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Incentivizing Net Greenhouse Gas Emissions Reductions in Rice Production: The Case of Arkansas Rice

Nate Lyman and L. Lanier Nalley

U.S. rice industry producers face pressure from consumers, suppliers, and the government to reduce the greenhouse gas (GHG) emissions associated with rice (*Oryza sativa* L.) production. Arkansas rice cultivar-specific net GHG emissions information allows models of paddy rice emissions. Baseline levels of profit, yield variance, and GHG emissions are established using extension data. Varietal selection is then optimized to maximize profits and minimize GHG emissions, both constrained and unconstrained by baseline yield variance. Carbon abatement functions are estimated to examine the effects of hypothetical carbon prices on varietal selection.

Key Words: agricultural emissions, carbon abatement, carbon policy, greenhouse gas, rice

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Increased consumer demand for agricultural products with lower greenhouse gas (GHG) emissions and continued pressure from government have put pressure on row crop producers to reduce emissions associated with crop production. More importantly, agricultural producers face increasing demand from private industry to reduce GHG emissions associated with crop production. Wal-Mart has announced a potential plan to label each of its products with a sustainability rating and subsequently requested every Wal-Mart supplier provide its product's GHG footprint, a direct measure of climate impact (Wal-Mart Corporate–Sustainability Index, 2011). Timberland, Patagonia, and other companies already market products based on GHG footprint. In response to these pressures, agricultural producers and processors seek to increase production efficiency with respect to GHG emissions.

Rice production (from seed to farm gate) has been identified as a significant source of atmospheric methane (CH_4) emissions from U.S. agricultural production (U.S. Environmental Protection Agency, 2011). As a result, producers and large purchasers of U.S. rice have attempted to increase the GHG emissions efficiency of rice production. Since 2007, the California Rice Commission has worked with the Environmental Defense Fund (EDF) to reduce the CH_4 emissions associated with California rice production. Best management practices for GHG reduction developed by the partnership might allow California rice producers to participate in voluntary carbon offset markets. Offset generating practices include shorter duration winter floods, dry-seeding, and straw removal after harvest.

Nate Lyman is a research assistant, Department of Agricultural Economics and Agribusiness, University of Arkansas, Fayetteville, Arkansas. L. Lanier Nalley is an assistant professor of agricultural economics and agribusiness, Department of Agricultural Economics and Agribusiness, University of Arkansas, Fayetteville, Arkansas.

The EDF has since partnered with Arkansas-based Winrock International to extend the product to Arkansas (Bennett, 2011). Kellogg, a large purchaser of U.S. rice, is working with Louisiana rice producers to increase the sustainability of Kellogg's rice-based supply chain (Schultz, 2011). Mars, another major purchaser of U.S. rice, recently hired a rice scientist to assist Mars' sustainability effort (Mars, 2011). Increasing pressure on rice producers to reduce their GHG emissions will likely have significant implications for Arkansas, home to nearly half of U.S. rice production.

Recent research has estimated the effects of carbon policies on agricultural producer welfare, cropping patterns, and rice cultivar selection at the national and state levels (Beckman and Hertel, 2009; McCarl, 2007; Nalley et al., 2009; Outlaw et al., 2009; Reilly and Paltsev, 2009). However, a gap exists in the literature on potential emissions reduction policies and private sector incentive structures based on emissions differences across varieties. Varietal specific input (water, fertilizer, fungicides, etc.) requirements and sequestration potentials driven by yield potentials (Kim and McCarl, 2009) may increase the attractiveness of some cultivars to producers given incentives to reduce emissions. That is, an incentive from the private or public sector to decrease GHG emissions could change the optimal variety selection of a rice producer. Unlike changing production practices or adopting new technology, which is often costly and can bring on additional risk (Key and Sneeringer, 2011), changing rice varieties based on GHG emissions is something most producers could do seamlessly with little additional cost, assuming varieties associated with GHG reductions are equally profitable or producers are compensated for the reduction.

Nalley et al. (2009) developed an Arkansas rice varietal selection model rooted in financial portfolio theory. Slight modification of the Nalley et al. (2009) model allows estimation of the potential for emissions reduction through cultivar selection. Cultivar-specific emissions and sequestration data incorporated to the model allow selection informed or constrained by net GHG emissions. The advent of hybrid rice that yields 15–20% more per acre with equivalent or fewer inputs makes possible producer reduction of GHG emissions without sacrificing profitability. Comparison of cultivar selection for profit maximization, emissions minimization, and carbon price scenarios to the 2009 baseline adds an important dimension to the existing literature on agricultural emissions reduction policies and incentive structures.

Using county-level, cultivar-specific GHG emissions data for Arkansas rice production and augmenting the methodology of Nalley et al. (2009), this study investigates the potential for carbon abatement based on cultivar selection. Cultivar selection has been largely overlooked as a method of GHG emissions reduction, but inherent GHG emissions differences across cultivars resulting from cultivar-specific production practices might provide producers a relatively easy way to reduce emissions at the farm level. A three-step process illustrates the magnitude and potential implications of these differences. First, baseline profit, yield variance, and net GHG emissions levels are established using actual varietal distributions from four Arkansas counties in 2009. Second, cultivar selection is optimized to maximize profits. Third, cultivar selection is optimized to minimize net GHG emissions per acre. For both the profit maximization and net GHG emissions minimization scenarios, yield variance is first constrained to less than or equal to the baseline level to maintain constant realization of producer risk; and second, yield variance is unconstrained to examine the tradeoffs among risk, profits, and net GHG emissions. Finally, a GHG emissions abatement function is calculated by optimizing cultivar selection across a range of hypothetical carbon prices where producers generate offset credits by reducing net GHG emissions from the maximum profit scenario.

Carbon Policies

Proposed climate change policies include a "Cap-and-Trade" system, a carbon tax, mandated reductions, or some combination of these related yet distinct options. All of these options place a monetary value on GHG emissions in units of carbon equivalent (CE). Carbon equivalent allows quantification of GHGs in a universal metric and includes carbon (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride. A "Cap-and-Trade" system places a cap on GHG emissions in the form of mandated reductions over time. The Kyoto Protocol, an international treaty to reduce global GHG emissions, implements a Cap-and-Trade program. Emitters can buy the right to pollute, in the form of tons of CO_2 (carbon offsets), from operations that remove or sequester carbon from the atmosphere. Nalley and Barkley (2010) estimate the potential effects of such a program on the spatial distribution and net welfare of Arkansas agriculture. They find that a $30/ton CE offset payment would reduce Arkansas GHG emissions by 0.2% and would decrease Arkansas' net (emissions and sequestration) carbon footprint by 0.9%. To achieve these reductions, rice acreage would decrease by 0.6% and cotton, corn, and sorghum acreage would increase by 1.3%, 0.7%, and 22.2%, respectively. A carbon tax would impose a price and subsequent tax on per unit GHG emissions, either on overall emissions or above a set quota. Mandated reductions would impose a cap on GHG emissions using some enforcement mechanism, most likely a permit and inspection system as proposed by the U.S. Environmental Protection Agency (EPA).

As of January 2011, the EPA has the authority to regulate agricultural and industrial GHG emissions. Currently, agricultural GHG emissions are unregulated other than EPA regulation of traditional pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and lead. The EPA has proposed a reduction system that would mandate reductions using permits for entities emitting more than 100,000 tons of carbon dioxide-equivalent (CO_2e) per year such as solid waste landfills and large industrial manufacturers. Proposed regulations would not initially affect agriculture, but the EPA has reserved the right to begin regulation of entities which emit 50,000 tons of GHGs annually in April 2016. Although the proposed 50,000-ton permit would likely not affect individual rice producers, it may affect larger livestock and dairy operations. Additionally, large rice millers and parboliers may fall into the 50,000 tons of GHG emissions annually. Some rice millers such as Riceland Foods are producer-owned cooperatives. Regulation of such producer-owned cooperatives would likely decrease the welfare of the producer owners under such regulation. However, even if rice production (from seed to farm gate) avoids EPA regulation, some environmentalist critics of agricultural emissions argue for a pollution tax.

Lichtenberg (2004) argues that an agricultural pollution tax would be superior to a subsidy program (offsets) because it would make regulation "easier and more effective" (p. 31). He concludes that the price system remains the most efficient way of regulating pollution and imposes incentives for producers reflective of the impact of agriculture on the environment. Lichtenberg concludes, however, that agricultural pollution taxes face very difficult political and practical barriers: taxes are extremely unpopular politically; and, perhaps more importantly, it is very difficult to precisely quantify the level of pollution resulting from a single farmer's activities; therefore, imposition of a fair tax would be very difficult. Furthermore, taxes appear less likely than regulated offsets given the existence of voluntary offset markets both in the United States and European Union.

Voluntary offset markets have existed in the United States despite the lack of official climate change policy. Importantly, these markets offer opportunities for agricultural entities to buy and sell offsets. The Chicago Climate Exchange (CCX) is perhaps the most well-known U.S. offset market and offered offset opportunities for livestock and crop operations. To generate credits to sell on the CCX, farmers must commit to 5 years of continuous conservation tillage practices. Brye (2008) discusses the potential for Arkansas rice farmers to generate offsets on CCX and concludes that potential significant economic benefits exist because nearly 10% of Arkansas rice is produced using conservation tillage methods. Importantly, the relevance of offset credits to rice farmers depends almost entirely on the value of the offset credit. Brye uses $4/ton CO_2e to calculate the benefit of offsets to farmers, the value of an offset credit on the CCX at the time of his study. An exception would be a carbon tax with no provision for offsets. However, such a tax would likely be calculated in terms of tons CE per acre.

Existing and past climate exchanges as well as estimates by the EPA provide examples of carbon prices. At their peak, offset credits traded on the CCX for nearly \$10/mt CO_2e (roughly \$40/mt CE) on the European Climate Exchange, a regulated market, carbon offset permits trade for nearly \$20/mt CO_2e (roughly \$75/mt CE). The Montreal Climate Exchange currently allows agricultural offset credit generation under similar requirements as the Chicago Climate Exchange. September 2012 futures contracts on the Canadian market last closed at \$5/mt CO_2e (roughly \$20/mt CE). Lastly, the EPA had predicted a U.S. carbon price between \$10 and \$30/mt CO_2e (\$36–110/mt CE) if the Waxman-Markey bill had passed (US EPA, 2011).

Portfolio Theory

Traditional portfolio theory, as developed by Markowitz (1959) and Tobin (1958) with extensions by Lintner (1965) and Sharpe (1970) focuses on financial investments. A "portfolio" is defined as a combination of items: securities, assets, or other objects of interest. Portfolio theory derives efficient outcomes through identification of a set of actions or choices that minimize variance for a given level of expected returns or maximize expected returns given a level of variance. Decision-makers can use the efficient outcomes to find expected utility-maximizing solutions to a broad class of problems in investment, finance, and resource allocation (Robinson and Brake, 1979).

Applied to agricultural production, portfolio theory provides producers a tool for varietal selection and planting decisions. Robinson and Brake (1979) thoroughly review the applications of portfolio theory to agriculture and agricultural finance. Redmond and Cubbage (1988) apply the capital asset pricing model to timber asset investments in the United States. Figge (2004) summarizes the literature on applications of portfolio theory to biodiversity and Sanchirico, Smith, and Lipton (2005) use portfolio theory to develop optimal management of fisheries. Nyikal and Kosura (2005) use quadratic programming to solve for the efficient mean-variance frontier to better understand farming decisions in Kenyan agriculture.

More recently, Nalley and Barkley (2010) implement portfolio theory to estimate wheat yield stability in Mexico. Nalley et al. (2009) show that unique rice varieties allow rice producers to allocate money across investment opportunities, each with varying relative risks and yields. Rice varieties respond differently to environmental conditions (climatic, pests, and agronomic) and therefore varietal performance (yield) and risk are likely correlated. Positive and negative correlations exist at both strong and weak levels across rice varieties. For example, given a set of environmental conditions, certain combinations of varieties will result in the highest expected yield. Arkansas agricultural extension services recommend diversity in seed selection. The University of Arkansas Extension Service advises, "seeding a large percentage of acreage to a single cultivar is not recommended. Planting several varieties minimizes the risk of damage from adverse weather and disease epidemics and allows for a timely harvest which increases the chance of obtaining good quality seed with maximum milling yields" (Slaton, Moldenhauer, and Gibbons, 2001, p. 16). However, such extension services do not offer advice based on historical structural interactions between varieties. Nalley et al. (2009) develop a portfolio model for rice varietal selection and show the potential for significant increases in profits.

As mentioned, multiple studies estimate the potential impact of carbon policy on national cropping patterns and Nalley and Barkley (2010) find that potential carbon policy could change cropping patterns within Arkansas. These studies use life cycle assessments for carbon emissions and carbon sequestered at the crop and county level. Only a small body of research exists on carbon policy at the varietal level. Ridgewell et al. (2009) suggest that selecting different varieties of the same crop species to maximize solar radiation reflexivity could cool the planet, for which producers could potentially receive carbon credits. McFadden, Nalley, and Popp (2011) calculate carbon emissions and sequestration for a selection of the most popular long and medium grain rice varieties grown in Arkansas. Because each of the 14 rice varieties in the McFadden, Nalley, and Popp (2011) study are genetically different, they each contain different biotic and abiotic resistance packages. That is, some varieties are resistant to blast (a common fungus in rice) and thus do not need to be sprayed with a fungicide, whereas others lack resistance. The authors then calculated the CE difference between varieties based on the CE in the active ingredient in the fungicide as well as the CE of the fuel used to spray for blast. Nitrogen (N) fertilizer requirements also differ across varieties because of genetic differences in N uptake efficiencies. Emissions from fertilizer application are estimated using the standard 1% N_2O loss from N fertilizer found in Smith et al. (2007) and include emissions associated with N fertilizer production.

Methods

This study updates the Nalley et al. (2009) portfolio model to include varietal-specific, net GHG emissions (CE) estimates found in McFadden, Nalley, and Popp (2011). The revised model can optimize varietal selection given yield, profit, emissions, or risk objectives.

Absent a carbon policy, let producer profit per acre (π) equal total returns less costs. Let total returns per acre be defined as a function of the return to planting a portfolio of varieties ($\boldsymbol{x'R}$) where $\boldsymbol{x}$ and $\boldsymbol{R}$ are (n $\times$ 1) vectors of portfolio weights and returns, respectively. Elements of the returns vector, $R_i = p_i Y_i$ for $i = 1, \ldots, n$, where p_i is the price ($/bu) of variety i and $Y_i \sim N(\mu_i, \sigma_i^2)$ is the yield (bu/ac) of variety i. Total cost per acre is then $\boldsymbol{x'C}$ where $\boldsymbol{C}$ is the (n $\times$ 1) vector of static costs for each variety i for i = 1, . . ., n. Expected profit is

$$(1)\qquad \begin{aligned} E(\pi) &= E(\boldsymbol{x'R} - \boldsymbol{x'C}) \\ &= \boldsymbol{x'}E(\boldsymbol{R}) - \boldsymbol{x'C} \\ &= \boldsymbol{x'}\mu_{\boldsymbol{R}} - \boldsymbol{x'C}. \end{aligned}$$

Holding constant price and costs, portfolio yield variance equals

$$(2)\qquad \begin{aligned} \sigma_Y^2 &= \mathrm{var}(\boldsymbol{x'Y} - \boldsymbol{x'C}) \\ &= \mathrm{var}(\boldsymbol{x'Y}) \\ &= \boldsymbol{x'}\Sigma\boldsymbol{x}. \end{aligned}$$

where $\boldsymbol{\Sigma}$ is the (n $\times$ n) covariance matrix of Y. Let $\boldsymbol{x}_{bk}$ represent the baseline portfolio in county k, where $\boldsymbol{x}_{bki}$ equals the ratio of harvested acres of variety i to total harvested rice acres in county k.[1]. Substitution of $\boldsymbol{x}_b$ in equations (1) and (2) gives baseline expected profit ($E(\pi)_b$) and variance $\left(\sigma_{\pi b}^2\right)$.

Rice producers choose $\boldsymbol{x}$ that maximizes expected profit:

$$(3)\qquad \max_x E(\pi) = \boldsymbol{x'}\mu_{\boldsymbol{R}} - \boldsymbol{x'C},$$

subject to:

$$(4)\qquad \boldsymbol{x'1} = \boldsymbol{1},$$

$$(5)\qquad x_i \geq 0\,\forall\, i = 1, \ldots, n,$$

$$(6)\qquad \sigma_Y^2 = \boldsymbol{x'}\Sigma\boldsymbol{x} \leq \varphi,$$

Equations (4) and (5) ensure the portfolio weights sum to one and are nonnegative. Equation (6) sets an exogenous target yield variance φ, where $0 < \varphi < \infty$. Additionally, we constrain the percentage of medium-grain cultivars selected to the 2009 baseline level for each county to avoid shifts from long- to medium-grain production, which is unfeasible because most, if not all, Arkansas medium-grain rice is grown on contract. Selection of Clearfield® and hybrid Clearfield® cultivars is constrained to the baseline level in each county to simulate producer adherence to Clearfield® seed technology best management practices and location-specific response to weed outbreaks necessitating the Clearfield® technology.[2]

Net GHG emissions (Γ) from a given portfolio are given by $\boldsymbol{x'\gamma}$ where $\boldsymbol{\gamma}$ is the (n $\times$ 1) vector of county-specific net GHG emissions per acre associated with each cultivar (listed in

[1] County subscripts (k) will hereafter be suppressed for notational clarity. Independent analyses are carried out for each county; thus, the subscript is of little statistical or notational significance in describing the methodology.

[2] Clearfield® rice cultivars allow producers to control an invasive week known as red rice (*oryza punctata*), a relative of commercial rice. The effectiveness of Clearfield® seed technology relies on the genetic resistance to the Newpath® herbicide. Clearfield® stewardship instructions advise against consecutive seeding of cultivars with the Clearfield® trait to avoid herbicide-resistant weeds.

Table 1. Greenhouse Gas Sequestration and Emissions (tCO_2e/acre) by Cultivar

		Emissions		Net
	Sequestration[a]	$CO_2 + N_2O$	CH_4	Emissions
Bengal	1.15	1.32	2.26	2.43
Cheniere	1.10	1.32	2.40	2.62
CL151	1.24	1.24	2.22	2.21
CL171-AR	1.03	1.30	2.40	2.67
CL181-AR	1.08	1.30	2.40	2.62
CLXL729	1.39	1.18	2.63	2.43
CLXL745	1.38	1.32	2.43	2.36
Cocodrie	1.14	1.32	2.44	2.62
Francis	1.21	1.32	2.29	2.40
Jupiter	1.31	1.32	2.37	2.38
Taggart	1.06	1.32	2.55	2.81
Templeton	1.07	1.23	2.55	2.72
Wells	1.14	1.32	2.40	2.58
XL723	1.29	1.18	2.63	2.53

[a] Average sequestration (tCO_2e/ac) across Arkansas, Desha, Mississippi, and St. Francis Counties where sequestration is a function of county-specific yield.

Table 1). Given $\boldsymbol{\gamma}$, the net GHG emissions minimization function is:

$$(7)\qquad \max_{x}\ \Gamma = \boldsymbol{x}'\boldsymbol{\gamma}$$

subject to (4), (5), (6), and

$$E(\pi) \geq \Pi,$$

where Π is target expected profit.

Let $\boldsymbol{x}^*$ be the vector of weights that maximizes equation (3) and Γ^* be the net GHG emissions associated with the profit-maximizing portfolio of cultivars. Assuming producers are eligible for offset credit generation based on net GHG reductions from an initial portfolio of profit-maximizing cultivars, the producer faces the following maximization problem:

$$(9)\qquad \max_{x}\ E(\pi) = \boldsymbol{x}'\mu_{\boldsymbol{R}} - \boldsymbol{x}'\boldsymbol{C} + p_c(\Gamma^* - \boldsymbol{x}'\boldsymbol{\gamma}),$$

where the difference $\Gamma^* - \boldsymbol{x}'\boldsymbol{\gamma}$ represents the reduction in net GHG emissions from the profit-maximizing level and p_c represents the price of carbon ($/t). Maximization of equation (9) is subjected to the constraints listed previously.

Assuming a producer's objective is to choose the optimal allocation of rice cultivars to plant and has X total acres dedicated solely to rice. Quadratic programming is used to solve for the efficiency frontier of mean-variance combinations. This frontier is defined as the maximum expected profit as a function of mean yield, returns and costs for a given (or target) level of variance, or conversely, the minimum variation for a given (or target) profit using a portfolio of rice varieties. This is of importance if a producer wants to create a portfolio of varieties to achieve a net emissions outcome that results in the same yield risk and/or profitability as the baseline program. The inclusion of the covariance across elements of a portfolio is imperative for efficient diversification as a means of hedging against risk and or between policies (Heady, 1952; Markowitz, 1959). Inclusion of varietal yield covariance allows the model to hedge risk in a similar fashion because the covariance between varieties in the same location picks up historical susceptibility for location-specific weather, pest, and disease events.

Hazell and Norton (1986) explained that the intuition behind the constraint in equation (6) is total farm variance for all acres (rice cultivars) planted $\left(\sigma_Y^2\right)$ is an aggregate of the variability of individual cultivars and covariance relationships between the cultivars. The authors drew two important conclusions on diversifying crop cultivar selection: first, "combinations of varieties that have negative covariate yields will result in a more stable aggregate yield for the entire farm than specialized strategies of planting single cultivar"; and second, "a cultivar that is risky in terms of its own yield variance may still be attractive if its returns are negatively covariate with yields of other varieties planted" (p. 81).

Data

Arkansas Rice Performance Trials (ARPT) test plot data from 2008–2010 is used to estimate this model. The ARPT data consist of four university-run experiment stations: Pine Tree (St. Francis County), Stuttgart (Arkansas County), Rowher (Desha County), and Keiser (Mississippi County). Although a gap exists between experimental and actual yields, Brennan (1984) notes, "the only reliable sources of relative yields are cultivar trials" (p. 182). Therefore, annual changes in relative yields are measured with performance test data. Cultural practices vary somewhat across ARPT locations, but overall the trials are conducted under conditions for high yield. Data on conventional, hybrid, Clearfield®, and Clearfield® hybrid varieties are used in this study.

Significant production and yield differences exist among conventional, Clearfield®, hybrid, and Clearfield® hybrid rice varieties. A discussion of these differences helps explain the data used in this study as well as the gap between producer and portfolio varietal selection. Clearfield® rice varieties allow producers to control an invasive weed known as red rice (*Oryza punctata*), a relative of commercial rice. Given the close relation of red rice to commercial rice, herbicides that kill red rice also kill non-Clearfield® commercial rice. Clearfield® seed technology, however, allows producers to spray a herbicide (Newpath®) that kills only red rice. Hybrid rice combines admirable traits from multiple cultivars to produce a single cultivar through hybrid vigor and often a disease-resistant cultivar. Hybrid seed, unlike conventional, is only useful in its first generation. That is, producers must purchase the hybrid seeds each year to receive the hybrid vigor benefits. Clearfield® hybrid varieties are hybrids produced with the Clearfield® technology. Clearfield® hybrid technology combines the yield advantage of hybrids with the Newpath®-resistant trait of Clearfield® cultivars. The benefits of Clearfield™, hybrid, and Clearfield™ hybrid cultivars are not without their costs. As shown previously, planting (production) and costs of these nonconventional cultivars are relatively high.

Cultivars for which McFadden, Nalley, and Popp (2011) provide estimated carbon emissions and sequestration per acre have been chosen for this analysis. Prices (P_i) of \$8.28/bu and \$5.21/bu for medium and long grain rough rice, respectively, are used to calculate expected returns. Costs of production for conventional, Clearfield™, and hybrid varieties are available from the University of Arkansas Cooperative Extension Service. Average costs (C_i) per acre are calculated as \$780 for conventional (university-released lines), \$825 for hybrid, \$844 for Clearfield®, and \$877 for Clearfield® hybrid.

Table 1 presents cultivar-specific CO_2e sequestration and emissions (tCO_2e/ac). Carbon emissions estimates per acre by location and by cultivar are taken from McFadden, Nalley, and Popp (2011). Unlike McFadden, Nalley, and Popp (2011), this study includes methane emissions values based on Rogers et al. (2012). Cultivar-specific methane emissions expressed in CO_2e are derived using the daily methane flux observed in Rogers et al. (2012) adjusted for cultivar-specific growth parameters including flood length, growth rate, and biomass accumulation based on the recommendations of Brye (2012). Cultivar-specific parameters are based on the preliminary results of the follow-up to Rogers et al. (2012) in which cultivar-specific methane fluxes are observed. Inclusion of methane emissions is paramount in this study because methane accounts for between 63% and 69% of GHG emissions from seed to farm gate.

Results and Discussion

As shown in Table 2, substantial differences exist among yield, profit, and net emissions across the baseline, profit-maximizing, and net emissions-minimizing scenarios. The baseline distribution represents what actually happened in 2009 in each county. Producer profitability in this scenario ranges between \$65.9/ac and

Table 2. Yield, Returns, and Emissions Estimates for Baseline, Profit-maximizing (maxΠ), and Net Emissions-minimizing (minΓ) Portfolios with Constrained[a] Yield Variance

	Arkansas			Desha			Mississippi[b]			St. Francis		
	Baseline	MaxΠ	MinΓ	Baseline	MaxΠ	MinΓ	Baseline	MaxΠ	MinΓ	Baseline	MaxΠ	MinΓ
Yield (bu/ac)	189	201	186	142	162	155	174	195	195	168	172	167
$\hat{\sigma}_{\text{Yield}}$(bu/ac)	6	6	6	4	4	4	14	12	12	5	5	5
Profit ($/ac)	332	391	312	66	196	153	235	352	337	284	306	279
Net emissions (tCO_2e/ac)	2.47	2.48	2.42	2.72	2.70	2.60	2.56	2.35	2.34	2.47	2.48	2.43
Cultivar Selection (%)												
Bengal	2	—	8	5	—	14	—	—	—	1	—	3
Cheneire	6	—	2	12	3	—	—	—	—	5	4	—
CL151	11	—	22	—	—	—	—	—	—	—	—	—
CL 171-AR	2	—	9	—	—	—	6	—	—	6	—	9
CL 181-AR	4	—	—	7	—	—	6	—	—	1	—	—
CL XL729	9	31	—	20	—	5	2	16	16	3	—	—
CL XL745	6	—	—	6	—	—	2	—	—	—	11	—
Cocodrie	1	—	—	7	—	2	6	—	—	1	—	—
Francis	30	21	46	7	3	32	—	80	84	15	—	30
Jupiter	6	8	—	9	14	—	3	4	—	20	22	19
Taggart	4	—	—	7	34	—	6	—	—	1	—	—
Templeton	4	—	—	7	3	—	6	—	—	1	—	—
Wells	13	27	9	8	—	13	57	—	—	43	59	40
XL723	4	13	5	7	43	33	6	—	—	1	5	—

[a] Yield risk ($\hat{\sigma}_{\text{Yield}}$) is constrained to less than or equal to its baseline level.
[b] Yield risk ($\hat{\sigma}_{\text{Yield}}$) associated with the profit-maximizing and net GHG emissions-minimizing solutions is less than the baseline level, meaning the yield risk constraint for this county is not binding.

\$332/ac in Desha and Arkansas Counties, respectively. Net emissions in the baseline range between 2.47 tCO_2e/ac in Arkansas and St. Francis Counties and 2.72 tCO_2e in Desha County. Yield risk in the baseline scenario is highest in Mississippi County ($\hat{\sigma}_Y = 14\,\text{bu/ac}$) and lowest in Desha County ($\hat{\sigma}_Y = 4.3\,\text{bu/ac}$). Table 2 compares the baseline cultivar portfolio with the profit-maximizing (maxΠ) and net GHG emissions-minimizing (minΓ) portfolios with yield variance constrained to less than or equal to baseline levels. Table 3 presents the comparison among scenarios with unconstrained yield variance. Scenarios are run with constrained and unconstrained variance to highlight the potential profitability gains if a producer is willing to accept additional yield risk. Absent a carbon policy, risk-return frontiers are developed to highlight the relationship between yield risk and net returns (Figure 1). Carbon abatement functions are then presented in Figures 2 and 3 for carbon prices between \$1/tCO_2e and \$30/ tCO_2e for both constrained and unconstrained yield variances, respectively.

Profit Maximization

Table 2 presents expected yield, yield risk, net returns, and net GHG emissions for the baseline, maxΠ, and minΓ scenarios with yield risk in the latter constrained to baseline levels. Net returns increase between 8% and 197% in the profit-maximizing scenario relative to the baseline. The large disparities between the profit-maximizing solution and the baseline in Desha and Mississippi Counties are likely the result of differences between farm and experimental yields over the sample period. The yield difference between maxΠ and the baseline resulting from shifts from relatively low-yielding cultivars in each county drives the increase in producer profitability. Yield risk in Mississippi County is lower in the maxΠ scenario than in the baseline. Across stations, the maxΠ portfolio consists of more hybrid and hybrid Clearfield® cultivars than the baseline. Additionally, maxΠ portfolios are much more concentrated than in the baseline. In Mississippi County, for example, Francis and CL XL729 make up 96% of the maxΠ portfolio.

Net GHG emissions in the maxΠ scenario decrease by 1.4% and 8.3% in Desha and Mississippi Counties, respectively, from the baseline level. These decreases in the maxΠ scenario are important to the specification of a carbon abatement function because carbon offset policy is defined relative to a benchmark or "business as usual" level (CCX). For this reason, this study defines the benchmark net GHG emissions level from which reductions generate carbon offset credits as those associated with the maxΠ portfolio of cultivars. Otherwise, as illustrated in Table 2, producers could receive offset credits for doing something that would be in their best interest without an offset payment.

Table 3 presents the profit-maximizing portfolios when yield risk is not constrained to the baseline level. Unconstrained by baseline yield risk, the profit-maximizing selection of cultivars concentrates on high-yielding long grains and high-priced medium grains. Arkansas County shifts to 61% hybrid, 31% hybrid Clearfield®, and 8% medium grain, completely abandoning conventional cultivars. Desha County, however, shifts to 86% Taggart, a conventional long-grain cultivar, and 14% Jupiter. The profit-maximizing solution in Mississippi does not change because the yield risk associated with the profit-maximizing portfolio of cultivars is less than baseline risk. St. Francis County also shifts toward Taggart but retains 29% hybrid Clearfield® and 11% medium grain (Table 3). In Arkansas, Desha, and St. Francis Counties, the yield risk associated with the profit-maximizing yields increase between 100% and 450% from the baseline levels. Whether producers would accept this increased risk associated with the higher expected returns is beyond the scope of this analysis. Net GHG emissions associated with the maxΠ solutions not subject to yield risk constraints increase from the baseline in Arkansas, Desha, and St. Francis Counties by between 1% and 8%. Again, the solution for Mississippi County has not changed from the yield risk constrained maxΠ scenario.

Figure 1 presents the yield risk-return frontiers for the four counties included in this study. The frontiers are presented in terms of percentage change in yield risk ($\hat{\sigma}_Y$) and profits

Table 3. Yield, Returns, and Emissions Estimates for Baseline, Profit-maximizing (maxΠ), and Net Emissions-minimizing (minΓ) Portfolios with Unconstrained Yield Variance

	Arkansas			Desha			Mississippi[a]			St. Francis		
	Baseline	MaxΠ	MinΓ	Baseline	MaxΠ	MinΓ	Baseline	MaxΠ	MinΓ	Baseline	MaxΠ	MinΓ
Yield (bu/ac)	189	216	190	142	167	158	174	195	195	168	177	169
$\hat{\sigma}_{\text{Yield}}$ (bu/ac)	37	25	10	19	24	22	14	12	12	28	11	18
Profit ($/ac)	332	456	345	66	240	139	235	352	337	284	333	202
Net emissions (tCO_2e/ac)	2.47	2.49	2.34	2.72	2.74	2.44	2.56	2.35	2.34	2.47	2.66	2.24
				Cultivar Selection (%)								
Bengal	2	—	—	5	—	—	—	—	—	1	—	—
Cheneire	6	—	—	12	—	—	—	—	—	5	—	—
CL151	11	—	31	—	—	—	—	—	—	—	—	—
CL 171-AR	2	—	—	—	—	—	6	—	—	6	—	—
CL 181-AR	4	—	—	7	—	—	6	—	—	1	—	—
CL XL729	9	31	—	20	—	—	2	16	16	3	11	—
CL XL745	6	—	—	6	—	—	2	—	—	—	—	—
Cocodrie	1	—	—	7	—	—	6	—	—	1	—	—
Francis	30	—	61	7	—	100	—	80	84	15	—	100
Jupiter	6	8	8	9	14	—	3	4	—	20	22	—
Taggart	4	—	—	7	86	—	6	—	—	1	68	—
Templeton	4	—	—	7	—	—	6	—	—	1	—	—
Wells	13	—	—	8	—	—	57	—	—	43	—	—
XL723	4	61	—	7	—	—	6	—	—	1	—	—

[a] Estimates for Mississippi County are identical to those presented in Table 2 because the yield variance constraint was nonbinding in that analysis.

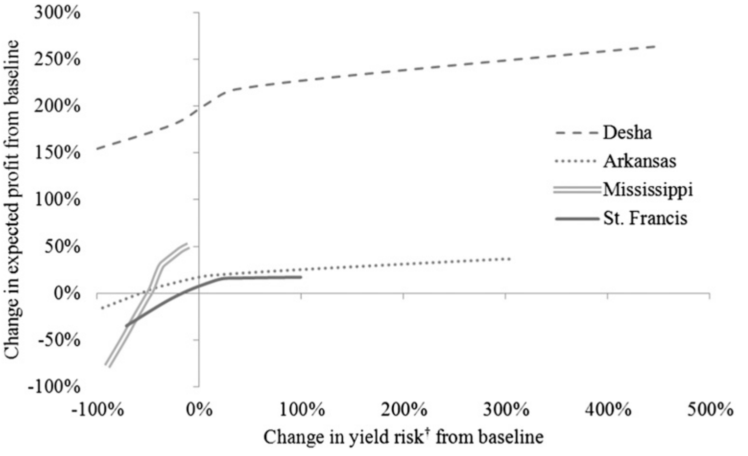

Figure 1. Risk-return Frontiers Relative to the Baseline (*Changes in yield risk and expected profits are presented relative to the baseline to highlight the relationship between yield risk and expected profits in a way comparable across stations. For example, segments of the frontiers in the upper-left quadrant imply a potential to increase profit and reduce yield risk simultaneously, where segments in the lower-left quadrant illustrate the risk-return tradeoff. †The frontiers represent the profit-maximizing solutions with yield variance first minimized and incrementally increased to the unconstrained yield variance associated with the profit maximizing solution.)

($/ac) from the baseline scenario. This method outlines frontiers similar in shape to those common in financial models over the range [min $\hat{\sigma}_Y$, max $\hat{\sigma}_Y$]. Mississippi and Desha Counties stand out in this analysis; the former because the entire frontier lies left of the vertical axis and the latter because of the dramatic increases in producer profitability relative to the baseline.

Arkansas plays a relatively small role in world rice price determination and for that reason, the price effects given estimated changes in yield are assumed nonexistent. Previous research on the effects of carbon policy on Arkansas agriculture uses similar reasoning to justify constant prices given a 12% reduction in statewide rice acreage (Nalley, Popp, and Fortin, 2011). Extension of this analysis to the entire U.S. rice

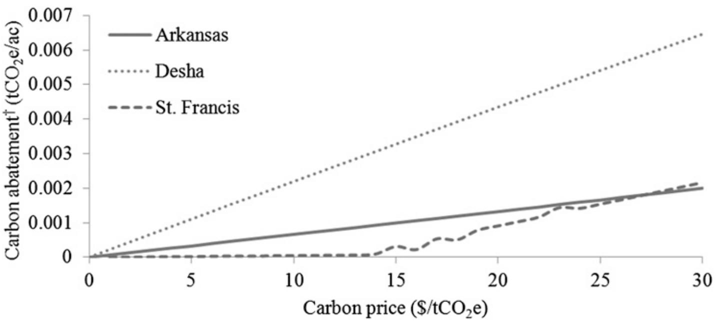

Figure 2. Carbon Abatement Functions under Constrained Yield Variance Profit Maximization (*Yield variance is constrained to the yield variance associated with the baseline estimates for profit maximization given carbon prices (p_c) between $1/t$CO_2$e and $30/t$CO_2$e. †Carbon abatement is calculated as the difference between net greenhouse gas (GHG) emissions at the profit-maximizing solution given a carbon price and the net GHG emissions at the profit-maximizing solution absent a carbon policy.)

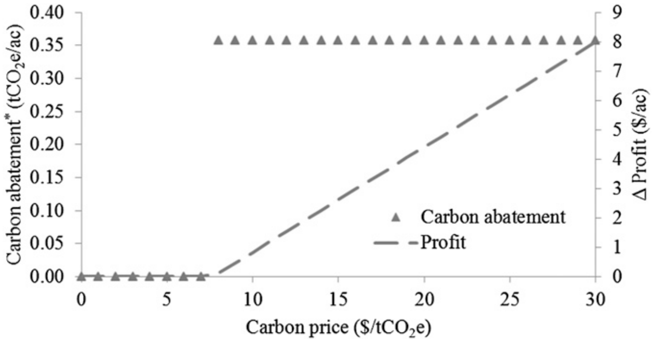

Figure 3. Carbon Abatement Function for St. Francis County under Unconstrained Yield Variance Profit Maximization (*Carbon abatement is calculated as the difference between net greenhouse gas [GHG] emissions at the profit-maximizing solution given a carbon price and the net GHG emissions at the profit-maximizing solution absent a carbon policy.)

industry would justify a more in-depth look at potential price effects.

Net Greenhouse Gas Emissions Minimization

Although minimizing net GHG emissions (minΓ) does not constitute a sensible carbon policy, it provides an empirical lower bound for cultivar selection-driven emissions reductions (Table 2). The difference between the net GHG emissions associated with the maxΠ and minΓ scenarios represents the maximum potential reduction in emissions to sell for offset credits. Relative to the baseline, minΓ reduces emissions between 0.05 tCO_2e/ac (1.9%) and 0.22 tCO_2e/ac (8.6%) in St. Francis and Mississippi Counties, respectively, with yield risk held constant at the baseline level. Yield risk held constant, profits in the minΓ scenario decrease slightly in Arkansas and St. Francis Counties but increase dramatically in Desha (132%) and Mississippi (43%). Profits decrease in Arkansas and St. Francis Counties because the cultivars associated with the least GHG emissions have lower yield potential than those capable of maximizing net returns.

Removal of the yield risk constraint increases the net GHG emissions reductions across counties with the exception of Mississippi County, which remains unaffected by the constraint's removal. Net GHG emissions reduction potential increases from between 1.9% and 8.6% in minΓ constrained by baseline yield risk to between 5% (0.13 tCO_2e/ac) and 11% (0.28 tCO_2e/ac) in the minΓ scenario unconstrained by baseline yield risk. As net GHG emissions decline, producer profits increase relative to the baseline in Arkansas, Desha, and Mississippi Counties (Table 3). Under constrained yield risk, producer profits declined in Arkansas County, whereas the relaxation of that constraint allows selection of greater proportions of cultivars with moderately high yield potential and low GHG emissions. In St. Francis and Desha Counties, the portfolio unconstrained by yield risk consists of only Francis (Table 3). The minimized net GHG emissions, both constrained and unconstrained, provide reference points for the effectiveness of carbon-offset payments discussed in the following section.

Carbon Abatement Function

Figure 2 illustrates the carbon abatement functions for Arkansas, Desha, and St. Francis Counties based on the constrained yield risk profit maximization problem described in equation (9). This study has illustrated the abatement function over the range of internationally observed carbon prices between \$1/tCO_2e and \$30/tCO_2e. Desha County exhibits the most elastic response over this range of carbon prices and Mississippi County does not at all respond. Despite the relatively elastic response of Desha County, a \$30/tCO_2e carbon price is associated with only 0.007 tCO_2e/ac abatement. At this price, abatement in Arkansas and St. Francis Counties is roughly 0.002 tCO_2e/ac. The carbon abatement function associated with St. Francis County is nonlinear between \$14/tCO_2e and \$24/tCO_2e because the model trades yield increases and emissions reduction between these levels, where a decrease in abatement indicates that at the increased price, the profit-maximizing solution contained slightly higher yielding, higher emitting cultivars and an increase in abatement indicates the model selects lower yielding cultivars with relatively less emissions, benefitting from the carbon price. The downward-sloping sections of the abatement function represent those points where, given a carbon price increase, a larger proportion of the higher yielding, higher emitting cultivar maximizes profits.

Context is critical to interpretation of these figures. Carbon offsets are sold in contracts of 1,000 tCO_2e, so one contract at \$30/tCO_2e would gross \$30,000 before transaction costs. This means producers must aggregate 1000 tCO_2e to participate in the offset market. This is impossible given abatement rates between 0.002 tCO_2e/ac and 0.007 tCO_2e/ac. There are simply not enough acres of rice in Arkansas, Desha, and St. Francis Counties for the producers to aggregate the acreage required to participate in the offset markets. At 0.007 tCO_2e/ac, Desha County producers would have to aggregate 1000/0.007 = 142,857 acres to sell one contract. Desha producers harvested only 34,600 acres of rice in 2009 (Wilson, Runsick, and Mazzanti, 2010). Cultivar selection would have to be bundled with other GHG abatement practices, perhaps similar to the California program (Bennett, 2011).

Removal of the yield risk constraint dramatically changes this result. Figure 3 illustrates the carbon abatement function for St. Francis County, the only county in this study that reduces net GHG emissions from the profit-maximizing level given carbon prices above \$8/tCO_2e. Changes in profitability as the carbon price increases are also illustrated in Figure 3. At \$8/tCO_2e, the profit-maximizing portfolio of cultivars includes Francis instead of Taggart because Francis emits 0.36 tCO_2e less per acre. The switch increases yield risk by 20% and leads to 0.36 tCO_2e per acre carbon abatement. Producers would need to aggregate 1000/0.36 = 2778 acres to participate in the offset market at this rate. Carbon prices between \$8/tCO_2e and \$30/tCO_2e would increase producer profitability but would not lead to additional carbon abatement (Figure 3).

Conclusion

Rice production in the United States has experienced increased demand from private industry to reduce GHG emissions associated with rice production. This study investigates the potential for carbon abatement based on cultivar selection. Carbon abatement potential is estimated with constrained and unconstrained yield variance to explore the relationship between abatement potential and yield risk.

The results of the three scenarios and calculation of carbon abatement functions calculated in this study offer conclusions relevant to rice industry interests. Relative to the 2009 baseline, minimizing GHG emissions increases producer profits in two of four counties. Environmentally and economically beneficial outcomes are thus profitable without carbon abatement payments for these producers. Cultivar selection for profit maximization increases significantly producer profits under constrained and unconstrained yield risk, consistent with Nalley and Barkley (2010).

This study's relevance depends on how political and market regulators treat emissions and sequestration from rice paddies in the United States. Policy rewarding environmentally efficient cultivar selection may have the ability to reduce emissions, but extremely large payments required and inability of producers to aggregate enough acres to sell offset credits makes the success of such policies and programs highly unlikely under the current framework. The likely high transaction costs might induce formation of a third-party firm specializing in organization of producer cultivar selection over a large enough area to generate carbon offset permits. Incorporation of additional, practices-based offset generation mechanisms would likely increase the volume of abated carbon and the potential gains from linking cultivar selection with these alternate mechanisms would build on this analysis.

Implications of this study for future research stem primarily from the assumptions used in building the cultivar selection model. The assumption of constant market prices for rice and carbon offsets precludes any discussion of carbon abatement response to price dynamics. Schneider and McCarl (2006) show the assumption of constant prices inflates abatement potential estimates. Inflated abatement potential would not likely change the already limited estimated potential for carbon abatement by cultivar selection found in this study but could play a larger role if cultivar selection were incorporated into a larger framework of carbon abatement mechanisms. The use of static cultivar-specific net greenhouse gas emissions precludes a stochastic analysis of carbon abatement potential likely necessary for integration of cultivar selection into the wider framework of offset credit generation. Experimental generation of more data on cultivar-specific GHG emissions will allow future studies to incorporate GHG emissions uncertainty to stochastic analyses of carbon abatement.

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