; University of California Cooperative Extension, 2015). That is not to say that there are not areas in the US that have possibly reached the attainable yield ceiling. There is evidence that production systems in northern CA and the western rice area of TX are closer to yield potential than other areas (Fig. 3). Corresponding decreases in the rates of yield increase further support these conclusions (Fig. 4; Table 1), as intuitively it follows that the rate of yield increase will decrease as average yields approach the exploitable yield. However, identifying yield plateaus is fraught with difficulty (Grassini et al., 2013), hence the utility of this measure is unclear.

The southern rice area of CA stood out as an area where a high yield gap did not coincide with a greater rate of annual yield increase (Fig. 5). This area was estimated to have the highest yield potential in the US, primarily driven by low night-time temperatures caused by cool winds originating from the San Francisco Bay. Reports of yields up to 14 Mg ha^{-1} under experimental conditions in this area corroborate estimates of high yield potential (Espe et al., 2015). However, these weather patterns can also induce spikelet sterility, drastically reducing yields (Board et al., 1980). Previous work has shown the ORYZA model does not simulate cold-induced sterility well and that structural changes to the model are required to correct this (Espe et al., 2016). Estimates here may be accurate if the rice crop does not experience cold-induced spikelet sterility,

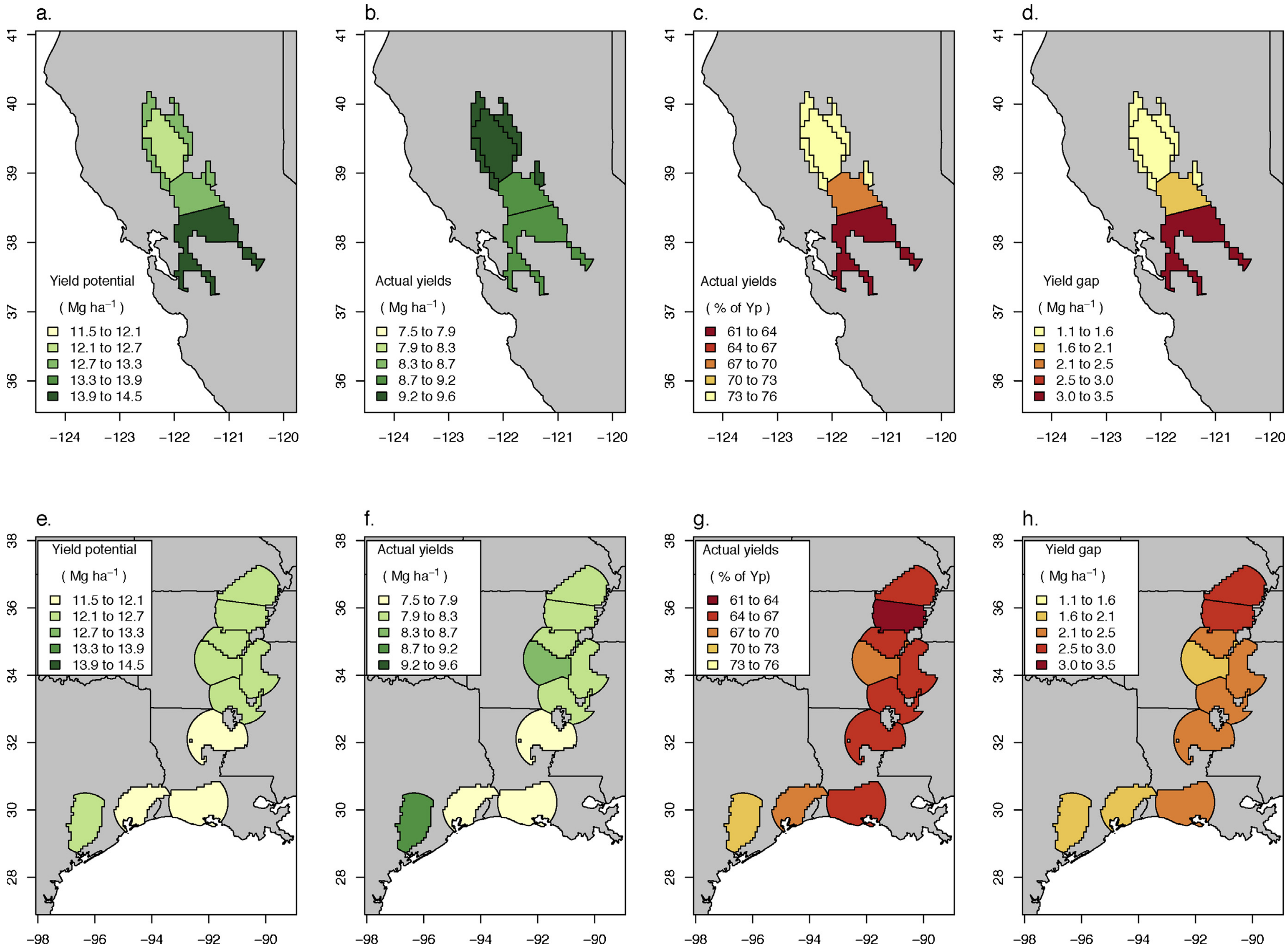

Fig. 3. Simulated rice yield potential (a and e), actual yields (b and f), actual yields expressed as a percentage of yield potential (c and g), and the estimated exploitable yield gap (d and g) for US rice production in California (top row) and the Southern US (bottom row). Each was estimated for 14 zones which together represent 87% of US rice production area. Here, the exploitable yield gap is calculated as the difference between 85% of yield potential and the actual yield.

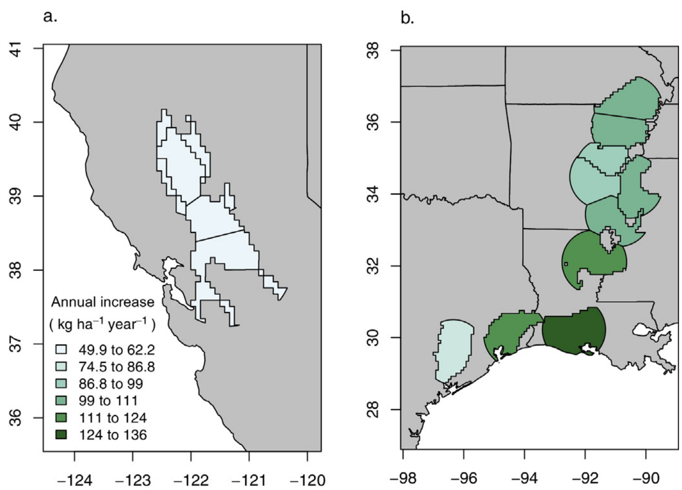

Fig. 4. Annual yield increases from 1999 to 2014. California (a.) experienced lower rates of annual yield increase compared to most of the Southern US (b.). Yield increases were estimated by linear regression of yearly estimated actual yields within each zones. Actual yields were estimated as the area-weighted average of county-level reported data from the USDA National Agricultural Statistics Service from 1999 to 2014.

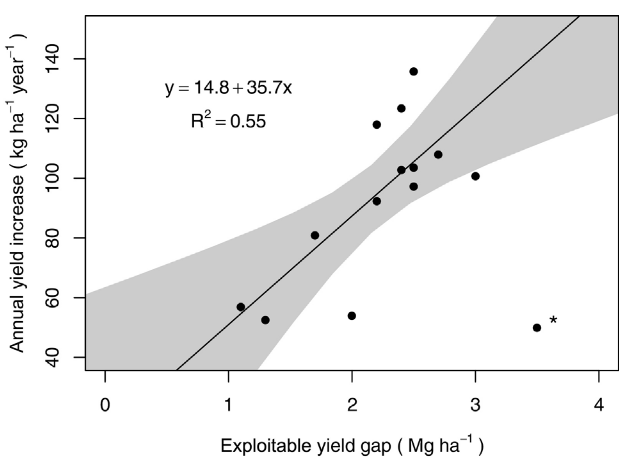

Fig. 5. Relationship between growth in rice yields over the period 1999–2014 and the estimated exploitable yield gap in 14 zones that constitute 87% of US rice area. Areas with larger exploitable yield gaps also experienced greater rates of yield growth. The southern rice area of California (marked with *) is an exception and was excluded from the regression *a priori* due to known issues with the simulation of cold-induced sterility. The gray shaded area is the 95% credible interval.

but the low rate of yield gains in this area despite large estimated exploitable yield gap suggests this is not often the case (Fig. 5). Currently, rice production in this area is limited to less than 4000 ha (You et al., 2016), therefore the impacts of this error are low from a national perspective. Breeding efforts aimed at reducing the impact of cool temperatures on floret fertility (McKenzie et al., 1994) could increase yields and thereby increase the viability of rice cultivation in this region.

Table 1
Estimated relationship between annual yield increases and the yield gap. Areas with a larger estimated yield gap have experienced faster rates of yield increase. Annual yield increases were estimated from linear regression of rice yields from 1999 to 2014, while yield gaps were estimated using simulations. One zone in the southern rice production area of California was not included in the regression.

Parameter	Estimate	95% credible interval
Intercept	14.8	−20.7 to 54.8
kg ha^{-1} year^{-1} Mg^{-1} yield gap	35.7	19.3 to 55.1

Many climate models predict increased temperatures and variability in the future (Stocker et al., 2013). Increased respiratory losses under warmer temperatures are predicted to decrease yields (Peng et al., 2004; Lyman et al., 2013; Lobell, 2007; Rehmani et al., 2014). Simultaneously, previous work suggests areas where yields are more variable from year to year due to pest and climatic phenomenon may have a lower exploitable yield gap (Lobell et al., 2009). This is the result of farmers balancing potential yields against exposure to risk (i.e., the economic yield potential) (Fischer, 2015). Under scenarios where both temperatures and climate uncertainty increase, increasing rice production could be challenging (Challinor et al., 2014). Although researchers are exploring how to decrease the impact of high temperatures (Bita and Gerats, 2013), increasing the resilience of rice cropping systems to climate variability should also contribute to increasing rice production in US rice production systems.

4.2. Potential drivers of annual increases in yields

Annual increases in actual yields in many areas of US rice production may be due to expanded adoption of current technologies. Two technologies have seen increased use during the study period, precision land-leveling and hybrid rice varieties. Precision land-leveling increases yield by decreasing the land area in levees and increasing the uniformity of flood water depth, which supports uniform stand establishment, weed control, and pest management (Rickman, 2002). In CA, where rice is continuously cropped, adoption of precision land-leveling began as early as the 1970s (Dickey, 2015), and currently most fields are precision leveled (greater than 95%; University of California Cooperative Extension – personal communication). In the Southern US, precision land-leveling is not as widely adopted as in CA (50–60% as of 2006; (Yang et al., 2006; Smith et al., 2007)), though adoption is increasing as water resources become increasing constrained (Yang et al., 2006; Smith et al., 2007). Unlike precision land-leveling, adoption of high-yielding hybrid and herbicide resistant varieties has been increasing rapidly in the Southern US (Nalley et al., 2016) but not in CA (Dickey, 2015). Nalley et al. (2016) estimate hybrids and herbicide resistant varieties have a yield advantage over conventional varieties of 1.66 and 1.82 Mg ha^{-1}, respectively. They also report the percent of land planted with these varieties rose from 0 to roughly 50% (hybrid and herbicide-resistant combined) over the last ten years. Increased adoption of these varieties could explain a substantial amount of the annual yield increases observed in the Southern US. The lack of these types in CA may also help explain why the difference in yield potentials is not greater between the two regions (Fig. 3a and e), despite CA experiencing environmental conditions favorable for higher yield potential (e.g., low night-time temperatures, high solar radiation, low disease and pest pressure). The adoption of high-yielding, temperate hybrid *japonica* varieties, such as those currently being developed in China (Li et al., 2012), may allow for even greater yield potential in CA. Further research on the impact of technology adaption is needed that spans broad spatial and temporal scales to clarify these matters.

While the long-term average date when 50% of planted area has reached emergence was used in these analyses, this event can take place across a range of dates (Fig. 2). Additionally, there is evidence that emergence dates may be shifting earlier in the spring in some states (Fig. S2) (US Department of Agriculture - National Agricultural Statistics Service, 2016). Although the present study lacks the data to definitively test the effect of earlier emergence dates, previous reports from rice researchers in each state show yield advantages to earlier planting and emergence (Hardke et al., 2013; Wilson, 2011, 2010; Golden et al., 2014; Linquist and Espe, 2015; Fontenot, 2016). The ORYZA model also predicts increased yield potential as emergence dates move earlier for these regions

(Fig. S3). Earlier emergence may allow increased capture of solar radiance, crop avoidance of high temperatures typical of late August and September, and increased length of grain filling period. These effects might be partially responsible for yield increases in areas where planting dates may be changing, though more study is needed.

There may be a limit to how early in the season emergence dates can be moved using current technologies and varieties. The earliest date of planting and emergence is restricted by the ability of soils to dry sufficiently for seedbed preparation, by soil/water temperatures, and by the availability of water for either flood establishment (CA) or flushing. Increasing the ability of rice seed to germinate at low temperatures and increasing seedling vigor in cool temperatures or water-limited environments could help alleviate some of these restrictions (McKenzie et al., 1994). While the emergence dates used for this study are reflective of the long-term average for emergence dates in each state (Fig. 2), these results may need to be revised if earlier plantings become more common (Fig. S2). Lastly, it should be noted that the effect of earlier planting will not decrease yield gaps but rather will increase production, as increased yield potential is expected to be accompanied by increased actual yields.

4.3. Potential improvement in yield gap estimates

Although the yield gap estimates here align better with both average and top yields in high yielding environments compared to estimates based on quantile methods (e.g., estimated yield potential is not less than average yields and are similar to yields from yield contests), there are areas of uncertainty inherent in all model-based estimates. Broadly, these fall into four categories: (1) data availability, (2) data quality, (3) model performance, and (4) spatial scaling. The first two, data availability and quality, are often major concerns for yield gap analyses in developing areas, where data can be sparse, poorly maintained, and not freely available (van Ittersum et al., 2013; Grassini et al., 2015; van Wart et al., 2013). For the current study, these concerns are minor due to the density and general quality of weather station networks and agricultural databases (e.g., USDA-National Agricultural Statistics Service) in the US with publicly accessible data. Likewise, since the ORYZA model was first calibrated and validated using large, multi-year, multi-site data sets (Espe et al., 2016), model performance is adequate for the purposes of this study. However, like most model-based studies, estimates could be further improved by increasing model accuracy via more sophisticated parameterization, expanding the number of calibrated varieties, or even substituting the ORYZA(v3) model for one that better captures the effects of cold and heat on grain yield (e.g., Van Oort et al., 2014; van Oort et al., 2015). Likewise, as varieties are introduced with improved yield potential and replace current ones, new calibrations could be used to update estimates here. This highlights one strength of these methods; the relative ease of updating yield potential estimates given improved models.

The fourth concern, spatial scaling, can be difficult to assess as it is intimately tied to the intended use of the yield gap assessment. For the purposes of motivating future research and policy, the methods here attempt to capture major differences in environments and important production areas in the creation of agro-ecological and buffer zones. This results in analyses at finer scale than many other yield gap assessments (van Wart et al., 2013). However, some purposes, such as investigating yield gaps in response to local policy or input availability, will necessitate finer scale analyses. Moving to a finer spatial scale will create additional complexities and will require revisiting the above concerns. Estimates of yield potential and yield gaps at a finer scale will require at minimum (1) more climatic and crop data, which could create issues with data coverage, quality, and availability, (2) validation of methods to representatively aggregate simulated yields to the appropriate scale, and possibly (3) calibration and validation of models to represent unique conditions of each locality. Further research is needed to develop protocol for robust and scientifically rigorous analyses of yield gaps at fine scale.

5. Conclusions

Estimated yield gaps in US rice production ranged from 1.1 to 3.5 Mg ha^{-1}, suggesting that, contrary to previous estimates, there is room to improve yields. Most of these gains are possible in the Southern US, despite this area having a lower yield potential. However, constraints on yield such as increased respiration due to warmer temperatures and increased yield variability due to large scale weather events will continue to be factors in these areas. In other areas where actual yields are closer to yield potential, adoption of earlier planting dates and varieties adapted to variable conditions may be able to increase yield potential and allow further gains. Decreasing yield gaps in a highly intensified rice production system will require a combination of crop improvement and classic agronomy, along with detailed studies to further quantify the contributions of new and existing technologies to increase yield potential in highly intensified rice systems. New protocol are needed for studying yield gaps at finer scales and in response to changes in technology or input availability. This study suggests the potential impact of broader adoption of current technologies should not be overlooked in efforts to increase yields in rice systems, including those already highly intensified.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fcr.2016.07.011.

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