Rapid Yield Estimation Methods for Unharvested Rice Cultivated for Migrating and Wintering Waterfowl

Cole A. Howard[1], *College of Arts and Science, Tennessee Technological University, 1 William L. Jones Drive, Cookeville, TN 38505*

Nicholas M. Masto, *College of Arts and Science, Tennessee Technological University, 1 William L. Jones Drive, Cookeville, TN 38505*

Jay Hitchcock, *U.S. Fish and Wildlife Service, Dale Bumpers White River NWR, 57 S. CC Camp Road, St. Charles, AR 72140*

Nick Wirwa, *U.S. Fish and Wildlife Service, Wheeler National Wildlife Refuge, 2700 Refuge Headquarters Road, Decatur, AL 35603*

Danny McCarty, *Rice Research and Extension Center, University of Arkansas Division of Agriculture Research and Extension, 2900 Highway 130 E, Stuttgart, AR 72160*

Heath M. Hagy, *U.S. Fish and Wildlife Service, National Wildlife Refuge System, 6772 HW 76 South, Stanton, TN 38069*

Bradley S. Cohen, *College of Arts and Science, Tennessee Technological University, 1 William L. Jones Drive, Cookeville, TN 38505*

Abstract: Land managers in the southeastern United States cultivate rice (*Oryza sativa*) to provide calorie-dense forage for autumn-migrating and wintering waterfowl and other migratory birds. Conservation planners require accurate yield estimates for rice and other energy-rich croplands to parameterize bioenergetic models and support data-driven, adaptive resource management efforts. We developed a rapid method to efficiently estimate rice yield and quantified associated precision, accuracy, sampling time, and operating costs in the Lower Mississippi Alluvial Valley ($n = 16$ fields). We compared a visual index of seed-head size and density using ocular scores (1–10; i.e., rapid assessment) to 1-m^2 harvested plots within each field. We regressed our visual index against known rice yield estimates (kg [dry] ha^{-1}) and related our yield estimates to rice cultivation practices to inform management actions that maximize yield and cost efficiency for wildlife management. Our model ($R^2_{adj} = 0.80$) reliably estimated rice seed yield within 20–40 min per field. We found that yield was positively correlated with input cost, but that 125–180 kg ha^{-1} of post-emergence nitrogen and at least one herbicide application seemed to balance yield production while minimizing costs (US$900–1200 ha^{-1}). We suggest our rapid visual index method be incorporated into resource monitoring protocols to improve conservation planning initiatives.

Key words: bioenergetics, carrying capacity, National Wildlife Refuge, *Oryza sativa*, sampling

Journal of the Southeastern Association of Fish and Wildlife Agencies 11:119–126

Migratory waterfowl spend 7–9 months in migration and wintering areas where habitat resource management activities focus on production of natural and agricultural food to support energetic needs (Nelms et al. 2007). Many conservation planners in these regions use bioenergetic models as planning tools based on some evidence for cross-seasonal effects (Sedinger and Alisauskas 2014, Osnas et al. 2016). Some agencies also use bioenergetic models to set objectives for land management tracts (e.g., U.S. Fish and Wildlife Service [USFWS] National Wildlife Refuges; Hagy et al. 2021b) and to help quantify contributions to the North American Waterfowl Management Plan (NAWMP; USFWS and CWS 1986, Williams et al. 2014, USFWS and CWS 2018). The NAWMP established Migratory Bird Joint Ventures (JV) in 1986 which are cooperative, regional, public-private partnerships that work to conserve migratory bird habitat (USFWS and CWS 1986, 2018). Many JVs located within non-breeding season geographies step-down continental waterfowl population objectives to their respective regions and use bioenergetic models to translate regional population goals into foraging habitat objectives (Wilson and Esslinger 2002, Lower Mississippi Valley JV [LMVJV] 2015). Provision of high-energy foraging resources for migrating and wintering waterfowl are critically important to meeting habitat objectives in many geographies (LMVJV 2015, Brasher et al. 2018, Hagy et al. 2021b).

Rice (*Oryza sativa*) is a major agricultural commodity and critical food resource for wintering waterfowl in the Mississippi Flyway, Texas Gulf Coast, and California's Central Valley (Petrie et al. 2014, LMVJV 2015, Marty et al. 2015). Indeed, over 800,000 ha^{-1} are cultivated in rice throughout the Mississippi Alluvial Valley (MAV), >200,000 ha^{-1} in the Gulf Coast Prairies of Louisiana and Texas, and >200,000 ha^{-1} in California's Central Valley annually (Petrie et al. 2014). Waste-grain and unharvested rice seeds

1. E-mail: choward43@tntech.edu

account for approximately 12% of the estimated wintering wetland forage needed to support target waterfowl population objectives within the LMVJV and 42% within the Gulf Coast JV region (Petrie et al. 2014). However, more efficient farming techniques and earlier planting and harvest dates continue to reduce waste-grain rice available for waterfowl (Manley et al. 2004, Stafford et al. 2006). State, federal, and private land managers increasingly cultivate rice and leave it unharvested and flooded to efficiently meet habitat resource management goals (LMVJV 2015). Unharvested rice can provide 45 times greater energy biomass compared to harvested rice (Hagy et al. 2021a). Given the importance of unharvested rice to waterfowl and its increasing use by waterfowl and wetland managers, accurate biomass estimates are needed to parameterize bioenergetic models for conservation planning and implementation (Petrie et al. 2014, Williams et al. 2014, Marty et al 2015, Hagy et al. 2021b).

Biomass of harvested rice historically has been estimated using soil cores (Manley et al. 2004, Stafford et al. 2005, Havens et al. 2009, Marty et al. 2015). In unharvested fields, harvested samples known as crop-cuts have been used (Fermont and Benson 2011, Sapkota et al. 2016). However, both soil cores and crop-cuts are labor intense and typically cost-prohibitive for operational monitoring (Low and Bellrose 1944, Gray et al. 1999, Sapkota et al. 2016). Therefore, our goal was to design a rapid assessment methodology based on visual assessments of rice density and quality with acceptable levels of precision (coefficient of variation [CV] = 15–20%; Stafford et al. 2006). Specifically, we sought to: (1) quantify precision and accuracy of multiple methods to estimate rice seed production within the Mississippi Alluvial Valley; (2) assess speed, bias, and precision trade-offs among different rapid assessment variants; (3) evaluate unharvested rice yields relative to total input costs and fertilizer and herbicide applications; and (4) recommend the most appropriate rapid assessment method(s) and optimal input costs, nutrient, and chemical applications to wetland biologists and managers.

Study Area

Our study fields were located in two states within the MAV at three USFWS National Wildlife Refuges (NWR) and one Tennessee Wildlife Resource Agency (TWRA) refuge. Specifically, fields were in Overflow NWR (N 34.3575, W 91.1211) and Dale Bumpers White River NWR (N 33.0791, W 91.6664) in Arkansas, and Hatchie NWR (N 35.4983, W 89.2631) and Hop-in Refuge (N 36.2511, W 88.9709) in Tennessee. Unharvested rice fields were bounded by levees and infrastructure for hydrological management within each impoundment to control weeds during the growing season and capture or flood impoundments during the non-growing season. Unharvested rice fields were planted with a seed drill or broadcaster during summer (i.e., May–July) after fields were brought to adequate nutrient and pH levels. After germination, shallow intermediate flooding schedules and sometimes herbicides were used to control weeds. Concurrently, some fields had post-planting fertilizers applied, typically in the form of urea, to provide nitrogen. Some years insecticide applications were also required to prevent crop destruction (Hardke 2021).

Methods

Field Sampling of Rapid Methods

We sampled unharvested rice in October 2020–2022 within a 1-m^2 quadrat among five locations along a systematic random transect spanning an entire rice field to capture any heterogeneity of rice production within each field (Martin et al. 2022, Highway 2022). We entered each field at a random location and placed our first quadrat 10–50 m from the field edge to establish our first sampling location (Sapkota et al. 2016). The four subsequent sample locations were spaced evenly along the transect to encompass the entire field using a systematic-random design (Martin et al. 2022, Highway 2022). If rice levees were present and dividing the field into sections, we used multiple transects to distribute plots across different paddies within each field. At each sample location, we used the following methods described below to estimate rice seed production (Figure 1).

We developed a qualitative visual index (VI) to estimate seed production based on ocular seed-head size and density scores. We estimated seed-head size and density scores on a 1 to 10 scale within each 1-m^2 quadrat where 1 represented the lowest score and 10 the highest, for a total possible score of 20. Lower scores of 1–4 indicated low quality, potentially dirty (mixed with moist-soil plants) or ratoon rice, while high scores, such as 8–10, were near commercial rice production grade. We conducted VI scoring at each sampling location preceding all other rapid assessment methods.

Following the VI method, we randomly collected five seed heads from each quadrat. Next, we divided the quadrat into four, 0.25-m^2 subplots. We randomly selected one of the four subplots and counted all stems within that subplot (0.25 m^2; StemcountA). Then we counted all stems in the remaining subplots collectively (0.75 m^2; StemcountB). We summed stem counts of the one and three quarter subplot samples for the total number of stems within the entire 1-m^2 plot (StemcountC). Following stem counts, we sequentially hand-harvested all seed heads from the randomly selected subplot first (0.25 m^2; OneQuarterCC), followed by harvesting all seed heads from the remaining three quarter subplots (0.75 m^2; ThreeQuarterCC). We stored all seeds in separate paper bags for each sampling method to allow them to dry.

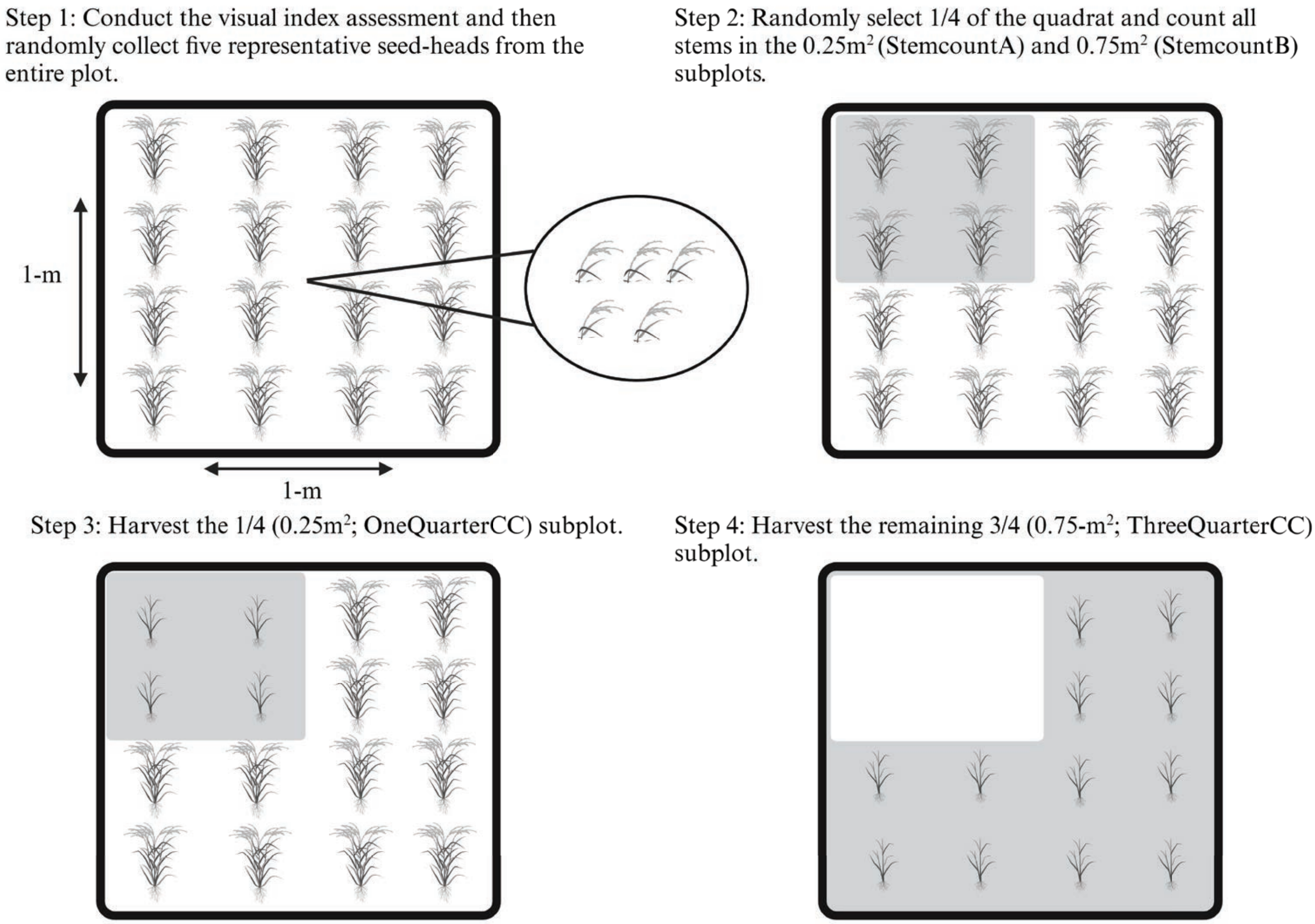

Figure 1. During October 2020, 2021, and 2022, we sampled unharvested rice grown for migrating and wintering waterfowl in the Mississippi Alluvial Valley to evaluate a series of rapid assessment methods that estimated rice seed yield. This is a graphical interpretation of rapid assessment methodologies created with Biorender.com demonstrating rice seed sampling using a visual assessment of the entire 1-m^2 plot, stem count methods, and crop-cut methods.

Laboratory Methods

All seed heads were air dried at room temperature in paper bags for ≥1 wk, then thrashed from their panicles leaving only the seeds, and weighed to the nearest 0.1 g (Sapkota et al. 2016). For the crop-cut methods, we used a mechanical seed thrasher in 2020 and 2021 and hand thrashed samples in 2022. All seed heads collected for the stem count methods were hand thrashed. For each individual sample, we randomly selected 20 dried seeds and recorded the number of blank seeds to develop a correction factor for the number of blank seeds in each sample so we did not overestimate rice yield. Blank seeds are caused by sterile florets that do not produce a functional seed and are primarily the hull. The prevalence of blank seeds can be affected by rice variety, planting dates, soil temperature, irrigation before seed heading, excessive fertilization, and irrigation using cold water (Board and Peterson 1980). After samples were weighed, we combined biomass estimates from the 0.25-m^2 subplot and the 0.75-m^2 subplot to calculate seed biomass (g [dry]) across the entire quadrat (WholeCC). The WholeCC biomass was assumed to be the true biomass for each quadrat on which we compared rapid assessment methods.

To correct for sampling loss, processing loss, and blank seeds, we calculated correction factors to adjust our measured weight. First, we assumed a 3% loss of seed weight during sampling, collecting, sorting, and weighing of all samples regardless of method based on Hagy et al. (2011). Next, we collected samples of seeds lost (i.e., discarded by the mechanical thrasher) during the thrashing of the crop-cut samples (OneQuaterCC, ThreeQuarterCC, WholeCC). The stem count samples were hand thrashed in such small batches no seeds were lost. Thus, no thrashing correction factors were needed. Then, we randomly selected and weighed 50 blank and 50 whole seeds to the nearest 0.1 g and calculated mean weights which gave us a factor to adjust mass based on the number of blank seeds in each sample. Last, to account for excess weight from chaff (rice plant stems or parts of seed heads that are not actual grains), we collected eight samples of seeds after they were thrashed and weighed them before and after a thorough cleaning. Adjusting our measured weights accordingly with these corrections, we could then extrapolate rice seed density (kg ha^{-1}). We gathered information about agricultural practices and financial costs regarding rice cultivation for each field from state and federal wetland managers. Specifically, we collected total input cost, fertilizer rates (kg ha^{-1}), and number of herbicide applications (1–2+).

Statistical Analysis

The WholeCC (1 m^2) represented true seed biomass (kg ha^{-1}). Therefore, we compared estimated rice yield derived from rapid methods to the WholeCC (Sapkota et al. 2016). We first applied our correction factors at the subplot-level and then extrapolated subplot samples to estimate rice seed biomass (kg ha^{-1}). For the stem count methods, we calculated average weight of the five randomly selected seed heads from each quadrat and multiplied mean weight by the stem density (g m^{-2}) and converted estimates to kg ha^{-1}.

We estimated rice yield for the VI by regressing WholeCC biomass (i.e., true biomass [kg ha^{-1}]) on our VI Total scores (i.e., whole-plot estimate (kg ha^{-1}; Naylor et al. 2005). We calculated adjusted marginal coefficient of determination (R^2_{adj}) to estimate variance in total biomass explained by the visual estimation method. We calculated 95% confidence (CI) and prediction intervals (PI) because both estimates of variance may be of interest to conservation planners and biologists. Confidence intervals are most useful to conservation planners to predict average seed yield across many rice fields in a landscape; PIs may be more useful to biologists measuring variance of predictions within single units (Naylor et al. 2005). Last, we compared mean precision and bias across each method. We used ANOVA to compare rapid yield estimation methods to our WholeCC method and set $\alpha = 0.1$ (Tacha et al. 1982). Non-significant results would indicate no detectable difference in yield estimation and thus a more efficient and comparable method. Additionally, we estimated the bias for each method assuming WholeCC estimates represented true biomass (i.e., Bias = [method estimate – WholeCC estimate] ÷ WholeCC estimate) and compared bias among methods with linear regression. All statistical analyses were performed in program R (R Core Team 2022).

We evaluated rice yield relative to financial input costs and agricultural practices. First, we assumed US$222 ha^{-1} for irrigation costs when these costs were unavailable (MSU 2021). We used a logarithmic regression to assess how yield from our WholeCC biomass related to input cost (i.e., WholeCC (kg ha^{-1}) regressed on log (input cost [$] ha^{-1}). We calculated adjusted marginal coefficient of determination (R^2_{adj}) to estimate variance in total biomass explained by the input cost and calculated 95% CI. For fertilizer rates, we standardized nitrogen applications (kg ha^{-1}) among fields post-planting by calculating kg ha^{-1} based on the known percentage of nitrogen in urea and ammonium sulfate. We separated these fields based on natural breaks in nitrogen applications into <50, 50–100, 125–155, 155–180 and >180 kg ha^{-1} groups ($n = 3$, 3, 3, 6, 1 respectively). We also evaluated the number of herbicide applications and grouped fields into 0, 1, or 2 applications. We then calculated mean and SE of rice yield relative to fertilizer rate and application.

Results

Yield Estimates and Comparisons

Blank seeds weighed 16.67% of whole seeds. Thus, we deflated seed mass by multiplying the percentage of blanks in each sample by 0.1667. We found the mechanical thrasher expelled 2.1% and 15.7% of whole seeds in 2020 and 2021, respectively. Hand-thrashing in 2022 expelled only 0.2% of whole seeds when thrashing crop-cut samples. We inflated seed yield by expelled seed-thrashing correction factors annually and only to crop-cut estimates because of their greater sample sizes. Last, we found that chaff created a 0.74% bias and thus corrected for this effect.

Yield estimates among all methods, years, and fields ranged from 1200–15,036 kg ha^{-1} (SE = 0.0–3584; 23–298 bu ac^{-1}). Within each year, rice yield averaged 5757 kg ha^{-1} (SE = 1320; 114 bu ac^{-1}) in 2020, 5520 kg ha^{-1} (SE = 838; 109 bu ac^{-1}) in 2021, and 6360 kg ha^{-1} (SE = 1325; 126 bu ac^{-1}) in 2022 (Table 1). Our visual index explained 80% of the variation in total rice seed biomass ($R^2_{adj} = 0.80$; Figure 2). In addition, the visual index only overestimated true yield by 1.2% ($P = 0.858$). We found differences in yield estimates among rapid assessment methods ($F_{6,105} = 1.90$, $P = 0.087$; Figure 3). The stem count methods overestimated rice production by 29% using StemcountA ($P = 0.006$), 37% using StemcountB ($P < 0.001$), and 34% using StemCountC ($P = 0.001$; Figure 3); whereas, crop cuts did not (QuarterCC, $P = 0.784$; ThreeQuaterCC, $P = 0.897$). Lastly, each method yielded similar precision of mean CVs ranging from 24.7–35.0% across all five methods. The VI had the greatest precision (CV = 24.7%; Figures 2 and 3).

Table 1. Yield in both kilograms per hectare (kg ha^{-1}, with SE) and bushels per acre (bu ac^{-1}) of fields sampled with unharvested rice grown for wintering waterfowl to evaluate methods to estimate rice yield on four refuges in Arkansas (Overflow National Wildlife Refuge [NWR] and Dale Bumpers White River [DBWR] NWR) and Tennessee (Hatchie NWR and Hop-in Refuge [state refuge]), 2020–2022.

		2020 Yield			**2021 Yield**			**2022 Yield**		
Refuge	**Field**	**kg ha^{-1}**	**SE**	**bu ac^{-1}**	**kg ha^{-1}**	**SE**	**bu ac^{-1}**	**kg ha^{-1}**	**SE**	**bu ac^{-1}**
Overflow NWR	Jackson	3171.2	1115.1	62.9						
	Middle Long	1592.6	320.8	31.6	4722.1	260.4	93.6			
	North Long	2972.0	205.9	101.9	5141.1	335.8	101.9			
	North Flat Slough				4420.1	781.5	87.6			
DBWR NWR	Powerline				6872.9	289.6	136.3			
	Simmons 40	8306.9	428.8	164.7	8510.1	762.0	168.7	9657.8	451.6	191.5
	Simmons 11							6572.8	989.1	130.3
	Turner East	9141.4	536.8	181.2						
	Turner North	7817.7	328.1	155.0						
Hatchie NWR	Triangle				3456.7	627.1	68.5			
Hop-in Refuge	North							4460.2	639.0	88.4
	South							4747.1	844.1	94.1

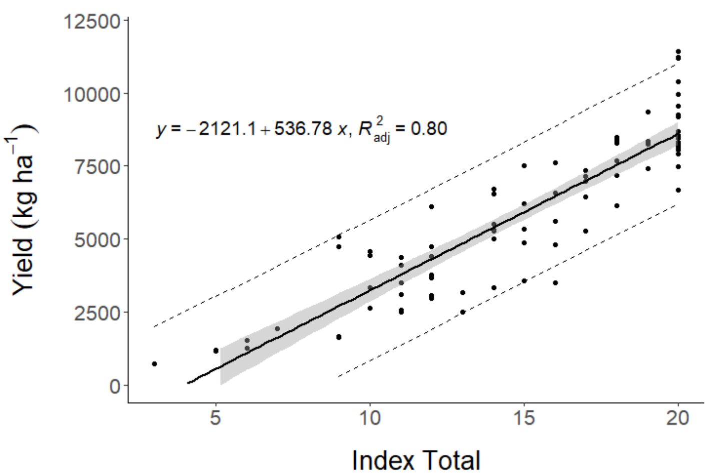

Figure 2. Linear relationship and associated 95% confidence (gray shade) and prediction intervals (dashed lines) between unharvested rice yield estimates (kg ha^{-1}) from whole-plot crop-cuts (i.e., true biomass) and estimated Visual Index Scores (seed density + quality indexed from 1–10 for each metric) from fields in the Mississippi Alluvial Valley, October 2020, 2021, and 2022. Black dots are individual data points collected across 16 rice fields.

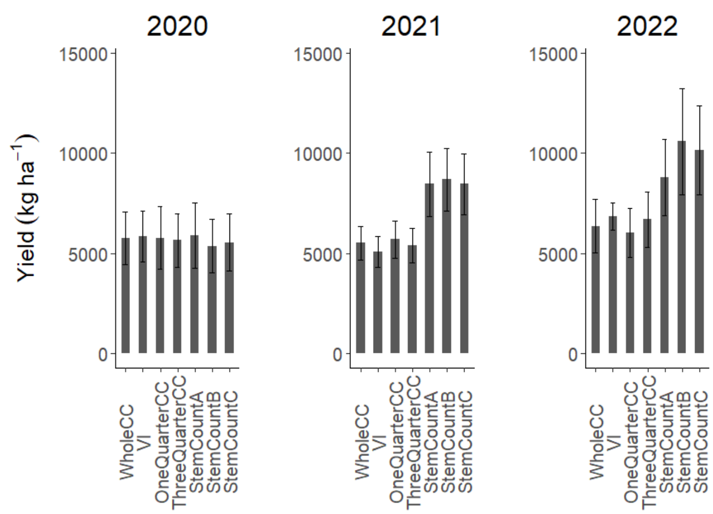

Figure 3. Comparison of unharvested rice yield (kg ha^{-1}) in 2020, 2021, and 2022 for each rapid assessment method conducted on 16 fields in the Mississippi Alluvial Valley. Sampled include included 1-m^2 whole plot crop-cut (WholeCC), visual index (VI), 0.25-m^2 quarter plot crop-cut (OneQuarterCC), 0.75-m^2 crop-cut (ThreeQuarterCC), stem count method with quarter plot stem counts (0.25 m^2; StemCountA), three-quarter plot stem counts (0.75 m^2; StemCountB), and whole plot stem counts (1 m^2; StemCountC). Error bars are ± 1 SE.

Agricultural Practices

In general, input cost was positively corelated to yield (95% CI: 2729.5–5540.4) explaining 74% of the variation in total rice seed biomass ($R^2_{adj} = 0.74$, $F_{1,13} = 40.4$, $P < 0.001$; Figure 4). Managers that applied <50 kg ha^{-1} post-planting nitrogen fertilizer yielded 2579 (SE = 496) kg ha^{-1} of rice seed. However, levels greater than 180 kg ha^{-1} (i.e., 432 kg ha^{-1}) of post-planting nitrogen yielded similar production of 3457 kg ha^{-1}. Other than one field, greater amounts of post-planting fertilizer increased rice seed production. Managers that applied 50–100 kg ha^{-1} of post-plant nitrogen fertilizer produced 4761 (SE = 209) kg ha^{-1} of rice on average compared to applications of 125–155 kg ha^{-1} producing 5675 (SE = 1075) kg ha^{-1} and applications of 155–180 kg ha^{-1} producing 8177 (SE = 501) kg ha^{-1} of rice. Similarly, as managers increased the number of

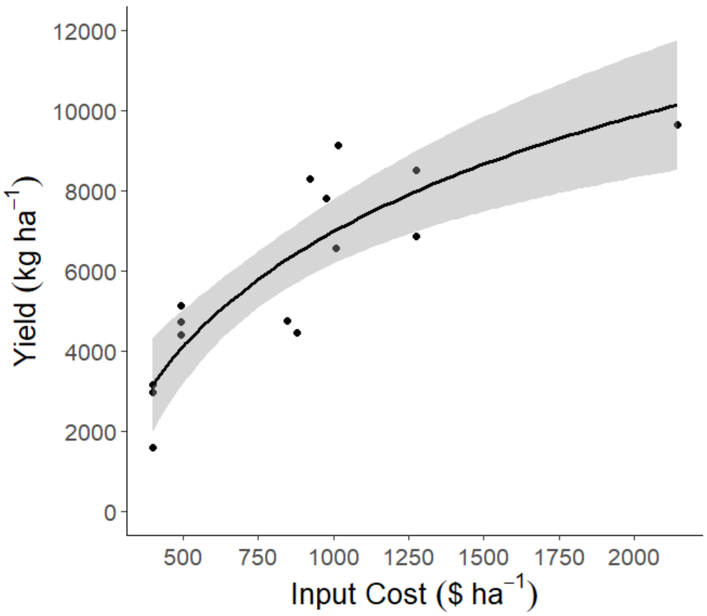

Figure 4. Logarithmic regression of the estimated unharvested rice yield (kg ha^{-1}) on the associated input cost (US$ ha^{-1}; estimated based on information from field managers) with the 95% CI (gray shade) for 16 fields in the Mississippi Alluvial Valley, October 2020, 2021, and 2022.

herbicide applications, their yields also increased. Mangers that applied no herbicide produced the least yield at 2579 (SE = 496) kg ha^{-1}. Subsequently, managers that applied one herbicide application produced 5978 (SE = 646) kg ha^{-1}, and managers that applied two herbicide applications produced the greatest yields averaging 8016 (SE = 896) kg ha^{-1}.

Discussion

Given the importance of unharvested rice to waterfowl and its increasing use by waterfowl and wetland managers, we evaluated rapid assessment methods to estimate rice seed production to assess trade-offs among estimated accuracy, precision, and speed. Our visual index and smaller crop-cut size estimates were generally similar to inaugural whole-plot crop-cut estimates. While we did observe high levels of variability in some instances, we believe much of this was due to the variability of production within our sampled fields, especially when yields were low. The time saved using our visual index cannot be understated when compared to crop-cuts and stem count methods. No physical samples are required, which greatly increased in-field efficiency and eliminated post-processing. Combined with minimal calculations and an automated data processing application, we demonstrated accurate yield estimates can be obtained before even leaving the field.

We found no trade-off in precision vs. bias across crop-cut plot sizes, suggesting managers can use subsampled 0.25-m^2 crop-cuts and obtain similar yield estimates, thus increasing harvesting and post-processing efficiency. We acknowledge, however, that crop-cuts required mechanical seed-thrashing (which expelled >10% of whole seeds) or large amounts of time for hand thrashing. We believe that the large amounts of seed expelled during mechanical thrashing was a result of different seed weights due to drying times. We strongly advise managers using mechanical thrashers to dry rice seeds for at least 1 wk first and then use our correction factor for seed loss from 2020.

The stem count method overestimated rice yield compared to the whole-plot crop-cut. Five seed heads may also not be a large enough sample to precisely estimate seed mass compared to average mass across the entire plot. Sapkota et al. (2016) showed the use of smaller sample sizes when using crop-cuts could lead to the overestimation of wheat yield. Conversely, observer bias may have been injected when selecting random seed heads and thus unknowingly but consistently larger or heavier seed heads were selected compared to the plot average. Similar observer biases have been demonstrated with moist-soil vegetation rapid assessment methods (Martin et al. 2022). Therefore, we do not recommend the stem count method or its variants because of overestimation properties which could result in positive bias of foraging energetic carrying capacities.

Importantly, the visual index method required no harvesting or post-processing and estimated rice yield most precisely and accurately. This visual estimation method required 20–40 min per field and explained 80% of variation in rice production. Therefore, we recommend the visual index scoring system to be used over all other methods. We acknowledge our regresion model predicts negative rice yields at low index scores, similar to moist-soil rapid assessment methods (e.g., Martin et al. 2022); yet, negative yields are impossible. Therefore, we suggest any negative yields be treated as zeros. One drawback to the visual index is observers must be familiar with the variability of rice growth, seed sizes, and densities in their region to accurately assign visual quality scores. Therefore, similarly encouraged by researchers developing moist-soil rapid assessment methods, we suggest annual training on rice variability and scoring to standardize estimates regionally (Naylor et al. 2005, Martin et al. 2022). We also advocate for the fewest number of observers across fields with established sampling protocols to reduce likely observer biases. Last, we recommend using applications that build in examples for observers paired with application-based data management and analysis.

In rice fields with predictably high yield and low variation, seed density and size scores could be reasonably estimated at the field level by traversing randomized transects encompassing the entire variability of a field. Exploring this relationship, regressing yield and infield variation, we found that yields exceeding 297 kg ha^{-1}

(120 bu ac^{-1}) had a CV < 20%. Thus, yields exceeding this threshold will appear homogeneous to observers and could be sampled with a single transect. This will increase the efficiency of the method with little to no effect on yield estimates. Similar variations to Naylor et al. (2005) to estimate moist-soil seed production have been used successfully thereby significantly reducing time in the field (Martin et al. 2022). Conversely, if in-field variation is high, established plots are likely necessary to obtain precise yield estimates.

Unsurprisingly, generally greater input costs produce greater rice yield (MSU 2021); however, there appears to be a threshold at which input costs will be at a diminishing rate of return. In other words, managers can expect a greater yield with higher input cost, but at a lower rate of return as the yield per additional cost decreases. Based on total input cost (seed, contracted services, fertilizer, herbicide, insecticide, and irrigation) for each field, we determined an optimal cost range and recommended managers target \$865–1235 ha^{-1} (\$350–500 ac^{-1}; MSU 2021). Once a field has reached adequate pre-planting conditions, greatest benefits of post-planting nitrogen inputs appeared around 125 kg ha^{-1} (112 lbs ac^{-1}) and benefits diminished when inputs exceeded 180 kg ha^{-1} (160 lbs ac^{-1}). Lastly, herbicide applications always increased yield, so at least one application is prudent to limit weed competition that can dramatically reduce yield. Federal and state lands are generally located on marginal to low soil production capacity from an agricultural standpoint; thus, providing adequate growing conditions through fertilization and controlling herbaceous competition is necessary if greater than marginal yields are to be expected.

Management Implications

From our evaluation of agricultural inputs and yields, we have identified several key practices to maximize production efficiency. Our visual index score is a cost-effective and time-efficient method to estimate unharvested rice yield accurately and precisely. Public and private land managers are constrained by time and personnel; therefore, our method promotes the monitoring of rice yields at local and landscape scales because it is accurate, efficient, and thus not burdensome on wetland biologists and managers. Effectively and efficiently monitoring yields in these energy-rich croplands will accomplish two goals: (1) provide wetland managers with needed monitoring so they may adapt annual agricultural practices to increase rice yield while reducing input costs (Rains and Thomas 2009); and (2) allow conservation planners to most accurately step-down NAWMP habitat resource goals to inform wetland management at the JV, regional, and wetland complex scales (LMVJV 2015, Hagy et al. 2021a).

Acknowledgments

We thank the USFWS National Wildlife Refuge System and the Center for the Management, Protection, and Utilization of Water Resources (Water Center) at Tennessee Tech for funding and in-kind support. Additionally, we thank TWRA biologists, especially Rob Lewis, for allowing us to sample unharvested rice on these properties. We thank USFWS personnel for assisting with data collection and technical support. We also thank the University of Arkansas Rice Research and Extension Center for technical support and use of their equipment, specifically, Hunter Northcutt, Dustin North, Dr. Karen Moldenhauer, and Dr. Christian DeGuzman. Any use of trade, product, or firm names are for descriptive purposes only and do not imply endorsement by the U.S. Government. The views expressed in this article are the authors' own and do not necessarily represent the views of the USFWS.

Literature Cited

Board, J. E. and M. L. Peterson. 1980. Management decisions can reduce blanking in rice. California Agriculture 34:5–7.

Brasher, M. G., B. C. Wilson, M. W. Parr, B. M. Allston, N. M. Enwright, S. J. DeMaso, W. G. Vermillion, and the Gulf Coast Joint Venture Waterfowl Working Group. 2018. Contemporary refinements to Gulf Coast Joint Venture population and habitat objectives and landscape assessments for wintering waterfowl: September 2018. Gulf Coast Joint Venture, Lafayette, Louisiana.

Department of Agricultural Economics, Mississippi State University (MSU). 2021. Rice 2022 planning budgets. Budget Report No. 2021-04, Starkville.

Fermont, A. T. and T. Benson. 2011. Estimating yield of food crops grown by smallholder farmers: a review in the Uganda context. International Food Policy Research Institute (IFPRI), IFPRI Discussion Paper 1097, Washington, D.C.

Gray, M. J., R. M. Kaminski, and G. Weerakkody. 1999. Predicting seed yield of moist-soil plants. Journal of Wildlife Management 63:1261–1268.

Hagy, H. M., J. N. Straub, and R. M. Kaminski. 2011. Estimation and correction of seed recovery bias from moist-soil cores. Journal of Wildlife Management 75:959–966.

______. 2021a. Energetic carrying capacity constants for waterfowl on National Wildlife Refuges in the Southeast. U.S. Fish and Wildlife Service, Atlanta, Georgia.

______, D. Richardson, R. Crossett, R. Eastridge, G. Hanks, A. Mini, T. Peacock, M. Purcell, M. B. Rice, J. Stanton, W. Stanton, V. Van Druten, R. Wilson, and N. Wirwa. 2021b. Waterfowl monitoring plan for National Wildlife Refuges in the Southeast. U.S. Fish and Wildlife Service, Atlanta, Georgia.

Hardke, J. 2021. Arkansas rice production handbook. University of Arkansas Division of Agriculture Cooperative Extension Service, Little Rock.

Havens, J. H., R. M. Kaminski, J. B. Davis, and S. K. Riffell. 2009. Winter abundance of waterfowl and waste rice in managed Arkansas rice fields. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 63:41–46.

Highway, C. 2022. Depletion of unharvested flooded corn and drivers of mallard activity patterns during winter in western Tennessee. M.S. thesis, Tennessee Technological University, Cookeville.

Low, J. B. and F.C. Bellrose. 1944. The seed and vegetative yield of waterfowl food plants in the Illinois River Valley. Journal of Wildlife Management 8:7–22.

Lower Mississippi Valley Joint Venture (LMVJV). 2015. MAV waterfowl stepdown state summaries. LMVJV Waterfowl Working Group, Lower Mississippi Valley Joint Venture, Vicksburg, Mississippi.

Manley, S. W., R. M. Kaminski, K. J. Reinecke, and P. D. Gerard. 2004. Waterbird foods in winter-managed rice fields in Mississippi. Journal of Wildlife Management 68:74–83.

Martin, B. C., H. M. Hagy, R. J. Askren, and D. C. Osborne. 2022. Large-scale assessment of rapid monitoring methods for estimating moist-soil seed production. Journal of Fish and Wildlife Management 13:144–154.

Marty, J. R., J. B. Davis, R. M. Kaminski, M. G. Brasher, and G. Wang. 2015. Waste-rice and natural seed abundances in rice fields in Louisiana and Texas coastal prairies. Journal of the Southeastern Association of Fish and Wildlife Agencies 2:121–126.

Naylor, L. W., J. M. Eadie, W. D. Smith, M. Eicholz, and M. J. Gray. 2005. A simple method to predict seed yield in moist-soil habitats. Wildlife Society Bulletin 33:1335–1341.

Nelms, K. D., B. Ballinger, and A. Boyles, editors. 2007. Wetland management for waterfowl handbook. Mississippi River Trust, Stoneville, Mississippi.

Osnas, E. E., Q. Zhao, M. C. Runge, and G. S. Boomer. 2016. Cross-seasonal effects on waterfowl productivity: implications under climate change. Journal of Wildlife Management 80:1227–1241.

Petrie, M., M. Brasher, and D. James. 2014. Estimating the biological and economic contributions that rice habitats make in support of North American waterfowl. The Rice Foundation, Stuttgart, Arkansas.

R Core Team. 2022. R: A language and environment for statistical computing. Version 4.2.2. R Foundation for Statistical Computing, Vienna, Austria.

Rains, G. and D. Thomas. 2009. Precision farming: An introduction. University of Georgia, Athens.

Sapkota, T. B., M. L. Jat, R. K. Jat, P. Kapoor, and C. Stirling. 2016. Yield estimation of food and non-food crops in smallholder production systems. Pages 163–174 *in* T. S. Rosenstock, M. C. Rufino, K. Butterbach-Bahl, E. Wollenberg, and M. Richards, editors, Methods for measuring greenhouse gas balances and evaluating mitigation options in smallholder agriculture. Springer International Publishing AG, Switzerland.

Sedinger, J. S. and R. T. Alisauskas. 2014. Cross seasonal effects and the dynamics of waterfowl populations. Wildfowl Special Issue 4:277–304.

Stafford, J. D., R. M. Kaminski, K. J. Reinecke, M. E. Kurtz, and S. W. Manley. 2005. Post-harvest field manipulations to conserve waste rice for waterfowl. Proceedings of the Southeastern Association of Fish and Wildlife Agencies 59:155–163.

_____, _____, _____, and S. W. Manley. 2006. Waste rice for waterfowl in the Mississippi Alluvial Valley. Journal of Wildlife Management 70:61–69.

Tacha, T., D. William, W. Burnham, and K. Burnham. 1982. Use and interpretation of statistics in wildlife journals. Wildlife Society Bulletin. 10:355–362.

U.S. Fish and Wildlife Service and Canadian Wildlife Service (USFWS and CWS). 1986. North American Waterfowl Management Plan. U.S. Fish and Wildlife Service, Washington, D.C., and Canadian Wildlife Service, Ottawa, Ontario.

_____ and _____. 2018. North American Waterfowl Management Plan (NAWMP) update—connecting people, waterfowl, and wetlands. U.S. Fish and Wildlife Service, Washington, D.C., and Canadian Wildlife Service, Ottawa, Ontario.

Williams, C. K., B. Dugger, M. Brasher, J. Collucy, D. M. Cramer, J. M. Eadie, M. Gray, H. M. Hagy, M. Livolsi, S. R. McWilliams, M. Petrie, G. J. Soulliere, J. Tirpak, and L. Webb. 2014. Estimating habitat carrying capacity for migrating and wintering waterfowl: considerations, pitfalls and improvements. Wildfowl Special Issue 4:407–435.

Wilson, B. C. and C. G. Esslinger. 2002. North American waterfowl management plan, Gulf Coast Joint Venture: Texas mid-coast initiative. North American Waterfowl Management Plan, Albuquerque, New Mexico.