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Original Article

Rapid Assessment of Rice Seed Availability for Wildlife in Harvested Fields

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ABSTRACT Rice seed remaining in commercial fields after harvest (waste rice) is a critical food resource for wintering waterfowl in rice-growing regions of North America. Accurate and precise estimates of the seed mass density of waste rice are essential for planning waterfowl wintering habitat extents and management. In the Sacramento Valley of California, USA, the existing method for obtaining estimates of availability of waste rice in harvested fields produces relatively precise estimates, but the labor-, time-, and machinery-intensive process is not practical for routine assessments needed to examine long-term trends in waste rice availability. We tested several experimental methods designed to rapidly derive estimates that would not be burdened with disadvantages of the existing method. We first conducted a simulation study of the efficiency of each method and then conducted field tests. For each approach, methods did not vary in root mean squared error, although some methods did exhibit bias for both simulations and field tests. Methods also varied substantially in the time to conduct each sample and in the number of samples required to detect a standard trend. Overall, modified line-intercept methods performed well for estimating the density of rice seeds. Waste rice in the straw, although not measured directly, can be accounted for by a positive relationship with density of rice on the ground. Rapid assessment of food availability is a useful tool to help waterfowl managers establish and implement wetland restoration and agricultural habitat-enhancement goals for wintering waterfowl.

KEY WORDS California, harvested rice, rice seeds, Sacramento Valley, seed availability, seed density, waterfowl food, wintering waterfowl.

Rice farms have displaced much of the original marshland in many major waterfowl wintering regions of North America (Eadie et al. 2008). However, rice fields flooded after harvest function like managed wetlands by providing foraging and roosting habitats for wintering waterfowl and other waterbirds (Elphick 2000). Rice seed remaining in flooded and dry fields after harvest (waste rice) constitutes a critical food resource for wintering waterfowl, including dabbling ducks (tribe Anatini), diving ducks (tribe Aythyini), geese (tribe Anserini), and swans (tribe Cygnini; Heitmeyer 1989, Miller et al. 1989, Ackerman et al. 2006, Central Valley Joint Venture 2006, Stafford et al. 2010). This food is essential for sustaining large wintering populations of waterfowl in many locations, including California's Central Valley, USA (Miller and Newton 1999, Central Valley Joint Venture 2006).

The Central Valley Joint Venture (2006) uses availability of rice seed for bioenergetics-based habitat-planning models to estimate winter food requirements of wintering waterfowl. The energy requirements convert to habitat restoration and enhancement objectives to support objective levels of wintering waterfowl populations in the Sacramento Valley, the major rice-growing region in California (Eadie et al. 2008). Rice farming in the Sacramento Valley is under intense

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economic pressures from urbanization, with attendant competition for land and water (Hill et al. 2006). Because of this pressure and concern that the harvest of rice fields is becoming more efficient, leaving less waste seed available for waterfowl (Elphick et al. 2010, Miller et al. 2010), regular long-term monitoring is needed to accurately track rice availability with a precision that can detect trends for timely management responses.

Waste rice results from preharvest seed loss (seed shatter prior to harvest), gathering seed loss (cutting too high, reel shatter, excess rotor speed, excessive forward speed, downed rice), and processing seed loss (threshing, separator, cleaning shoe, body leakage; Quirk 2003). Most harvesting machines have spreaders that disperse processed seeds and straw, so waste rice tends to be widely spread. Previous studies estimated the amount of waste rice in the Sacramento Valley after conventional harvest (Miller et al. 1989) and strip-harvest (Miller and Wylie 1996). These 2 studies produced relatively precise estimates of the density of rice seed remaining after harvest (CV = 5.2–12.9%), but the method used was relatively time-consuming and labor-intensive. Additionally, the method was dependent upon the use of large-sized sampling frames, a variety of field machinery (all-terrain vehicles [ATVs], generators, wet–dry shop vacuums, shears), and follow-up processing after the completion of field collections, including machine threshing of straw, machine seed separation, and hand sorting (Miller et al. 1989). In Arkansas and Mississippi, USA, investigators have used 10-cm core samples in flooded or moist fields, but the estimates are associated with wide confidence intervals (±30–45% of the mean) even with large sample sizes (Stafford et al. 2006, Havens 2007, Kross et al. 2008). There is a need to develop a more rapid method to routinely estimate the amount of rice available that employs minimal use of personnel and sampling machinery and involves no postcollection processing.

We evaluated practical methods for waterfowl managers to rapidly obtain accurate and precise estimates of the seed mass density of waste rice remaining in fields immediately after harvest. We used a computer simulation to better understand factors related to the performance of each method and determine the potential efficiency of experimental methods against the standard method (Miller et al. 1989) to predict known simulated seed-mass densities with a random spatial distribution of seeds. We followed the simulation analysis with field tests of each method to grade their relative performance for accuracy, precision, sampling time, and number of samples required to detect a standard trend. We adopted a requirement that for any method to be acceptable, it must accurately and precisely predict the true rice seed-mass density, require a minimal amount of time in the field, and require no additional processing once the field work is completed.

STUDY AREA

We conducted simulation analyses at the Dixon Field Station of the Western Ecological Research Center, in Dixon, California, USA, and sampled 4 harvested rice fields in Sutter and Yolo Counties in the Sacramento Valley. These counties were 2 of the 8 counties that combined annually contributed about 98% of all the rice grown in California (National Agricultural Statistics Service 2006). Sampled fields ranged in size from 16 ha to 59 ha, and were planted in late April or early May 2009. All sampled fields were planted with M206 medium grain rice, which constitutes >95% of the rice grown in the Sacramento Valley. Fields were harvested conventionally between mid-September and mid-October 2009, and sampled within 1 week of harvest.

METHODS

The Standard Method (Control Plots) for Simulations and Field Tests

The standard method used to obtain estimates of rice seed-mass density in harvested fields in the Sacramento Valley employs sample frames at ≥2 random points located in individual fields across the rice-growing region distributed proportionately by each county's contribution to the rice harvest (Miller et al. 1989, Miller and Wylie 1996). Pick-up trucks are used to travel between sample fields, haul the samples as they are collected each day, tow or carry ATVs that are used in fields to get from one random sample point to the next, and carry field equipment to the sampling sites. The standard sample frame is a strip-quadrat (Bonham 1989) measuring 6.0 m × 0.3 m, the length of which is the most common width of modern harvester headers used in the Sacramento Valley. This provision insures that the plot accounts for all variation of seed density across the harvested swath (Miller et al. 1989), which decreases variation between sample points (Bonham 1989). We used the standard plot as a control plot for computer simulations and field sampling. Here we describe the field applications of the control and experimental methods. We then follow with descriptions of how we constructed these for the computer simulations.

Immediately following harvest, we laid out the control plots using tape measures, stakes, and brightly colored cord, and then used electric hedge trimmers and pruning shears to cut out the straw layer from on top of the stubble inside the control plots, being careful to not disturb seeds lying on the ground. We saved the straw, which contained variable numbers of seed heads and loose seeds, in labeled sample bags. We then conducted the experimental methods appropriate for the specific control plot, after which we cut out and discarded the stubble. Then we vacuumed the area inside the control plot using generator-powered 30.3-L wet–dry shop vacuums (Miller et al. 1989). We saved this ground-level vacuumed material in labeled sample bags. Once we sampled all fields, we processed bagged samples in facilities equipped with a threshing machine and a seed cleaner (Model 150HD; Farmstead Products, Hinckley, MN; Miller et al. 1989). Finally, we hand-processed samples to separate the rice seeds from dirt, blank seeds, small straw pieces, and other seeds, followed by drying and weighing (Miller et al. 1989). We adopted the convention that seeds are defined as those in which the kernels (endosperm) were ≥75% fully developed (Miller et al. 1989, Anonymous 2010), and used only these based on qualitative assessments in our determinations of seed mass density of waste rice. This is more restrictive than rules for acceptable rice seeds used in other rice-growing regions (50% developed; Stafford et al. 2006). We included broken seeds, which were uncommon, only if they were ≥50% of a full seed. We dried seeds at 70° C to constant mass and converted the mass density of seeds from g/m^2 to kg/ha (Miller et al. 1989, Miller and Wylie 1996). We used this standard to serve as the control plots for all experimental methods in the field except the wandering-quarter method (WQ), which required a different approach. We conducted all of the field and simulation experimental methods inside control plots. The control plot data served as the true seed-mass density against which we tested experimental methods for accuracy, precision, and time requirements for completion.

In the field, we determined the density of seeds separately for the straw samples and ground samples in the control plots (Miller et al. 1989, Miller and Wylie 1996). The experimental methods only sampled the ground, as heavy straw would interfere with measurements. Therefore, to account for total seeds (straw plus ground), we examined whether or not the density of rice in the straw could be predicted and used to adjust final estimates of total seed-mass density for experimental methods.

The Experimental Methods for Simulation and Field Tests

The experimental methods we tested are generally from the plant community ecology literature (Daubenmire 1968, Bonham 1989, Higgins et al. 1994). We assumed that estimation of the density of waste rice on the ground in a harvested field is similar to estimation of plant stem density. We further assumed that there would be a direct positive relationship between seed density, or a negative relationship between the distance between seeds, and the seed mass density. We tested 13 methods in the field and 11 by computer simulation. The methods included 1) line-intercept (INTERCEP), 2) point-frequency (POINTFREQ), 3) small-rectangular frames (SMALREC), 4) small-circular frames (SMALCIRC), 5) step-point (STEPOINT), 6) closest-individual (CLOSIND), 7) nearest-neighbor (NEARN), 8) corrected-point-distance (CPD), 9) point-centered-quarter (PCQ), 10) angle-order (AOR), 11) wandering-quarter (WQ), 12) stem density (STEMDEN), and 13) stubble height (STUB). We tested the results of each experimental method against the results from its associated control plot. We tested all of these methods by computer simulation, except for STEMDEN and STUB, for which we had no appropriate field data to set up simulations. The simulations consisted of 10 replicates of each experimental method, and the field study consisted of 4 replicates of each method in each of 4 harvested fields (16 total replicates). All replicates in each field occurred within an area of about 300 m × 50 m.

We conducted all experimental sampling inside and for the entire length of the control plots to represent the same amount of variation as the control plots themselves. For all methods except STEPOINT and WQ, >1 experimental method was associated with each control plot. In particular, we conducted the following groups of experimental methods in the same control plots: INTERCEP and POINTFREQ; SMALREC and SMALCIRC; CLOSIND, NEARN, and CPD; and PCQ and AOR. In each case, care was taken not to disturb seeds when conducting each method. We conducted STEMDEN and STUB on all control plots. All experimental method data were obtained on the ground after the straw was collected and stubble had been removed, and prior to vacuuming the control plots. This approach minimized variation from sampling error that invariably would have occurred if we had obtained control and experimental samples at different locations. We collected data for control plots and associated experimental sampling methods at about the same time daily, and recorded start and end times for each sample of each method. M. R. Miller and P. S. Coates oversaw all field procedures to reduce observer error.

Quadrat-based methods.—Quadrat-based methods involve counting seeds within a defined area and directly calculating density as seeds per unit area. In our study, quadrat-based methods included INTERCEP, POINTFREQ, SMALREC, SMALCIRC, and STEPOINT. We weighed 18 1,000-seed samples of M206 medium-grain rice to obtain an average seed mass of 0.026 g (SE < 0.001). We then multiplied rice seed density (seeds/m^2) by 0.255 to convert seed density (seeds/m^2) to seed mass density (kg/ha) for all quadrat-based methods.

The INTERCEP method uses segments of a line as observational units (Daubenmire 1968, Bonham 1989). Inside a control plot, we established a 6-m × 6.35-mm-wide line with alternating red and white sections, each 10 cm long. This yielded 30 10-cm sections of each color (total of 60) in each control plot. We treated the line as a series of narrow quadrats because the width of the line was nonnegligible relative to the size of a rice seed. We recorded the number of seeds on the ground intercepted (touched on either side of the line or lying wholly or partly under the line) by each red and white segment separately as a measure of variability. We calculated rice density along the intercept line as the number of seeds intercepted by the line divided by the area sampled (Table 1). We determined the area sampled by applying a 5.4-mm (the average dimension [(length × width)/2] of an M206 rice seed) buffer to the line by assuming that rice seeds were oriented randomly. Therefore, each section sampled 0.001175 m^2. We evaluated all 60 segments of the line, and evaluated the red and white segments separately.

The POINTFREQ method (Daubenmire 1968, Higgins et al. 1994) requires the use of rods lowered to the ground. We successively lowered 10 6.35-mm diameter rods to the ground through holes set 3 cm apart drilled in a 32-cm-long bar supported by a frame above the ground (Bonham 1989, Higgins et al. 1994). When each rod hit the ground, we recorded the number of seeds hit by each rod. The frame was then shifted along the line to a point immediately adjacent to the previous frame position, and the procedure was repeated for the entire length of the control plot for 16 frame sets and 160 rod drops. From these data, we calculated rice density within the area covered by all rod drops as the total number of

Table 1. Methods used to determine waste rice seed-mass density (kg/ha) in harvested fields (waste rice) in the Sacramento Valley, California, USA, September–October, 2009.

Method	Abbreviation	Explanation	Equation[a]
Control plot[b,c]	CP	Standard method used in the Sacramento Valley; 6.0 m × 0.3 m (1.8 m^2) area vacuumed in field, processed in lab	$\text{waste} = 5.5556 \times m$
Line-intercept[d,e,f]	INTERCEP	Seeds counted in 10-cm segments of 6-m line	$\text{waste} = \frac{n}{0.001175N} \times 0.255$
Point-frequency[e,f]	POINTFREQ	Seeds hit by 160 0.64-cm-diam rods	$\text{waste} = 6.892 \times n$
Small-rectangular frame[f]	SMALREC	Seeds counted in 5 0.51-m × 0.102-m rectangular frames	$\text{waste} = 0.9804 \times n$
Small-circular frame[f]	SMALCIRC	Seeds counted in 5 0.127-m-radius circular frames	$\text{waste} = 1.00063 \times n$
Step-point[e]	STEPOINT	Seeds counted in 24 1.27-cm-radius loops	$\text{waste} = 10.3234 \times n$
Closest-individual[e,g]	CLOSIND	Distance (cm) to nearest seed (d_1) from each of 5 systematic points	$\text{waste} = \frac{N-1}{\pi \sum_{i=1}^{N} d_{1i}^2} \times 2,550$
Nearest-neighbor[e,g]	NEARN	Distance (cm) from seed nearest each of 5 systematic points to its nearest neighbor (d_2)	$\text{waste} = \frac{N-1}{\sum_{i=1}^{N} (\pi d_2^2)_i} \times 2,550$
Corrected-point distance[e,h]	CPD	Distance (cm) to nearest seed (d_1), its nearest seed (d_2), and its nearest seed (d_3) at each of 5 systematic points	$\text{waste} = \frac{\frac{\frac{N}{\pi \sum_{i=1}^{N} d_{1i}^2}}{3.473}(3.717)^{-\frac{1}{0.5227}\sqrt{\frac{N\sum_{i=1}^{N} d_{1i}^2-\left(\sum_{i=1}^{N} d_{1i}\right)^2}{\sum_{i=1}^{N} d_{1i}\sum_{i=1}^{N} d_{2i}}}} + \frac{\frac{N}{\pi \sum_{i=1}^{N} d_{1i}^2}}{3.473}(3.717)^{-\frac{1}{0.5227}\sqrt{\frac{N\sum_{i=1}^{N} d_{1i}^2-\left(\sum_{i=1}^{N} d_{1i}\right)^2}{\sum_{i=1}^{N} d_{1i}\sum_{i=1}^{N} d_{3i}}}}}{2} \times 2,550$
Point-centered-quarter[e,g]	PCQ	Distance (cm) to nearest seed (d_1) in each quadrant at 5 systematic points	$\text{waste} = \frac{4(4N-1)}{\pi \sum_{i=1}^{N} \sum_{j=1}^{4} d_{ij}^2} \times 2,550$
Angle-order[e,i]	AOR	Distance (cm) to third-nearest seed in each quadrant at 5 systematic points	$\text{waste} = \frac{(3-1)}{N} \sum_{i=1}^{4N} \frac{1}{d_i^2} \times 2,550$
Wandering-quarter[e,j]	WQ	Distance (cm) to nearest seed (d_1) in quadrant, which then becomes vertex to find next nearest seed, for 30 measurements	$\text{waste} = \frac{1}{\left(\frac{1}{N}\sum_{i=1}^{30} d_i\right)^2} \times 2,550$
Stem density[k]	STEMDEN	Regression of waste rice on rice stems counted in 5 0.127-m-radius circular frames	$\text{waste} = a + b \times n$
Stubble height[k]	STUB	Regression of waste rice on stubble ht (cm) measured at 5 points	$\text{waste} = a + b \times h$

[a] Equations are based upon an average rice seed mass of 0.026 g. waste = density of waste rice (kg/ha), m = mass (g), N = no. of samples (sections, points, etc.), n = no. of seeds or stems, h = ht (cm), d_x = distance (cm), where $x = 1$ is distance to nearest seed, $x = 2$ is distance from nearest seed to its nearest neighbor, and $x = 3$ is the distance from the nearest neighbor to its nearest neighbor, excluding the seed nearest the point ($x = 1$). If x is unspecified, the distance measurement is explicit in the explanation.
[b] Miller et al. (1989).
[c] Miller and Wylie (1996).
[d] Three submethods: all segments, red segments only, and white segments only.
[e] Bonham (1989).
[f] Daubenmire (1968).
[g] Parker (1951).
[h] Cottam and Curtis (1956).
[i] Morisita (1957).
[j] Catana (1963).
[k] For STEMDEN and STUB, waste = density of rice (kg/ha) in straw.

rice seeds divided by 0.037 (based upon a sampled area of 0.000231 m^2/rod, including the 5.4-mm buffer added to the radius to account for the size of an average rice seed; Table 1).

SMALREC and SMALCIRC were quadrats similar to the control plots, but at a smaller scale. For SMALREC, we used steel sample frames measuring 0.102 m × 0.51 m (area = 0.052 m^2). A rectangular shape is efficient for sampling vegetation because the elongate plot has a high probability of intercepting several plant clusters at once without falling entirely within or outside of a single cluster, and as a result, fewer plots are needed to obtain averages representative of the whole (Daubenmire 1968). For SMALCIRC, we used a circular steel frame with a radius of 0.127 m, which sampled an area of 0.051 m^2. A circular-shaped sample frame is efficient for vegetation because the small perimeter:area ratio could reduce the number of plants erroneously counted at the margin of the plot that actually fell outside (Daubenmire 1968). Whether these issues are relevant to rice seeds is unknown. In each control plot, we systematically distributed 5 sample points running from one end of the control plot to the other at 1-m intervals. At each point, we placed a rectangular and a circular frame next to one another, with the rectangles parallel with the control plot. We picked up all seeds and chaff from inside the frames using 18-V rechargeable hand-held wet–dry vacuums (Model DC515; DeWALT Industrial Tool Co., Baltimore, MD). We then counted the seeds in the field using graded sieves to separate seeds from the chaff. After we obtained seed counts, we returned all seeds to the control plot inside the respective small frames so they could be included in the control plot sample. We repeated this process for the other 4 sample points.

The STEPOINT method consisted of collecting seed counts at sample points at 0.5-m intervals along each side of 2 6-m lines in control plots for 24 sample points per line and 48 in each control plot. We used this extra sample length to increase the number of seeds counted. We also adapted the loop method (Parker 1951, Bonham 1989) to increase the likelihood of intercepting seeds relative to using dimensionless points. At each sample point in succession we lowered an aluminum tube that had a 2.54-cm-diameter open-circle loop attached at the bottom to the ground. We recorded the number of seeds touched and enclosed by the loop, and adjusted the sampled area to account for the average dimensions of a rice seed as for INTERCEP and POINTFREQ. We calculated seed density as the total number of seeds divided by the area sampled by the loops (0.0243 m^2).

Distance-based methods.—Distance-based methods use the distance between individuals to determine vegetation density (Bonham 1989), and they are especially efficient for sampling items that are sparse and widely scattered (Ludwig and Reynolds 1988). Results vary widely among the several methods available, however, even when they are used for the same plant species in the same plots at the same time (Laycock and Batcheler 1975, Oldemeyer and Regelin 1980, Bonham 1989, Higgins et al. 1994). We suspect that this phenomenon could be an issue with rice seeds as well. The distance methods we used were CLOSIND, NEARN, CPD, PCQ, AOR, and WQ. For each distance-based method, measurements were made in cm; we therefore multiplied seed density (seeds/cm^2) by 2,550 to obtain mass density (kg/ha).

For CLOSIND, NEARN, and CPD, we established 5 sample points in each control plot systematically located 1 m apart. At each sample point we measured and recorded the distance from the point to the nearest rice seed, which was the CLOSIND measurement. We then measured the distance from that seed to its nearest seed, the NEARN measurement, and finally we measured the distance from that seed to its nearest seed, an additional measurement used by the CPD method to correct for nonrandom seed distributions, before moving to the next sample point and repeating the process. CLOSIND and NEARN are theoretically similar, with similar equations for estimating density that rely upon the assumption of random seed dispersion (Table 1). The CPD method uses all 3 distance measurements to estimate seed density corrected for nonrandom distributions (Table 1; Laycock and Batcheler 1975, Oldemeyer and Regelin 1980, Bonham 1989, Higgins et al. 1994).

PCQ and AOR consisted of measurements from a sample point to the closest seed and the third-closest seed in each of 4 quadrants centered on each of 5 sample points placed 1 m apart in the control plot. PCQ essentially measures the point-seed distance in each quadrant from a single point and estimates density using an extension of the CLOSIND estimator (Table 1). The AOR method attempts to correct for the potential nonrandom distribution of seeds. Seed density for AOR is estimated in 2 ways, and the final density estimate is based upon the relationship between the 2 estimators (Laycock and Batcheler 1975). Rather than use a different method to calculate density at each location, and in the spirit of developing a simple, rapid assessment method, we evaluated the appropriate equation for each of our 16 samples. We applied the estimator appropriate for 11 cases to all samples (Table 1).

The WQ method estimates population density of plants where no a priori assumption of randomness is made (Catana 1963, Bonham 1989). Traditionally, WQ consists of a sequence of measurements of the distances between closest seeds along 4 azimuth lines positioned to form a rectangle to determine the mean distance between seeds. To reduce sample time, we chose to use only one azimuth line. We could not use standard control plots for this method because the sampling area determines the size of the control plot. Prior to initiating seed location and measurement, we removed straw from an area of about 1 m × 2 m. We chose a random point in this area, and set a directional line perpendicular to the direction of harvester travel. We used an aluminum form in the shape of a right-angled "V" to create a 90° inclusion angle. We placed the angle of this form at the nearest seed to a random point as the starting point. We measured the distance to the nearest seed within the 90° inclusion angle, then set the aluminum frame at that seed, with the azimuth line as a bisector. We repeated this process until 30 measurements between seeds had been taken.

We established a primary control plot a posteriori as the smallest rectangle that fit over all of the 30 sample points with a buffer of a distance half that between the random starting point and the first seed. Therefore, primary control plot size in WQ varied from sample to sample depending upon distance between seeds. The primary control plot was vacuumed after WQ measurements were obtained, as for other methods, and we estimated seed density. Because we established primary control plots after measurements were taken, and we had removed the straw a priori, we obtained seed numbers in the straw layer of an identically sized plot located immediately adjacent to the primary control plot, the nested plot. We used the standard density estimator for WQ (Table 1).

Other methods.—The STEMDEN method makes the assumption that the loss of seeds during harvest is related to the density of rice stems, which is assumed to be related to the standing crop of seed present prior to harvest. We obtained these data in all control plots, after the straw layer had been removed, by counting the number of stems contained within 5 SMALCIRC steel frames distributed across the control plot 1 m apart as in SMALCIRC. The STUB method assumes that the height of stubble is related to the condition of the rice field during harvest. For example, fields in which plants are erect, forming a uniform seed layer, are likely harvested more efficiently than are fields in which plants have fallen over (downed or lodged rice). We assumed that the former would leave tall stubble and the latter shorter stubble. We obtained stubble height measurements as the height of the stubble nearest the center of the same SMALCIRC frames used for STEMDEN. In addition to predicting the density of rice on the ground and total density of rice via regression, we also used STUB and STEMDEN to estimate the density of rice in the straw for use as a correction factor to add to the predicted ground density.

Computer Simulations

Great variation in seed density within and between harvested rice fields exists (Miller et al. 1989, Miller and Wylie 1996, Stafford et al. 2006, Eadie et al. 2008, Greer et al. 2009). It was, therefore, essential that we determine whether the performance of different estimators of seed density varied with seed density. We conducted a Monte Carlo simulation to understand the potential influence of seed density on the relative effectiveness of different sampling methods, facilitate prediction of experimental methods that might offer only low likelihood of achieving accurate and precise assessments of seed density, and enable predictions of the outcomes of field sampling methods without consideration of the length of time required to complete them (Engeman et al. 1994). We qualitatively compared the accuracy and precision of computer-simulated methods against the performance of the methods in field applications, where the length of time required for completion of the methods is a critical consideration. This comparison facilitated the development of hypotheses to explain how methods performed in the field and served as an informal sensitivity test to departures from assumptions implicit in each method.

We designed the computer simulation using ArcGIS Desktop 9.3, and created a Personal Geodatabase to store all feature classes used in the simulations. We organized all files within Feature Datasets for each experimental sampling method to ensure consistency in coordinate systems and *XY* resolutions among all files. We set coordinates to a Universal Transverse Mercator map projection because of its ability to represent small shapes and angles accurately with minimal distortion of area (ESRI 1994). We created multiple-feature class polygons and stored them in the geodatabase to simulate rice seed sampling tools used in the field and simulate the rice field itself. Using data from Miller et al. (1989) and the method of Pielou (1960), we found that seeds tended to be randomly distributed at a landscape scale. Thus, we assumed random distributions of seeds on a homogeneous landscape instead of clumped seed distributions or variation in rice seed densities across the harvester path.

Base polygon and control plots.—We performed 10 simulations at each of 4 realistic rice seed-mass densities of 50 kg/ha, 200 kg/ha, 350 kg/ha, and 700 kg/ha in harvested fields for each method. These levels cover the range of seed mass densities known to occur in the Sacramento Valley (Miller et al. 1989, Miller and Wylie 1996), and 350 kg/ha approximates the average estimate in the Sacramento Valley from the 1980s (Miller et al. 1989). We populated a Base Polygon (Base Field) with the random seed distributions representing the 3 study densities. We defined a 6.0-m $\times$ 0.3-m control plot in the Base Field, which had dimensions defined by 3-m buffers on all sides of the control plot, or 12.0 m $\times$ 6.3 m (75.6 m^2). Simulations for all experimental sampling methods started inside the control plots, and the Base Field created an ample buffer for any experimental method that might cross the boundary of the control plot. Harvester travel was set as north–south, and we oriented all control plots east–west to represent field conditions in which plots must be oriented perpendicular to the direction of harvester travel (Miller et al. 1989). Based on the randomly generated numbers of seeds in the control plots, we calculated seed densities for all experimental methods as if they had been performed in the field.

Rice seeds.—We simulated rice seed density by generating point features in the Base Field using ArcMap's Create Random Points tool. This tool uses a random number generator to place a user-specified number of points at random coordinates within a given area. The input number of points for the tool was chosen from a table of seed numbers created in SAS software (SAS Institute, Inc., Cary, NC) using a Poisson random number generator based on the 3 seed density values simulated. For example, the mean number of seeds for our Base Field at 350 kg/ha is 115,043 seeds (75.6 m^2 $\times$ 1521.73 seeds/m^2). The corresponding Poisson table contained values with a mean of 115,043 and which simulated the probable variance in the number of seeds remaining in areas of that size. We selected a random number for each iteration, which resulted in a different number and distribution of point features for each simulation. The vector points in ArcMap are simple feature locations defined by an *X*,*Y* coordinate and have no dimension.

Therefore, for the purposes of simulation, we considered the points themselves to be center points of the rice seeds, and a 0.15875-cm buffer was applied in all experimental methods to approximate actual seed dimensions (seed width = 0.318 cm).

Experimental methods.—The INTERCEP method required the creation of a 6.35-mm-wide polygon, the intercept line, extending the length of the control plot to simulate the line used in the field. The full polygon consisted of 60 10-cm adjacent features (sections) arranged end to end along the line to simulate alternate red and white-colored 10-cm sections on lines used in the field. We performed a "Select by Location" to find all seeds that intersected or occurred in each 10-cm section of the full polygon.

The POINTFREQ method required the creation of circle polygons to simulate the round rods used in the field. We arranged the polygons into 16 sections along the length and inside of the control plot; each section contained 10 circles of a 2.5-mm radius 3 cm apart. This array ran the total length of the control plot. We found all circles that intersected or contained seeds and counted the number of seeds intersected by each circle.

We simulated the SMALREC (10 cm × 5 cm) and SMALCIRC (12.6-cm radius) quadrat methods by creating 5 polygon features (rectangles or circles, respectively) spaced evenly across the control plot polygons at 1-m intervals. We selected the points that fell inside the rectangles or circles and recorded the total number of points within each rectangle or circle for each iteration.

The final quadrat-based method, STEPOINT, was simulated in a fashion similar to POINTFREQ. Circle polygons of 2.54-cm diameter were spaced at 0.5-m intervals on either side of 2 lines running parallel inside a control plot located within the Base Field. We recorded the total number of seeds that fell within the control plot and the number of seeds intersecting the circles.

Distance-based methods yield estimated distances from random sample points or between seeds. For the first group of distance measures (CLOSIND, NEARN, CPD), we created 5 feature-class points for each simulation and spaced them evenly 1 m apart in the control plot. CLOSIND requires a measurement from a starting point to the closest seed, and we used ArcMap's Near tool to calculate these distances. The tool appends the distance of the closest seed to each starting point into the attribute table of the starting points feature class, and we recorded each value. NEARN and CPD required subsequent measurements to the next closest seed and from that seed to its closest seed, respectively. The Near tool was not able to calculate measurements using only a single feature class, so we created a new feature class using the locations of the nearest seeds. Points already located were excluded from additional searches within the seeds layer to avoid repeating measurements. We repeated this process until all measurements were calculated and recorded based on the requirements of the experimental methods.

The second group of distance-based methods, PCQ and AOR, use distances to nearest seed and third nearest seed, respectively, in each of 4 quadrants around a sample point. We created 5 feature-class sample points spaced evenly 1 m apart in the control plots as before. Additionally, we created a polygon feature class of 4 squares per sample-point location to represent the quadrants needed around each sample point. For PCQ, the process was essentially the same as that used in CLOSIND, except that the Near tool was used to select seeds only in each individual quadrant. We recorded distances of closest seeds from the sample points in each quadrant for PCQ, and the third nearest seed for AOR.

The final distance-based method, WQ, used the distances between 30 nearest points in succession within 45° of either side of a compass bearing. A random seed point was chosen inside the Base Field using Hawth's Tools Create Random Selection tool (Beyer 2004). Starting from the random seed location, ArcMap's Near tool was used to find the nearest seed along a 90° or 270° compass bearing (to stay perpendicular to harvester travel). For each seed selection, the Near tool appended the distance and angle measurements into the attributes of the seed points feature class. The closest seed falling within ±45° of the bearing was then selected and its distance recorded, and it was exported into a feature class so that it could be used for the next Near operation. This process was repeated until the distance between 30 closest seeds had been measured. A post hoc control plot was created to surround the WQ seeds. The plot was created by using ArcMap's Buffer tool to buffer each set of WQ seeds by half the distance between the sample point and the first seed, then running a Bounding Containers Python script (Patterson 2008) to create a rectangular feature class with the same extent as the buffer layer. We then found the total number of seeds located inside the control plot.

Field Study: Experimental Estimates of Rice Density

We obtained permission from 3 rice growers to conduct our studies in their harvested fields. We selected 4 fields that would not receive a postharvest treatment (e.g., mowing, chopping, stomping, baling, plowing, or flooding) within about 1 week after harvest, so that we would have time to obtain field data. We selected fields planted with M206 medium-grain rice. Additionally, these fields were harvested conventionally (Miller and Wylie 1996) and available for sampling from mid-September to mid-October to reduce the likelihood of encountering rainy periods. It was not necessary that study fields represent the entire rice-growing region, only that they be harvested using routine conventional techniques that would result in seed distribution patterns representative of average conditions. We hoped to find a wide range of seed densities within and among fields to facilitate development of robust regression equations so that we could predict seed mass density for any rice field with seed mass densities likely to be encountered. Previous work in the Sacramento Valley suggested our sample should achieve this goal (Miller et al. 1989).

We chose to work only in conventionally harvested fields because they present the most difficult sampling conditions because of the heavy straw load (Miller et al. 1989). Approximately 80% of rice in the Sacramento Valley is harvested conventionally (J. Fleskes, U.S. Geological Survey, unpublished data). Additionally, the conventional fields allowed us to obtain estimates of the density of seeds in the straw layer and on the ground separately. The former could then be used as necessary to adjust results of the different experimental methods, which only obtain data from the ground. We chose not to work in burned fields (because autumn burning only rarely occurs now; Connelly–Areias–Chandler Rice Straw Burning Reduction Act of 1991: AB 1378, Ch. 787, 1991), or stripped fields (Miller and Wylie 1996), although our methods, without adjustments for seeds in the straw layer, would be adequate for them. We also chose not to work in baled, mowed, chopped, rolled, or stomped fields, which are methods requiring additional vehicle traffic in harvested fields, thereby pushing more seeds into the soil. For application in the future, we assume a priori that harvested fields will need to be sampled prior to most postharvest treatments.

Evaluation of Experimental Method Performance

We used several criteria (R^2, mean squared error [MSE], bias, time required to conduct a sample, no. of samples required to detect a standard trend, and total time required to detect a standard trend) to evaluate the performance of each experimental method for the field experiment. Evaluation of performance of the simulation experiment was limited to R^2, MSE, and bias. We used linear regression to examine how well each experimental method predicted the density of rice on the ground. We used raw data collected in the field or calculated in GIS (seed counts or distances) from each experimental method as predictor variables. We determined the necessity of transformation of the response variable, and which transformation to use, with a maximum-likelihood estimate of λ for the Box–Cox family of transformations, where the response (Y) is transformed according to Y^λ when $\lambda \neq 0$, and $\log(Y)$ when $\lambda = 0$ (Quinn and Keough 2002). Because we were primarily interested in predicting the response variable, rather than interpretation, we used the maximum-likelihood estimate of λ (Faraway 2005). Within each experimental method, we compared the fit of a model predicting rice density using each experimental method with a null (intercept-only) model using the Bayesian Information Criterion (BIC). Using BIC allowed us to explicitly specify uniform prior probabilities to the model set and calculate the posterior probability of each model (Link and Barker 2006). Because different control plots were used for most experimental methods, we could not directly compare experimental methods using information criteria (Burnham and Anderson 2002). We therefore qualitatively compared experimental methods using adjusted R^2.

We also used simple measures of precision and bias to compare experimental methods. We examined the ability of each method to predict the density of rice using squared error, which is the squared difference between the expected (known control plot) and observed (based on experimental methods) densities. Methods with lower MSE better predict rice density. In addition to MSE, we calculated the bias associated with each experimental method as the raw difference between the expected and observed densities. An ideal method would have a mean bias of zero. We compared squared error and bias among methods using linear models with experimental method as the predictor variable to a null model of no difference among methods in squared error or bias with BIC using uniform prior probabilities. If the method model had a greater posterior probability than the null, we fit an alternative parameterization of the method model without an intercept. This model compares the mean response (squared error or bias) for each method to zero, and identifies those methods for which MSE or mean bias is significantly different from zero. We presented MSE as root mean squared error (RMSE) for interpretation on the original scale of measurement.

Because our goal was to establish a rapid and efficient method of estimating rice density in the field, we also compared the amount of time required to conduct each method. We calculated the number of minutes required for a single sample (defined as the effort expended to characterize the control plot) for each method, and compared them using 1-way analysis of variance (ANOVA). The model with time varying by method was compared to a null model with BIC, with a prior probability of 0.5 for each model. We made pairwise comparisons between methods with t-tests using Bonferroni correction for multiple testing (Quinn and Keough 2002). For instances in which a method was nested within another method, we could not derive an independent measure of time to conduct each specific method, but instead we provided estimates.

We further examined efficiency as the ability of each method to detect a standard trend. We used Program MONITOR 11.0 (Gibbs and Ene 2010) to determine the number of samples required to detect a 1% annual trend over 10 yr with monitoring at 5-yr intervals. We used simple regression, assumed a constant coefficient of variation, set significance to $\alpha = 0.10$ and power $= 0.80$ for all methods, and evaluated each method over 1,000 iterations using the empirical mean among samples as the starting value and the standard deviation among samples as our measure of total variation. We systematically varied the number of samples until simulations resulted in 95% detection of both a 1% annual increase and a 1% annual decrease. For quadrat-based methods, we used the mean and standard deviation of raw seed counts, but distance-based methods required use of estimated densities. After determining the number of samples required to detect the trend, we multiplied the mean time to conduct a sample of each method by the number of samples to determine the total sampling time required to detect the trend.

As an overall measure of method performance, we ranked each method by R^2, RMSE, bias, time per sample, number of samples required, and total sampling time required. We then calculated the mean rank of each method as a measure of overall performance.

Because a portion of rice seeds remain in the straw in many fields (those harvested conventionally and not baled or burned), we used linear regression to examine the use of different measures for predicting the density of rice in the straw, which was not directly measured by any of our experimental methods. In particular, we compared the ability of STEMDEN, STUB, and ground density (as measured by the control plot) against a null model to examine which method (if any) best predicted the amount of rice in the straw as a correction factor to add to the ground density of rice to determine the total amount of waste rice. We compared models using BIC with a uniform prior probability of 0.25 placed upon each model. To further examine the variation in the relationship of the best predictor of the density of rice in the straw over time, we used model selection to determine whether the relationship of the best predictor variable and the density of rice seed in the straw varied between our study and data from the Sacramento Valley collected in 1985. We fit models representing a different relationship (interaction between time period and the predictor), the same relationship with a different constant (additive model with time period and the predictor), the predictor only, and time period only. Models were again compared using BIC with a uniform prior probability of 0.25 placed upon each model.

All analyses (exclusive of simulating data and power analysis) were conducted in R version 2.11.0 (R Development Core Team 2010). We calculated the maximum-likelihood estimate of λ using the package MASS (Venables and Ripley 2002). Where appropriate, we established $\alpha = 0.05$ to determine statistical significance.

RESULTS

Computer Simulation

Several methods performed well in computer simulations (Fig. 1). Using seed counts and distances, 2 methods (STEPOINT and SMALCIRC) had an adjusted R^2 of 1.00 (Table 2). Four methods (CPD, NEARN, POINTFREQ, and CLOSIND) had an adjusted $R^2 < 0.90$ (Table 2). Although RMSE varied among methods, the probability that method explained variation in squared error relative to a null model was <0.001. Bias varied among methods, however, with POINTFREQ, NEARN, and AOR exhibiting negative bias, and CPD exhibiting positive bias (Table 3). Therefore, based upon simulated data, STEPOINT, small frames (SMALCIRC and SMALREC), all 3 versions of INTERCEP, and WQ performed well for estimating the density of rice seeds (Fig. 1).

Field Experiments

Experimental methods generally performed more poorly for predicting the density of rice in the field than they did for computer simulations. When using field-collected raw data as the predictor variable, only one method, the red sections of INTERCEP, had an adjusted R^2 of 0.90 or greater (Table 4; Fig. 2). Two methods, STUB and STEMDEN, performed poorly (adjusted $R^2 \leq 0.32$), and the latter predicted rice density more poorly than the null model (Table 4). The probability that experimental methods differed in squared error, compared to a null model of no difference among methods, was only 0.20. Methods varied in their bias (probability of an effect of method on bias >0.999), with NEARN and CPD exhibiting negative bias, and STEPOINT and AOR exhibiting positive bias (Table 5; Fig. 3).

The density of rice on the ground was the best predictor of rice in the straw; other models had very little support (Table 6). The relationship between the density of rice on the ground and the density of rice in the straw did not vary between 1985 and 2009 (Table 7). The amount of rice in the straw increased with an increasing amount of rice on the ground ($\lambda = 0.07$; adjusted $R^2 = 0.46$, intercept = 1.21 [SE = 0.014], slope = 3.3×10^{-4} [3.4×10^{-5}]; Fig. 4).

Methods varied substantially in efficiency. The probability that the time to complete experimental methods differed from one another was >0.999. The most rapid method was STUB plus STEMDEN, which averaged 7.1 (SE = 0.43) min/sample (Table 8). SMALREC, which was the most precise and least biased method, took the longest, with an average of 56.5 (SE = 5.26) min/sample (Table 8). Of the methods that were unbiased, CLOSIND took the least time. Conducting this method plus NEARN and CPD took an average of 22.4 (SE = 2.21) min/sample. Because CLOSIND only requires measurement to the first seed, the actual time per sample is approximately 33% of that time, or 7.5 min. When all sections were counted, INTERCEP took an average of 39.7 (SE = 5.13) min; however, conducting INTERCEP with only the white or red sections would take half that time (19.9 min) with no apparent loss in performance (Table 8). Methods also varied substantially in the number of samples required to detect a standard trend in 95% of simulations. INTERCEP required the fewest samples (510–550), and SMALREC and STEPOINT also required relatively few samples (740 and 790). NEARN required the greatest number of samples (2,150) to detect the trend (Table 8). When both the number of samples and the time required to collect them were considered, CLOSIND detected the trend in the least amount of sampling time (150.4 hr); INTERCEP (red) and INTERCEP (white) were also efficient methods (168.6 and 181.8 hr). WQ, the least efficient method, would require 1,267.1 hr of sampling time to detect the trend (Table 8).

When all measures of performance were weighted equally, INTERCEP methods performed well, with the 3 lowest mean ranks (Table 9). In contrast, WQ, SMALCIRC, and AOR performed relatively poorly overall (Table 9).

DISCUSSION

The best overall method, and the one we recommend for monitoring the density of rice seeds in the Sacramento Valley, is INTERCEP. We recommend this method because it is relatively accurate, is unbiased, and takes little time in the field. Efficiency in the field can be increased by counting rice seeds on every other 10-cm segment of the line without any apparent loss in performance. Differences between red and white segments of the line were not significant, and were likely the result of sampling variation. Alternatively, light-colored rice seeds might be more visible when adjacent to a red segment than a white segment, and it is, therefore, prudent to sample red segments in preference to white segments. In addition to these effectiveness and efficiency con-

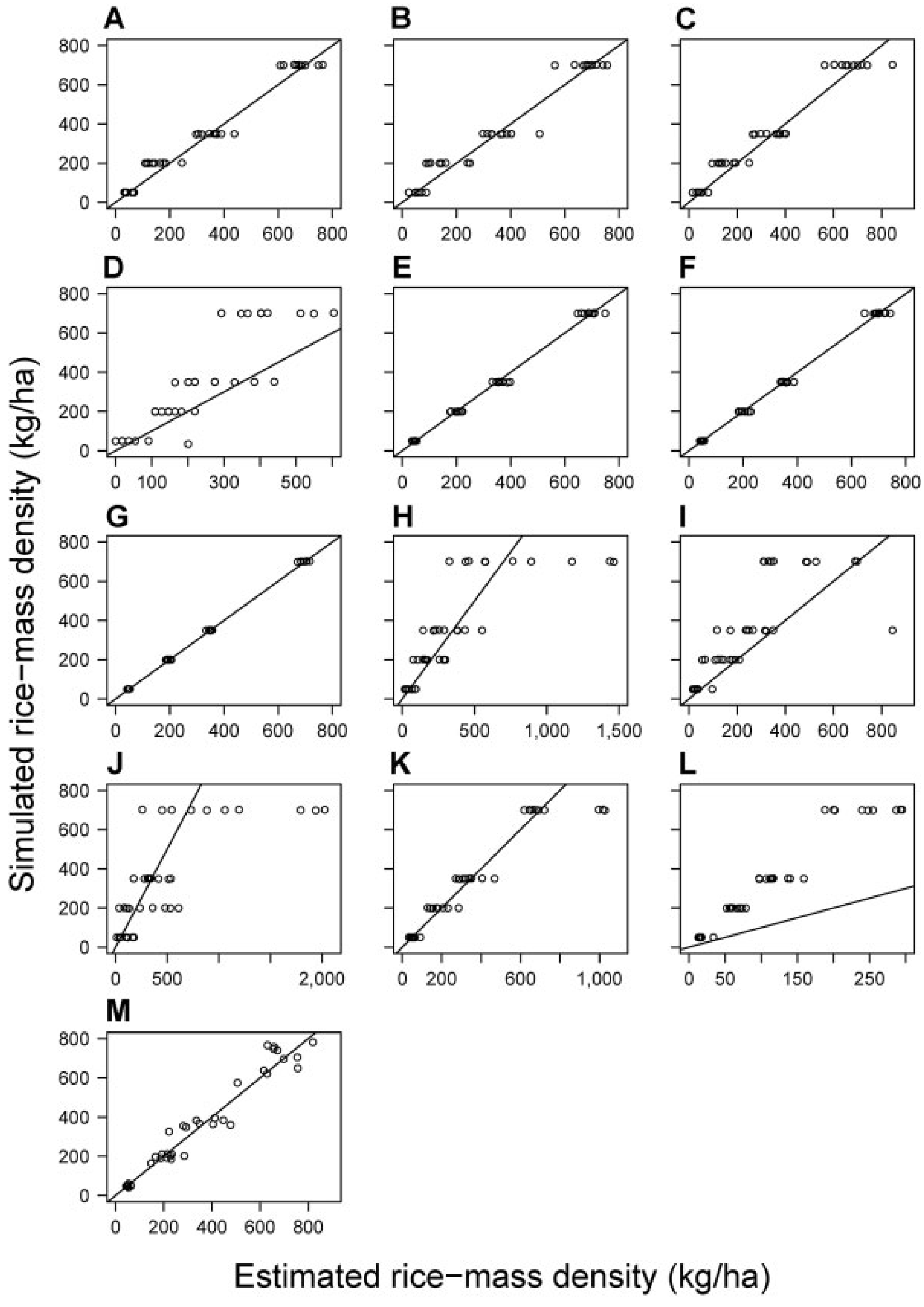

Figure 1. Calculated rice-mass density using experimental methods versus simulated rice-mass density. Circles represent individual simulations and corresponding density estimates using each experimental method. (A) INTERCEP = line-intercept (all sections of tape), (B) INTERCEP (red sections of tape), (C) INTERCEP (white sections of tape), (D) POINTFREQ = point-frequency, (E) SMALREC = small-rectangular frames, (F) SMALCIRC = small-circular frames, (G) STEPOINT = step-point, (H) CLOSIND = closest-individual, (I) NEARN = nearest-neighbor, (J) CPD = corrected-point-distance, (K) PCQ = point-centered-quarter, (L) AOR = angle-order, and (M) WQ = wandering-quarter. The line in each plot represents perfect correspondence between estimated and simulated densities.

siderations, INTERCEP requires little specialized equipment: a pitchfork to clear straw, a bypass pruner to cut stubble, a tape with 10-cm sections marked to obtain samples, 2 spikes to anchor the tape, and a pointed device (such as a wire flag or pocket knife) to carefully manipulate chaff on the ground to expose rice seeds. The only method that was ranked higher than INTERCEP for precision and bias in the field, SMALREC, took 3 times longer to conduct per sample, and required handheld cordless wet–dry vacuums, field generators, custom-built frames, sieves, and other supplies that increased cost. The modest (and statistically insignificant) gain in performance by using SMALREC would not, therefore, be cost- or time-effective.

Although we selected INTERCEP as the best overall method, we found little evidence for variation among methods in squared error. This result was likely caused by relatively large variation in squared error among samples within each method, resulting in low power to detect differences

Table 2. Performance of experimental methods based upon regression of raw data from the simulation study to predict the density of rice seeds. Methods are presented in order of decreasing adjusted R^2. All models had a probability >0.999 relative to a null model.

Method[a]	λ[b]	Adjusted R^2	Intercept (SE)	Slope (SE)
STEPOINT	0.99	1.00	4.05 (1.90)	0.18 (0.001)
SMALCIRC	0.97	1.00	7.91 (3.72)	0.74 (0.008)
SMALREC	0.89	0.99	13.46 (2.39)	0.43 (0.005)
WQ	−0.37	0.97	0.038 (0.003)	0.029 (7.6×10^{-4})
INTERCEP (all)	0.93	0.97	26.58 (6.94)	2.42 (0.071)
AOR	−0.34	0.97	0.06 (0.004)	0.016 (4.9×10^{-4})
INTERCEP (white)	0.90	0.95	31.65 (6.76)	3.86 (0.14)
INTERCEP (red)	0.88	0.95	24.92 (6.28)	3.38 (0.127)
PCQ	−0.20	0.92	0.22 (0.006)	0.034 (0.002)
CPD	−0.16	0.88	0.31 (0.008)	0.056 (0.003)
NEARN	−0.03	0.78	0.81 (0.004)	0.018 (0.002)
POINTFREQ	0.47	0.77	6.70 (0.76)	0.586 (0.052)
CLOSIND	0.00	0.75	6.79 (0.15)	−0.771 (0.071)

[a] INTERCEP (subset) = line-intercept method (sections of line used for analysis); POINTFREQ = point-frequency method; SMALREC = small-rectangular quadrat method; SMALCIRC = small-circular quadrat method; STEPOINT = modified step-point method; CLOSIND = closest-individual method; NEARN = nearest-neighbor method; CPD = corrected-point-distance method; PCQ = point-centered-quarter method; AOR = angle-order method; WQ = wandering-quarter method.

[b] The maximum-likelihood estimate of λ used for transformation following the Box–Cox procedure.

among methods. The inability to statistically distinguish among methods, though problematic for choosing a method, might alternatively indicate that all methods are equally good (or poor) estimators of density. Despite the lack of statistical differences among methods, a prudent choice of method remains one that exhibits lower, rather than higher, RMSE and takes less time to complete in the field at lower cost.

In contrast to RMSE, methods varied in their bias. Two general patterns were evident in bias. One pattern was a tendency for quadrat-based methods (except POINTFREQ) to be biased high (i.e., greater observed rice-seed nos. than expected). This systematic bias in quadrat-based methods could be caused by several mechanisms. For small quadrats, particularly those with indefinite outer edges where rice seeds that touch the edge of the quadrat are counted (INTERCEP, POINTFREQ, and STEPOINT), observers might have chosen to include rice seeds that are just outside the edge of the quadrat. Alternatively, buffer distances might have been estimated too small, resulting in extrapolation of seed counts to a smaller area and biasing density high. For the larger quadrats (SMALREC AND SMALCIRC), bias might have been induced by the uneven ground surface often present in rice fields. When the frames do not fully contact the ground, seeds from outside the quadrat might be accidentally vacuumed and included in the sample. Although field crew training and other measures were taken to minimize these potential sources of bias, it might be impossible to entirely eliminate them. Interestingly, the single quadrat-based method for which bias was negative, POINTFREQ, was also biased negative in the simulation study. This result suggests some error in the calculation of density from this method, which was originally developed to calculate percent cover. For all other quadrat-based methods, the simulation study demonstrated very little bias. Even using data collected in the field, bias in quadrat-based methods was not significant for any method except STEPOINT.

Table 3. Performance of experimental methods for predicting simulated rice densities based upon root mean squared error (RMSE) and mean error (Bias). Methods are listed in order of increasing RMSE. * = Value significantly different from zero at $\alpha = 0.05$.

Method[a]	RMSE	Bias
STEPOINT	8.3	−3.5
SMALCIRC	17.0	1.0
SMALREC	19.9	1.2
INTERCEP (all)	45.4	−15.5
WQ	54.0	−5.0
INTERCEP (red)	54.8	−10.1
INTERCEP (white)	56.3	−20.9
PCQ	95.6	12.7
POINTFREQ	164.1	−99.0*
NEARN	177.3	−90.2*
CLOSIND	218.7	17.2
AOR	267.4	−214.5*
CPD	380.0	122.9*

[a] INTERCEP (subset) = line-intercept method (sections of line used for analysis); POINTFREQ = point-frequency method; SMALREC = small-rectangular quadrat method; SMALCIRC = small-circular quadrat method; STEPOINT = modified step-point method; CLOSIND = closest-individual method; NEARN = nearest-neighbor method; CPD = corrected-point-distance method; PCQ = point-centered-quarter method; AOR = angle-order method; WQ = wandering-quarter method.

The other general pattern in bias was for distance-based methods (except WQ and AOR) to be biased low. This systematic bias in distance-based methods could be caused by several mechanisms. First, distance-based methods assume perfect detection. If the appropriate seed to which measurements should be made is misidentified (e.g., the second-nearest seed is measured, rather than the nearest), density will be biased low. Systematic measurement error, for example measuring to the outer edges of seeds, rather than their centroids, might also cause bias in density estimates using distance-based methods. Measurement error might be particularly relevant at high rice densities, where distances between rice seeds can be small relative to the size of the seeds, making determination of the centroid of the seeds

Table 4. Performance of experimental methods based upon regression of raw data from the field to predict rice-mass density on the ground in the Sacramento Valley, California, USA, in 2009. Methods are presented in order of decreasing adjusted R^2. All models had a posterior probability >0.999 relative to a null model except STEMDEN, which had probability = 0.113 relative to a null model.

Experimental method[a]	λ[b]	Adjusted R^2	Intercept (SE)	Slope (SE)
INTERCEP (red)	0.54	0.90	6.5 (1.5)	0.28 (0.024)
POINTFREQ	0.27	0.87	2.5 (0.17)	0.071 (0.007)
PCQ	−0.17	0.86	0.29 (0.013)	0.027 (0.003)
SMALREC	0.64	0.85	10.57 (3.15)	0.077 (0.008)
AOR	−0.10	0.84	0.47 (0.014)	0.014 (0.002)
INTERCEP (all)	0.51	0.84	6.51 (1.58)	0.11 (0.012)
CPD	0.29	0.82	7.28 (0.28)	−0.90 (0.11)
WQ	0.19	0.82	3.83 (0.12)	−0.24 (0.028)
CLOSIND	0.35	0.81	10.32 (0.45)	−1.38 (0.17)
SMALCIRC	1.00	0.76	88.32 (36.68)	0.47 (0.067)
NEARN	0.36	0.74	11.82 (0.69)	−1.68 (0.26)
INTERCEP (white)	0.53	0.71	8.55 (2.38)	0.22 (0.036)
STEPOINT	0.68	0.70	20.76 (7.78)	0.60 (0.10)
STUB	0.51	0.32	27.73 (1.59)	−0.092 (0.015)
STEMDEN	0.57	NA	27.04 (1.34)	NA

[a] INTERCEP (subset) = line-intercept method (sections of line used for analysis); POINTFREQ = point-frequency method; SMALREC = small-rectangular quadrat method; SMALCIRC = small-circular quadrat method; STEPOINT = modified step-point method; CLOSIND = closest-individual method; NEARN = nearest-neighbor method; CPD = corrected-point-distance method; PCQ = point-centered-quarter method; AOR = angle-order method; WQ = wandering-quarter method.
[b] The maximum-likelihood estimate of λ used for transformation following the Box–Cox procedure.

critical to successfully implement these methods. The more negative bias for CLOSIND, NEARN, CPD, and PCQ in field data than in simulations, where imperfect detectability and measurement error are nonexistent, suggests that imperfect detectability of rice seeds and measurement error in the field might cause the bias noted. Yet another potential mechanism that could cause bias in density estimates when using distance-based methods is the spatial dispersion of seeds. Some methods, such as CLOSIND and NEARN, assume a random dispersion pattern of objects. Although we used methods designed to correct for nonrandom dispersion patterns (CPD, AOR, and WQ), none of these performed well. Bias for CPD and AOR was large and in opposite directions for both simulated and field data. This discrepancy in the direction of bias might be caused by the dispersion pattern of rice seeds varying among samples, so that the

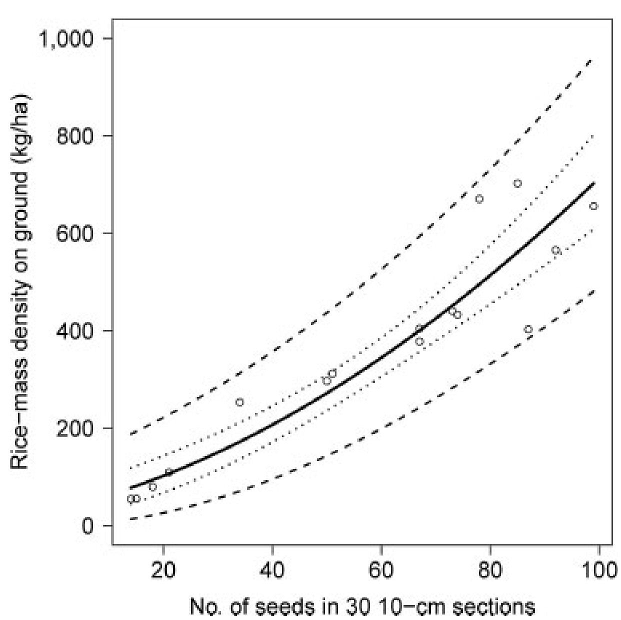

Figure 2. Relationship between the sums of seed counts in 30 10-cm red sections using INTERCEP (red sections of line) and rice-mass density on the ground in corresponding control plots in the Sacramento Valley, California, USA, September and October 2009. Circles represent individual simulations and corresponding density estimates using each experimental method. The solid line is the least-squares regression, interior finely dotted lines represent the 95% confidence interval for the line, and the outer dashed lines indicate the 95% prediction interval.

Table 5. Performance of field implementation of experimental methods for predicting rice-mass density on the ground based upon root mean squared error (RMSE) and mean error (Bias) in the Sacramento Valley, California, USA, in 2009. Methods are listed in order of increasing RMSE. * = Value significantly different from zero at $\alpha = 0.05$.

Experimental method[a]	RMSE	Bias
SMALREC	81.6	24.8
INTERCEP (red)	92.3	54.5
INTERCEP (all)	110.6	58.8
INTERCEP (white)	141.2	63.1
POINTFREQ	147.9	−78.7
CLOSIND	178.0	−87.8
PCQ	192.9	−77.4
SMALCIRC	245.2	133.9
NEARN	268.0	−150.8*
STEPOINT	338.9	229.4*
CPD	378.7	−322.8*
WQ	463.4	124.5
AOR	996.8	762.0*

[a] INTERCEP (subset) = line-intercept method (sections of line used for analysis); POINTFREQ = point-frequency method; SMALREC = small-rectangular quadrat method; SMALCIRC = small-circular quadrat method; STEPOINT = modified step-point method; CLOSIND = closest-individual method; NEARN = nearest-neighbor method; CPD = corrected-point-distance method; PCQ = point-centered-quarter method; AOR = angle-order method; WQ = wandering-quarter method.

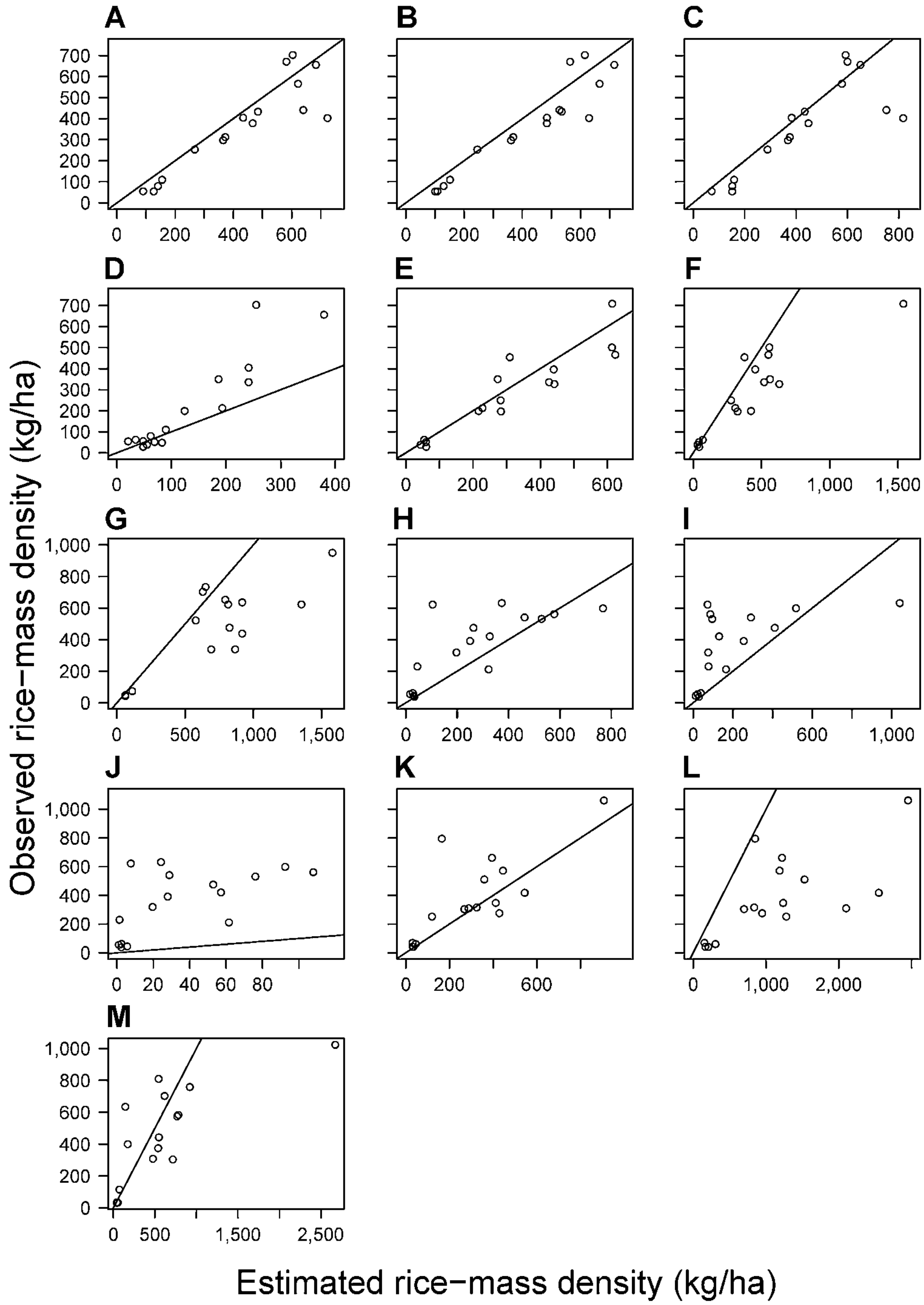

Figure 3. Estimated rice-mass density on the ground determined using experimental methods versus actual rice-mass density on the ground as determined in control plots in the Sacramento Valley, California, USA, September and October, 2009. Circles represent individual samples and corresponding density estimates using each experimental method. (A) INTERCEP = line-intercept (all sections of tape), (B) INTERCEP (red sections of tape), (C) INTERCEP (white sections of tape), (D) POINTFREQ = point-frequency, (E) SMALREC = small-rectangular frames, (F) SMALCIRC = small-circular frames, (G) STEPOINT = step-point, (H) CLOSIND = closest-individual, (I) NEARN = nearest-neighbor, (J) CPD = corrected-point-distance, (K) PCQ = point-centered-quarter, (L) AOR = angle-order, and (M) WQ = wandering-quarter. The line in each plot represents perfect correspondence between estimated and actual densities.

correction applied in the estimating equations was inappropriate in some instances. In the spirit of developing a rapid assessment method, however, applying different calculations for each sample was considered infeasible.

In general, we recommend using quadrat-based methods for estimating densities of rice. Because our goal was to determine rice seed densities, the most parsimonious method is to measure sample densities and convert these densities to the desired units. The high density of seeds, resulting in most quadrats of most sizes (except for POINTFREQ) containing ≥1 rice seed, is one reason quadrat-based methods perform well for determining seed densities. Provided that enough samples are collected and sampling is random, quadrat-based methods are relatively insensitive to the spatial dispersion

Table 6. Prior and posterior probabilities of models for predicting rice-mass density in straw in the Sacramento Valley, California, USA, in 2009. Models are listed in order of decreasing posterior probability.

Model	Prior probability	BIC[a]	Posterior probability
Ground density	0.25	−302.98	1.00
STUB	0.25	−253.19	0.00
Null	0.25	−235.43	0.00
STEMDEN	0.25	−231.07	0.00

[a] Bayesian Information Criterion.

Table 7. Prior and posterior probabilities of models examining the effect of time period (1985 vs. 2009) on the relationship between rice-mass density on the ground and rice-mass density in the straw in the Sacramento Valley, California, USA. Models are listed in order of decreasing posterior probability.

Model	Prior probability	BIC[a]	Posterior probability
Ground density	0.25	−213.15	0.71
Ground density + period	0.25	−211.15	0.26
Ground density × period	0.25	−206.77	0.03
Period	0.25	−149.35	0.00

[a] Bayesian Information Criterion.

pattern of seeds (Engeman et al. 1994). Although imperfect detectability can affect counts of seeds in quadrats, the small, well-defined search area that a quadrat provides helps to minimize errors of detection. Quadrat-based methods are also easy to implement in the field, provided that quadrats are not so large as to make counting seeds tedious and error-prone. The INTERCEP method meets this criterion. Distance-based methods are not without their merits, however. These methods are particularly useful for large, easy-to-detect objects that exist at low densities (Engeman et al. 1994, Ludwig and Reynolds 1988). In these situations, imperfect detectability is less problematic and establishing quadrats of a reasonable size, but large enough that most counts are nonzero, is impractical. It is for these situations, such as determining the density of trees or shrubs, that distance-based methods of estimating density were developed. For determining the density of small, difficult-to-detect objects occurring at high densities, however, we found that distance-based estimation of density was ineffective.

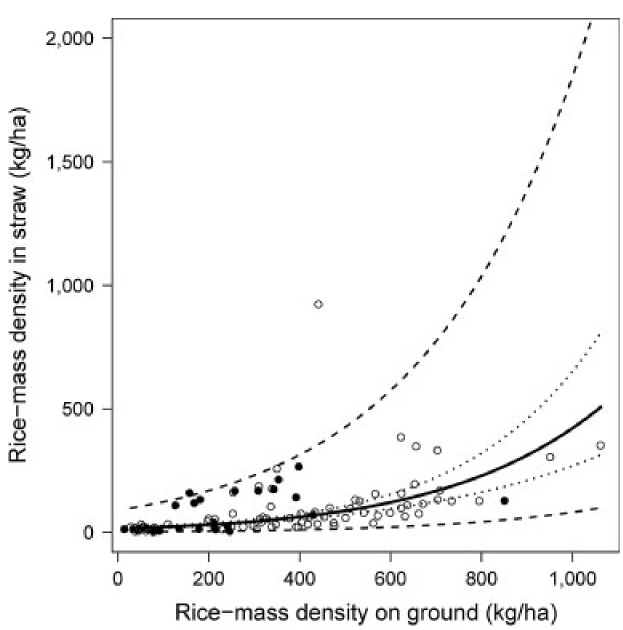

Figure 4. Estimated rice-mass density in the straw determined from control plots versus rice-mass density on the ground in the control plots in harvested rice fields in the Sacramento Valley, California, USA, September and October 2009 (circles), and in 1985 (black dots). The solid line is the least-squares regression, interior finely dotted lines represent the 95% confidence interval for the line, and the outer dashed lines indicate the 95% prediction interval.

Even with the use of quadrats, it might be desirable to use linear regression, rather than simple density conversions, to predict the mass density of rice based upon seed counts in quadrats. Unlike using simple scaling relationships, linear regression allows one to incorporate uncertainty in prediction into the estimated mass density. In particular, Bayesian analysis of the linear regression model would allow simple calculation of a posterior predictive distribution for rice mass density that properly accounts for propagation of error in prediction (Kéry 2010, Link and Barker 2010). Although multiple samples implemented in any chosen method will provide a measure of variance of the estimates, error in the predictive relationship itself, as might occur when trying to determine buffer distances for techniques like INTERCEP or POINTFREQ, is not accounted for by using simple scaling relationships.

Because our goal was to develop a rapid assessment method that could be completed in the field, we desired a way to quickly estimate not only the density of rice on the ground, which our methods were designed to measure, but also the amount of rice in the straw layer. The amount of rice seed remaining in straw is nonnegligible (Miller et al. 1989), and is also available as forage for waterfowl. Of the methods we tested, the density of rice seeds on the ground best predicted the density of rice seeds in the straw. The positive relationship between these 2 quantities can be used to predict the density of rice remaining in the straw. Quality of prediction, however, declines as rice density increases (Fig. 4).

Table 8. Time required to conduct one sample of each method in the field experiment, the number of samples required to detect 1% annual change over 10 yr in 95% of simulations and sampling at 5-yr intervals, and sampling time required per sampled year to achieve the required number of samples to detect the trend based upon data collected in the Sacramento Valley, California, USA, in 2009. Methods are presented in order of increasing total time required.

Method[a]	Min/sample (SE)[b]	No. of samples	Total time (hr)
CLOSIND[c]	7.5	1,210	150.4
INTERCEP (red)[d]	19.9	510	168.6
INTERCEP (white)[d]	19.9	550	181.8
STEPOINT	25.5 (4.9)[x,y]	790	335.8
INTERCEP (all)	39.7 (5.1)[w,x,y]	510	337.2
POINTFREQ	21.2 (2.6)[y,z]	1,050	370.1
NEARN[e]	15.0	2,150	537.2
CPD	22.4 (2.2)[y]	1,500	559.4
SMALREC	56.5 (5.3)[w]	740	696.8
AOR	55.9 (7.1)[w]	910	847.4
PCQ	55.9 (7.1)[w]	1,030	959.1
SMALCIRC	48.8 (4.7)[w]	1,220	991.25
WQ	44.2 (3.3)[w,x]	1,720	1,267.1
STEMDEN + STUB	7.1 (0.4)[z]	NA	NA

[a] INTERCEP (subset) = line-intercept method (sections of line used for analysis); POINTFREQ = point-frequency method; SMALREC = small-rectangular quadrat method; SMALCIRC = small-circular quadrat method; STEPOINT = modified step-point method; CLOSIND = closest-individual method; NEARN = nearest-neighbor method; CPD = corrected-point-distance method; PCQ = point-centered-quarter method; AOR = angle-order method; WQ = wandering-quarter method.
[b] Different superscripts placed on values represent statistically significant pairwise differences.
[c] Min/sample for CLOSIND = CPD/3.
[d] Min/sample for INTERCEP (red) and INTERCEP (white) = INTERCEP (all)/2.
[e] Min/sample for NEARN = CPD × 0.67.

Table 9. Method rankings for predicting rice densities in the field experiment according to R^2, root mean squared error (RMSE), bias, time, number of samples required, and total sampling time required, based upon field data from the Sacramento Valley, California, USA, in 2009. Low-ranking models perform better than high-ranking models (i.e., 1 is better than 10). Models are listed in order of increasing mean rank.

Method[a]	R^2	RMSE	Bias	Time	No. samples	Total time	Mean rank
INTERCEP (red)	1	2	2	3	1	2	1.8
INTERCEP (all)	6	3	3	8	1	5	4.3
INTERCEP (white)	12	4	4	3	3	3	4.8
POINTFREQ	2	5	6	5	8	6	5.3
SMALREC	4	1	1	13	4	9	5.3
CLOSIND	9	6	7	1	9	1	5.5
PCQ	3	7	5	11	7	11	7.3
STEPOINT	13	10	11	7	5	4	8.3
NEARN	11	9	10	2	13	7	8.7
CPD	7	11	12	6	11	8	9.2
AOR	5	13	13	11	6	10	9.7
SMALCIRC	10	8	9	10	10	12	9.8
WQ	8	12	8	9	12	13	10.3

[a] INTERCEP (subset) = line-intercept method (sections of line used for analysis); POINTFREQ = point-frequency method; SMALREC = small-rectangular quadrat method; CLOSIND = closest-individual method; PCQ = point-centered-quarter method; STEPOINT = modified step-point method; NEARN = nearest-neighbor method; CPD = corrected-point-distance method; AOR = angle-order method; SMALCIRC = small-circular quadrat method; WQ = wandering-quarter method.

Incorporating data from 1985 indicated that the relationship between the density of rice on the ground and the density of rice in the straw has remained similar through time. Although unchanged in nearly 25 yr, the relationship between the density of rice on the ground and the density of rice in the straw should be periodically evaluated to account for changes in harvester efficiency. A correction factor for rice remaining in straw is obviously unnecessary for fields in which straw has been baled, burned, or a stripper header used.

MANAGEMENT IMPLICATIONS

Based upon accuracy of estimation, time efficiency in the field, and overall cost-effectiveness, the best method for estimating the density of waste rice is the INTERCEP method. The time required by this method can be decreased by counting every other 10-cm section with no apparent loss of precision. The only method that had better accuracy (SMALREC) took 3 times longer to conduct in the field, required specialized equipment, and did not perform statistically better than INTERCEP. Where necessary, the density of rice seeds in straw can be calculated from the ground density using the provided equation, although this equation should be re-evaluated periodically. In general, we recommend that future studies employ INTERCEP to calculate rice seed densities because of its simple implementation and calculation, and relative robustness to imperfect detectability and varying dispersion patterns. Although we only tested methods to measure rice seed densities, we suspect that methods that performed well for rice seeds will also work well for other small, visible, easily counted seeds. To properly account for propagation of error, we recommend using linear regression, rather than simple scaling relationships, to predict the density of rice. This method provides a valuable tool for monitoring trends in rice harvester and harvest efficiencies, and for waterfowl managers to develop wetland restoration and rice-field enhancement goals for wintering waterfowl. Given millions of federal dollars being spent on subsidies, the habitat potential of agricultural easements, and need to identify key wildlife-friendly agricultural areas during periods of drought, these analyses are critical for managers to prepare viable field analyses for landscape-level conservation.

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