How Greenhouse Gas Emission Policy and Industry Pressure Could Affect Producer Selection of Rice Cultivars

Brandon R. McFadden, L. Lanier Nalley, and Michael P. Popp

This study estimates how potential carbon policies targeted at reduction of greenhouse gas (GHG) emissions could affect selection of rice cultivars by conducting a life cycle assessment of GHG emissions and estimating the carbon sequestered for fourteen commonly sown rice cultivars across Arkansas. Market-oriented carbon-offset credits based on additionality likely would be insufficient to convince producers to change cultivars; nonetheless, there may be upstream pressure as food retailers strive to lower their overall carbon footprints. Given their higher yield per unit of GHG emission, hybrid rice cultivars appear to be positioned to respond to industry demand.

Key Words: additionality, cap and trade, carbon offset, carbon policy, rice

The pressure to reduce carbon emissions is increasing in the face of pending government policies and industry demand for suppliers of agricultural commodities to decrease their overall greenhouse gas (GHG) emissions. Rice production (from seed to farm gate) has been identified as a significant source of atmospheric methane (CH_4) emissions from agricultural production in the United States (Environmental Protection Agency (EPA) 2011). As a result, both producer groups and large purchasers of U.S. rice are attempting to decrease GHG emissions and increase the GHG-emission efficiency of rice production. In 2007, the California Rice Commission (CRC), working with the Environmental Defense Fund (EDF), began efforts in California to reduce emissions of GHG in general and CH_4 emissions associated with rice production in particular. That effort generated a list of best management practices to reduce CH_4 emissions that are being reviewed by the American Carbon Registry and the Verified Carbon Standard. Once the best management practices are verified, California producers who use them would be allowed to participate in voluntary carbon offset markets. Practices under review that could generate carbon-offset credits include shorter durations of winter flooding, dry seeding (instead of water sowing) of rice seed, and removal of rice straw following harvest rather than burning the stubble. Upon receipt of a $1.1 million grant from the U.S. Department of Agriculture (USDA) in June 2010, the EDF partnered with

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Brandon McFadden is a Ph.D. student in the Department of Agricultural Economics at Oklahoma State University. L. Lanier Nalley is an assistant professor and Michael Popp is a professor in the Department of Agricultural Economics at University of Arkansas. Corresponding Author: *Brandon McFadden ▪ Department of Agricultural Economics ▪ 423 Ag Hall ▪ Oklahoma State University ▪ Stillwater, OK 74078 ▪ Phone 479.420.5662 ▪ Email brandon.mcfadden@okstate.edu*.

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Arkansas-based Winrock International to extend the California project to Arkansas and rice-producing states in the mid-southern United States (Bennett 2011).

Regardless of the development of carbon offset markets, food processors and retailers are striving to reduce their overall carbon footprints in an effort to capture the "green" market and consequently are looking to agricultural producers for assistance. The Kellogg's company (2010) conducted a recent carbon footprint assessment that indicated that more than half of its products' carbon emissions are attributable to production of the ingredients. Consequently, reductions in carbon emissions prior to the farm gate are important (Kellogg's 2010), and the company is working with Louisiana rice producers on various pilot programs aimed at increasing sustainable production methods for rice destined for use in its products. Mars, another major buyer of U.S. rice, recently hired a leading global rice expert to guide its sustainability efforts.[1] Wal-Mart is developing a sustainability index to create a more transparent supply chain and provide customers with information to assess products from a sustainability standpoint (Wal-Mart 2010). The sustainability index may accelerate adoption of GHG-emission-reducing practices by suppliers to Wal-Mart and increase demand throughout the supply chain, which includes production agriculture, for reductions in carbon emissions.

Given the numerous efforts to reduce carbon emissions, we estimate net carbon footprints (GHG emissions minus carbon sequestration) associated with production of fourteen of the most commonly sown rice cultivars at six locations in the major rice-growing areas of Arkansas to determine differences in carbon emissions. We examine conventional, Clearfield®, and hybrid cultivars. Producers, millers, and buyers can benefit from the resulting information about GHG emissions associated with various cultivars as they analyze the effects of potential carbon offset policies or respond to changes in demand for "green" products by determining potential yields and costs of production associated with switching to least-net-emitting cultivars. If cultivars with fewer emissions have similar lodging and disease-resistant properties but are less profitable and/or produce smaller yields, one can determine the carbon price needed to induce producers to choose the lower-emitting cultivars. Assessing the likelihood of cultivar changes with and without a carbon incentive, however, also has important global implications for humanitarian efforts. Rice is the most important food crop in the low-income world and is the staple food of more than three billion people, more than half of the world's population (International Rice Research Initiative (IRRI) 2011). Rice provides 21 percent of human energy per capita worldwide and 15 percent of per capita protein. Price and supply shocks could be induced by a carbon policy that results in smaller yields in favor of reduced GHG emissions. As such, the carbon policy would have a significant impact on low-income countries. In 2008, rice prices tripled, and the World Bank estimated that an additional 100 million people were pushed into poverty (IRRI 2011). In 2009, 10.2 percent of global rice exports were provided by the United States (Childs and Baldwin 2010) and nearly half of that was supplied by Arkansas. Therefore, the effects of a GHG-reduction policy could ripple across the world since a small supply shock can

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[1] See the Mars company website at *www.mars.com/global/news-and-media/press-releases/news-releases.aspx?SiteId=94&Id=2822* for full information.

have a large effect globally. Also, since rice is the largest GHG-emitting crop in the United States, rice acreage could decline if a GHG policy is implemented.

We thus examine ways to reduce GHG emissions through cultivar selection to determine if GHG-emission reductions can be obtained without pressuring total production. Our analysis is based on differences in GHG emissions per acre from cultivar-specific input requirements across types of rice (Clearfield, conventional, and hybrid) produced in six counties in Arkansas that involve unique production requirements.

Literature Review

Several studies have examined the potential role and economic feasibility of U.S. agriculture in mitigating GHG emissions. McCarl and Schneider (2000) suggested that agriculture could provide a way to reduce GHG emissions until future technologies can capture, trap, or otherwise reduce carbon. They argued that, with carbon prices below $100 per ton, agriculture has a comparative advantage in offering GHG emission reductions. Further, Schneider, McCarl, and Schmid (2007) suggested that reduced tillage and fertilization would be prevalent GHG reduction strategies when carbon prices are low and that idling of land would commence at higher carbon prices as a way to avoid GHG emissions from input use and soil.

Cross-Commodity versus Within-Commodity Effects

While there have been many studies on the impact of a carbon policy on national crop patterns (Reilly and Paltsev 2009, Outlaw et al. 2009, Beckman, Hertel, and Tyner 2009, McCarl 2007) and studies that estimated crop changes in Arkansas (Nalley, Popp, and Fortin 2011, Nalley and Popp 2010, Popp et al. 2011), few studies have looked at how carbon policies affect cultivar selection within a crop. Ridgwell et al. (2009) suggested that selecting cultivars within a crop species to maximize solar radiation reflexivity could cool the planet and that producers could potentially receive carbon credits. However, there has been relatively little analysis of how cultivar selection could be altered by a carbon policy. Nalley et al. (2012) analyzed tradeoffs in regional cotton production practices. Nalley, Popp, and Fortin (2011) estimated that GHG emissions associated with rice production in Arkansas are four times greater than for corn, the next highest emitter and the next most profitable crop. However, since rice is the most profitable crop choice in Arkansas, a high carbon price would be needed for producers to change from rice to corn. Therefore, if some form of carbon legislation were passed, producers likely would continue to grow rice rather than switch crops and would want to lower GHG emissions from rice production by either modifying cultivars or changing production practices.

GHG Emission Drivers across Production Practices

Research has shown that management practices have a significant effect on the GHGs emitted by rice production. Changsheng et al. (2004) examined effects of crop rotation, midseason drainage, tillage, straw amendment, percent of above-ground crop residue incorporated, and fertilizer type on carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) emissions. Only crop rotation and the percent of above-ground crop residue incorporated into the soil had notable impacts on net CO_2 emissions. However, Changsheng et al. (2005) found that switching from continuous flooding to midseason drainage reduced CO_2 emissions. In that study, fertilizer type was the only management practice that did not have a significant effect on CH_4 emissions but played a major role in CO_2 emissions. All of the management practices considered had some influence on N_2O emissions but none was as substantial as water management. These studies alerted producers to GHG emission differences in practices associated with managing rice production but did not address potential emission differences related to rice cultivars. The cultivars chosen are important because the production practices and input requirements for various rice cultivars (Clearfield, hybrid, and conventional) are different. Those variations in practices and inputs generate unique amounts of GHG emission per acre and per bushel of rice. Given recent introduction and adoption of hybrid rice in the mid-southern United States, implementation of a carbon policy may further motivate adoption of embedded seed technologies. Embedded seeds can generate input-use efficiencies that concomitantly increase producer profits and environmental benefits through reductions in GHG emissions because hybrid rice can yield 15–20 percent more than conventional cultivars under the same growing conditions and with roughly the same inputs.

Market-based GHG Reduction Using Additionality

The concept of additionality, included as a clean development mechanism (CDM) in Article 12 of the Kyoto Protocol (United Nations Framework Convention on Climate Change 2008), provides credits for carbon emission reductions (CERs) that are additional to others that can be given (Post et al. 2004). For example, a producer could undertake carbon-sequestering activities but continue to have the same level of GHG emissions. In that case, the producer could not be rewarded with credits for sequestration but could receive offset credits if the net carbon footprint (emissions minus sequestration) was smaller. So there is an opportunity for an additionality project when a producer is sowing a cultivar that does not have the smallest net carbon footprint. The producer could choose to switch to a lower-emitting cultivar and thus earn a CER credit based on the cultivar's net emission difference. Whether a producer will switch then becomes a function of the size of the CER, the price of carbon, and cultivar-related differences in production costs.[2]

Data and Methods

Life Cycle Assessment and Life Cycle Inventory

A life cycle analysis evaluates production processes, analyzes options for innovation, and improves understanding of the complex factors that influence sustainability in agricultural production systems. Broadly, a life cycle analysis consists of four stages: (i) defining the goal and scope; (ii) conducting a life cycle inventory (collection of data needed to perform the necessary calculations); (iii) performing an impact assessment; and (iv) analyzing and interpreting the

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[2] For example, assuming that producers choose among available and proven production practices, to date, little profit incentive has existed to use alternative, GHG-reducing production practices like center pivot irrigation and furrow irrigation or other such production practices that would conserve irrigation water and thereby reduce GHG emissions.

results. The structure of a life cycle analysis is determined by its purpose, and the scope of the analysis can be as broad as "all material and energy inputs and outputs of a process or product" or "GHG use in production of a crop." The scale of the purpose defines the scale of the analysis. Our purpose is to quantify and compare differences in GHG emissions and net GHG emissions per acre and per bushel of rice when producers sow various cultivars under the same environmental conditions.

We apply a life cycle inventory to direct and indirect GHG emissions associated with paddy rice production. Direct emissions are those that come from on-farm operations. Examples are CO_2 emissions from diesel used by tractors and irrigation equipment. Indirect emissions are generated off-farm from the manufacture of inputs used on the farm. GHGs emitted from natural gas used to produce commercial fertilizer are one such indirect source. Excluded from this study are embedded carbon emissions from upstream production of equipment and tools used on the farm for agricultural production and any GHG emissions that may occur beyond the farm gate. N_2O from applications of nitrogen (N) fertilizer are a large contributor to GHG emissions (Bouwman 1996, Smith, McTaggart, and Tsuruta 1997, Yanai et al. 2003, Del Grosso et al. 2005, Snyder et al. 2009) so we included N fertilizer application levels in our estimates. Methane emissions, which come from anaerobic decomposition of organic matter during flooding, are the largest contributor to total GHG emissions in paddy rice production. During flooding, methane is released mainly through plants; flooding of the fields prevents the soil from releasing it to the atmosphere. The emitted quantity of methane in paddy rice directly depends on two factors: the amount of above-ground dry matter and the number of days on flood with the latter varying by rice variety. Methane emissions increase as the rice plant grows, reach a peak, and then decrease as the plant nears the harvesting stage. Varieties that remain under flood longer release a greater quantity of methane. Typically, a spike in methane emission is noted four days after drainage regardless of the rice variety. This phenomenon is thought to occur because flooding is no longer a barrier to direct methane emission from soil to the atmosphere and is constant for each variety. EPA (2011) published quantities of methane emitted and acres harvested for rice cultivation in Arkansas for 2005 through 2009. We derived average methane emissions per acre from that data and further divided by the average days on flood for all 83 varieties of rice grown in Arkansas to obtain methane emissions per acre per day on flood as a function of the number of days on flood required by each cultivar.

Carbon Emission Calculations

Carbon Equivalent Values. Given the multiple GHGs associated with global warming, we converted each to its carbon equivalent (CE) to obtain a "carbon footprint," a process that stems from a rich engineering literature on carbon equivalence. Estimates by EPA (2007, 2009) of CE emissions for diesel fuel combustion were used (Table 1), and EcoInvent's life cycle inventory database through SimaPro (2009) was used to calculate upstream emissions from production of diesel. Values provided by Lal (2004), a synthesis of numerous studies measuring carbon emissions from farm operations, provided all other inputs (see Table 1). While the CE of one pound of urea produced at a specific location is nearly constant, the emission from an application of that nitrogen

Table 1. Carbon Equivalent Emission Factors by Input

Input	Carbon Equivalent	Source
Diesel	7.01 pounds C/gallon	EPA 2007, 2009; SimaPro 2009
Fertilizer		
Nitrogen	1.30 pounds C/lbs	Lal 2004
Nitrogen N_2O	2.18 pounds C/lbs	Del Grosso et al. 2005
Phosphate	0.20 pounds C/lbs	Lal 2004
Potash	0.16 pounds C/lbs	Lal 2004
Herbicide	6.44 pounds C/pint	Lal 2004
Insecticide	5.44 pounds C/pint	Lal 2004
Fungicide	5.44 pounds C/pint	Lal 2004

fertilizer is not. N_2O emissions are a function of location, temperature, soil conditions, and weather. Consequently, we obtained location-specific (state of Arkansas) N_2O emissions from the DayCent Century model (Del Grosso et al. 2005).

Input Use. The University of Arkansas Cooperative Extension Service (UACES) annually estimates the cost of major production methods associated with rice (UACES 2008). We disaggregated those costs to meet cultivar-specific input requirements so that we could represent the cost of production for Arkansas' fourteen commonly produced rice cultivars.

Recommended application rates for cultivar-specific nitrogen fertilizer ranging from 120 to 150 pounds per acre are shown in Table 2.[3] Diesel usage was calculated by summing the amount of fuel required for the cultivar-specific amount of irrigation, fungicide application, fertilizer application (via crop duster), pesticide application, and herbicide application as well as standard fuel usage for planting and harvesting equipment. Information on irrigation use by cultivar, which was expressed in acre-inches (the volume of water (27,154 U.S. gallons) required to apply water one inch deep across an acre of land), was provided by UACES and ranged from 30 acre-inches for conventional and hybrid cultivars to 36 acre-inches for Clearfield cultivars. Clearfield cultivars require more water due to their susceptibility to blast, a fungus that can be mitigated with deeper flooding. Clearfield cultivars (CL151, CL171, and CL181) also require the greatest average use of fuel (Table 2), not only because of elevated irrigation requirements but also because additional fungicide applications are needed to contain both blast and sheath blight, another common rice fungus. However, the three Clearfield lines require the least amount of herbicide per acre since producers can use the herbicide Newpath for efficient control of red rice (see Table 2). Red rice is a persistent problem in the Southeast and was estimated to be present in 60 percent of all rice acres in Arkansas in 2010 (Shivrain et al. 2010). Its dark kernel color requires costly separation during the milling process. Red rice also has a genetic structure that is nearly identical to

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[3] These figures represent the total amount applied—early (preflood) and mid-season applications. These are the amounts recommended for silt loam soils following a soybean rotation, which was the most prevalent practice in 2009 at 68 percent of the rice acres (Norman and Moldenhauer 2009).

Table 2. Average Per-acre Input Requirements by Cultivar on Silt Loam Soils

Cultivar	**Nitrogen**[a] *pounds per acre*	**Fungicide**[b] *pints per acre*	**Herbicide** *pints per acre*	**Diesel**[c d] *gallons per acre*	**Irrigation** *inches per acre*	**Days on Flood**
			Conventional			
Wells	150	0.29	6.76	46.29	30.66	85
Francis	150	0.37	6.76	46.33	30.66	85
Bengal	150	0.15	6.76	46.20	30.66	90
Jupiter	150	0.37	6.76	46.33	30.66	82
Cocodrie	150	0.35	6.76	46.32	30.66	90
Cheniere	150	0.40	6.76	46.35	30.66	86
Taggart	150	0.21	6.76	46.24	30.66	88
Templeton	135	0.14	6.76	46.19	30.66	88
			Clearfield			
CL151	120	1.20	2.56	53.73	36.80	82
CL171	135	1.03	2.56	53.63	36.80	85
CL181	135	0.99	2.56	53.61	36.80	85
			Hybrid			
XL723	120	0.08	6.76	46.06	30.66	83
XL729	120	0.08	6.76	46.06	30.66	82
XL745	150	0.14	6.76	46.09	30.66	77

[a] Sum of preflood and midseason nitrogen applications at nitrogen rate recommended for rice planted following soybeans.

[b] Sum of fungicide used to mitigate blast, sheath blight, and smut.

[c] Sum of diesel used in tractors, crop dusters, and diesel irrigation pumps.

[d] Assumes a required 1.022 gallons of diesel to raise an acre inch of water.

that of commercial rice so no previous herbicide was able to control it without also damaging or killing the conventional rice.

The hybrid cultivars examined in this study (XL723, XL729, and XL745), all released by Rice-Tec (a private seed company), require the least amount of fungicide and thus less fuel because they are resistant to blast and only moderately susceptible to sheath blight. Two of the hybrid cultivars, XL729 and XL745, contain the Clearfield trait but the Clearfield cultivars (CL151, CL171, and CL181) are not hybrids. Hybrids are first-generation (F_1) seeds of a cross of two genetically dissimilar parents. Yields from hybrids exceed yields from the best inbred cultivar grown under similar conditions by 15–20 percent because of hybrid vigor, enhanced function resulting from genetic contributions of genetically dissimilar parents (Virmani et al. 2003). Since the offspring of a hybrid (the second or F_2 generation) generally does not perform as well as its parents (F_1), producers must purchase F_1 seeds for each growing season. Hybrid seeds are difficult and expensive to produce so cost the most of the three types of rice—approximately $88 per acre compared to $42 per acre for Clearfield and $18 per acre for conventional cultivars in 2009.

Using the CEs from Table 1 and the recommended input usages for each of the fourteen cultivars, we estimated GHG emission per acre for each cultivar by location using a method similar to the one in Nalley, Popp, and Fortin (2011). In addition, we included an assumption that water for irrigation that was diesel-pumped from a depth of 100 feet required 1.022 gallons of diesel to raise one acre-inch of water irrespective of the cultivar chosen (Slaton 2001).[4]

Total Carbon Footprint versus GHG Efficiency

While the CE per acre is an important measure, particularly as a baseline against which to compare changes over time from potential carbon policies, the CE emitted per bushel of rice is a more comprehensive measure when comparing impacts of production choices across space and time with respect to the efficiency of GHG-reduction strategies. While carbon offsets focus more on GHG emission per acre, buyers of rice—such as food processors and retailers—will be more interested in GHG emission per bushel of rice so they can market the differences accordingly.

Modeling Uncertainty in Input Use

Quantitative uncertainty analysis is not new to environmental life cycle assessments, but it has not been widely adopted (Lloyd and Ries 2007). The assumption that producers use the exact recommendations set forth in UACES's enterprise budgets, which are developed for an "average" growing season, is naive. Producers may, for example, apply more nitrogen than recommended as insurance against nitrogen deficiency (Babcock 1992). Consequently, the amount and type of resources used varies for a given year and field, and it is impossible to monitor the resource use of every rice producer in Arkansas. This combination has led researchers to use simulations to estimate resource use. Huijbregts et al. (2001) argued that Monte Carlo simulation was a promising approach for dealing with data inaccuracies in life cycle inventories. To account for variation in recommended and actual use of inputs, the authors asked rice experts from University of Arkansas (and a soil chemist in the case of nitrogen) to estimate minimum and maximum levels of input application by cultivar since they would be familiar with how yields across cultivars are affected by nitrogen. A range of input use was thus created for each cultivar to cope with variability in disease damage, pests, and agronomic and climate conditions from year to year via Monte Carlo simulations.

To quantify the GHG emissions associated with mitigating blast, we translated the meaning of the rather broad terms provided by UACES to describe a cultivar—susceptible, moderately susceptible, resistant, and moderately resistant—into rates of fungicide application across cultivars. Several University of Arkansas plant pathologists were consulted regarding the probability of producers applying Quadris®, a fungicide used to mitigate blast, for each of the rice cultivars included in our study. In this sense, the probability of a disease outbreak was associated with the genetic level of blast tolerance possessed by each cultivar. Table 3 illustrates how the fourteen cultivars and associated probabilities of requiring one or two Quadris treatments were classified in

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[4] This calculation assumes 75 percent pump efficiency and 5 percent drive loss. Aquifer depth is assumed to be equivalent for all of the counties in the study.

Table 3. Genetic Blast Tolerance by Cultivar and Respective Probabilities of Quadris Applications

Cultivar	Blast Susceptibility Rating[a]	Probability (percent) of One Quadris Application[b]			Probability (percent) of Two Quadris Applications		
		Min.	Mean	Max.	Min.	Mean	Max.
			Conventional				
Wells	Susceptible	1	5	10	0	2	5
Francis	Very susceptible	5	15	25	1	10	20
Bengal	Susceptible	1	5	15	0	2	5
Jupiter	Susceptible	—	—	—	—	—	—
Cocodrie	Resistant	0	0	0	0	0	0
Cheniere	Susceptible	2	5	10	0	0	0
Taggart	Susceptible	1	6	15	0	2	5
Templeton	Resistant	0	0	0	0	0	0
			Clearfield				
CL151	Very susceptible	10	25	40	5	20	35
CL171	Moderately susceptible	0	0.5	1	0	0	0
CL181	Moderately susceptible	0	0.5	1	0	0	0
			Hybrid				
XL723	Resistant	0	0	0	0	0	0
XL729	Resistant	0	0	0	0	0	0
XL745	Resistant	0	0	0	0	0	0

[a] Susceptibility ratings provided by UACES (2010).

[b] Probabilities were obtained from University of Arkansas plant pathologists. Probabilities of a second Quadris application are always lower than a first application since these probabilities are based on having made a first Quadris application. However, Quadris applications do not affect the likelihood of other fungicide or irrigation ranges.

mitigating a blast outbreak. These probabilities allow for estimation of the quantity of Quadris required in an average growing year by cultivar and the estimated amount of fuel required to apply it via crop dusting.[5] Thus, a cultivar-specific GHG-emission probability density function could be approximated for mitigation of blast for each cultivar. As shown in Table 3, hybrid cultivars are more blast resistant than conventional and Clearfield cultivars and hence emit less GHGs per acre. Table 3 also illustrates differences within the conventional cultivars with respect to blast resistance. We used the same methodology to calculate the GHG emissions associated with mitigating sheath blight and smut (both fungi) by cultivar. Table 4 shows the mean, range, and simulated values used in our model for applications of fertilizer, fungicides, herbicides, pesticides, and water and how input use varies by cultivar.

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[5] Since crop dusting planes vary in engine size and nozzle type, we surveyed individuals from three crop dusting companies regarding their fuel use by acre and used that information to simulate fuel use per acre using a triangular distribution.

Table 4. Ranges and Modeled Values for Input Usage per Acre by Cultivar

Input	Min.	Mean	Max.	Modeled Value[a]
Fertilizer (lb/acre) by Cultivar				
Wells / Francis / Bengal / Jupiter / Cocodrie / Cheniere / Taggart / XL745	142.50	150	172.50	155
Templeton / CL171 / CL181	128.25	135	155.25	139.50
CL151 / XL723 / XL729	114	120	138	124
Fuel (gallon/acre) for Aerial Applications of Chemicals				
Crop duster	0.32	0.50	0.60	0.47
Fungicide (pints per acre)	Varies by reported cultivar susceptibility to blast, sheath blight, and smut			
Herbicide (pints per acre)[b]				
2, 4-D	0	0.20	2.50	0.90
Aim EC	0	1.50	8.80	3.43
Beyond	0	5.00	6.00	3.37
Command	0	0.80	1.60	0.80
Facet	0	0.25	0.67	0.31
Permit	0	1.00	1.30	0.78
Propanil	0	6.00	8.10	4.71
Newpath	0	8.00	12.00	6.67
Insecticide (pints pre acre)	0.025	0.10	0.35	0.16
Number of Applications per Acre by Crop Duster				
Fertilizer	2.00	2.10	2.70	2.27
Fungicide	Varies by cultivar			
Herbicide	1.00	1.50	2.00	1.50

[a] Values were estimated using a triangular distribution and represent the average of 5,000 simulations.
[b] Herbicide use varies by cultivar per UACES (2010).

To summarize, each cultivar has a mean carbon footprint as well as an estimated probability density function. Given the lack of annual data on input applications by variety, the estimated probability density function for each input could not be verified. Therefore, we set the probability of the amount of inputs used falling outside the maximum and minimum levels established by UACES to zero using a triangular probability density function. Additionally, given the complexities associated with input use (most notably for nitrogen fertilizer) and the correlation between disease pressure (which, for blast, is a function of humidity and nitrogen use) and yields, we modeled the input use ranges independently. Nonetheless, the triangular distributions describe skewness in input use and serve as expert-opinion-based measures of input use variability. Simulations of input use were performed using @Risk software (Palisade Corporation 2009) with Latin hypercube sampling and 5,000 iterations.

Carbon Sequestration Calculations

Above-ground and Below-ground Biomass Estimations. As in Popp et al. (2011) and using a methodology similar to Prince et al. (2001), we can estimate pounds of carbon sequestered from above-ground biomass (AGB_{ij}) per acre for rice cultivar *j* in test plot *i* by

$$AGB_{ij} = \left[\left(Y_{ij} \cdot \lambda_j \cdot (1 - \alpha_j) \right) \cdot \left(\frac{1}{H_j} - 1 \right) \cdot \beta_j \cdot \delta \cdot \eta \right] \tag{1}$$

where Y_{ij} represents experiment plot yields in bushels per acre, λ_j converts yields to pounds per acre, α_j is the moisture content of the grain harvested so that the yields can be converted to dry matter yields, H_j is the harvest index, β_j is the estimated carbon content of the above-ground biomass, δ is the estimated proportion of above-ground biomass incorporated into the soil as a function of conventional tillage, and η is the estimated fraction of plant residue that is in contact with and sequestered in the soil.[6] Note that all of the above-ground residue (rice straw) is assumed to have been left on the field and not burned.

Pounds of carbon sequestered from below-ground biomass (BGB_{ij}) per acre for rice cultivar *j* on test plot *i* can be estimated by

$$BGB_{ij} = \left[\chi_j \cdot \eta \cdot \left(\frac{\varphi_j \cdot \left[Y_{ij} \cdot \lambda_j \cdot \left(1 - \alpha_j \right) \right]}{H_j} \right) \right] \tag{2}$$

where χ_j is the carbon content of the below-ground biomass and ϕ_j is the shoot-to-root ratio; the other variables are defined as in (1). Total carbon sequestration (S_{ij}) per acre for cultivar *j* in test plot *i* under conventional tillage on primarily silt loam soils thus can be estimated by

$$S_{ij} = \left(AGB_{ij} + BGB_{ij} \right) \cdot \xi \tag{3}$$

where ξ is a soil factor that adjusts the carbon sequestration potential based on soil texture (Popp et al. 2011).[7] We modeled harvest indices, root-to-shoot ratios, and the carbon content of the above-ground and below-ground biomasses and estimated the amount of crop residue incorporated into the soil through conventional tillage using methods similar to Popp et al. (2011). Crop residue incorporation was estimated at 70 percent (δ) with 40 percent (η) of the carbon contained in the above-ground and below-ground biomasses potentially sequestered in the soil. Finally, since the texture of silt loam soils limits their ability to sequester carbon, we estimate that only 70 percent (ξ) of potentially sequesterable carbon remains in the soil with the remainder escaping into the atmosphere (Brye 2010). The per-acre averages of sources of GHG emissions, total emissions, and total sequestration for each cultivar are shown in Table 5.

Yields. We collected yield data for 1997 through 2009 (UACES 2010) for each cultivar from Arkansas Rice Performance Trial (ARPT) test plots at six

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[6] The harvest index is the ratio of dry matter yield to total dry matter produced above-ground. Per the UACES budgets, conventional tillage was used in the estimations.

[7] We chose the soil factor for silt loam because the majority of rice produced in Arkansas is grown in that type of soil.

Table 5. Average Carbon Emission and Sequestration per Acre by Cultivar and Inputs on Silt Loam Soils across the Six ARPT Test Plots

	Carbon Equivalent Emissions (lbs/ac)						
Cultivar	**Diesel**[a]	**Fungicide, Herbicide & Pesticide**	**Fertilizer**[b]	**N_2O**[c]	**CH_4**[d]	**Total Emissions (lb CE/ac)**	**Total Sequestration (lb CE/ac)**
			Conventional				
Wells	324	45	228	338	1,087	2,022	746
Francis	325	45	228	338	1,080	2,015	779
Bengal	324	44	228	338	1,113	2,047	715
Jupiter	325	45	228	338	1,084	2,020	775
Cocodrie	325	45	228	338	1,106	2,042	678
Cheniere	325	45	228	338	1,079	2,015	707
Taggart	324	44	228	338	1,132	2,067	654
Templeton	311	44	208	304	1,133	2,000	610
			Clearfield				
CL151	377	23	187	270	1,060	1,918	625
CL171	376	22	208	304	1,090	2,000	590
CL181	376	22	208	304	1,093	2,003	585
			Hybrid				
XL723	323	44	187	270	1,056	1,881	808
XL729	323	44	187	270	1,057	1,881	785
XL745	323	44	228	338	1,001	1,934	665

[a] Sum of diesel used for tractors and for irrigation applied.
[b] Sum of N-P-K application.
[c] Correlated with nitrogen fertilizer application.
[d] Correlated with days on flood.

locations dispersed throughout the major rice growing areas of Arkansas.[8] The ARPT data consisted of four university-run experiment stations—Pine Tree (St. Francis County), Stuttgart (Arkansas County), Rohwer (Desha County), and Keiser (Mississippi County)—and two test plots operated by farmers in Jackson County (Ahrent Farm) and Clay County (Rutledge Farm). Fourteen cultivars were tested: eight conventional cultivars (four from the University of Arkansas and four from Louisiana State University), three hybrid cultivars released by Rice-Tec, and three Clearfield cultivars. Table 6 provides the average yield and standard deviation for each cultivar for all locations. Yields for hybrid XL723 were highest in Clay and Jackson counties and yields for hybrid XL729 were highest in Arkansas and Mississippi counties. Yields for the conventional cultivar Francis were greatest in Desha and St. Francis counties. The yields

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[8] Note that these are paddy rice yields rather than head rice yields, which are calculated as the percent of rough rice that is milled and not broken. While this study shows that hybrids have higher paddy yields, the initial hybrid lines had lower (1–2 percent) head rice yields. Most modern hybrids (like the ones in this study) have closed this gap through genetic breeding. Many things, including chalk and climatic conditions, can cause variations in head rice yield. That being said, this study assumes constant head rice yields for each cultivar.

Table 6. Varietal Yield and Standard Deviation for Counties with Arkansas Rice Performance Test Plots

	Cultivar Yield in Bushels per Acre													
County	**Wells**	**Francis**	**Bengal**	**Jupiter**	**Cocodrie**	**Cheniere**	**Taggart**	**Templeton**	**CL151**	**CL171**	**CL181**	**XL723**	**XL729**	**XL745**
Arkansas	176 (17.68)	186 (17.40)	177 (14.65)	203 (28.19)	176 (19.57)	170 (15.19)	163 (27.71)	165 (27.86)	192 (16.75)	160 (9.93)	168 (6.14)	199 (16.48)	215 (15.11)	214 (7.54)
Clay	213 (24.84)	207 (21.73)	200 (15.35)	206 (15.36)	176 (24.86)	202 (13.89)	163 (27.70)	165 (27.85)	NA	218 (30.86)	NA	255 (36.09)	NA	NA
Desha	169 (26.28)	182 (25.46)	173 (27.66)	175 (14.74)	159 (28.42)	154 (10.71)	169 (18.50)	150 (18.71)	132 (6.63)	113 (20.45)	122 (17.45)	178 (27.81)	153 (9.06)	118 (5.04)
Jackson	209 (25.88)	218 (25.01)	195 (30.33)	238 (31.60)	199 (22.19)	201 (28.19)	181 (17.65)	127 (31.53)	NA	130 (8.37)	NA	248 (44.01)	NA	NA
Mississippi	189 (34.32)	194 (41.29)	169 (31.10)	175 (38.12)	161 (28.62)	178 (29.03)	161 (24.58)	185 (8.79)	156 (19.16)	162 (5.04)	168 (1.08)	184 (35.01)	238 (18.91)	173 (22.00)
St. Francis	193 (18.17)	212 (18.47)	187 (29.05)	197 (26.56)	173 (28.61)	184 (15.34)	170 (14.50)	149 (10.15)	164 (6.38)	129 (19.12)	146 (6.14)	185 (20.50)	203 (14.77)	179 (8.62)

Notes: Standard deviations for yield over time and across plots in a county are reported in parentheses. NA indicates that yield data for the corresponding cultivar and county were not available via the Arkansas Rice Performance Test Plots.

produced by the experimental test plots likely exceed yields from actual fields but no information was available for field yield by cultivar. However, Brennan (1984) argued that experimental test plots are the only reliable source of *relative* yields across cultivars. Therefore, the ARPT data allowed us to estimate relative differences in sequestration between cultivars using equations (1) through (3). In simulations of carbon sequestration and net returns, we used average yields and standard deviations from the ARPT plots over time and across plots for each cultivar at a location and assumed that the yields were normally distributed.

Net Returns and Prices. Per-acre net returns for each of the cultivars were simulated using 2007/08 prices for medium and long grain cultivars from the USDA Economic Research Service's (ERS's) *Rice Yearbook 2010* (ERS 2010), simulated ARPT yields, and simulated per-acre costs using the 2008 UACES budgets as a guideline. Price risk was similar across cultivars and was excluded from this analysis since 85–95 percent of Arkansas rice producers use marketing strategies to manage price risk (Nalley et al. 2009). The average price received by farmers in the 2008 market year was \$6.57 per bushel for medium grain cultivars and \$5.58 per bushel for long grain cultivars (ERS 2010).[9] Yield risk was included in simulation of net returns using ARPT data with a normal distribution assumed. Per-acre costs were calculated for field operations that included field preparation, seed, fertilizers, herbicides, fungicides, custom work, labor, fuel, the rice check-off, and interest on operating capital. They were estimated using the 2008 UACES budgets as a guideline. The same input uses that were simulated in calculating CE values were simulated in calculating per-acre costs. We again performed Monte Carlo simulations of net returns using @Risk software and the procedure previously described for input use.

Carbon Price or Price Premium Needed to Minimize GHGs

As discussed earlier, one can calculate the carbon price needed to induce a rice grower to engage in an additionality project. We restricted this calculation to counties in which an additionality opportunity existed and calculated the necessary carbon price (CP_{kt}) per ton in county t as

$$(4) \qquad CP_{kt} = \frac{(\pi_t^{\pi} - \pi_{kt})}{CF_t^{\pi} - CF_{kt}} \cdot 2{,}000 \;\; \forall\, CF_{kt} < CF_t^{\pi max} \in N_t$$

where π_t^{π} is the net return in dollars per acre and CF_t^{π} is the carbon footprint in pounds of CE per acre of the cultivar that provides the greatest net return among N cultivars in county t. π_{kt} is the net return in dollars per acre and CF_{kt} is the carbon footprint in pounds of CE per acre for cultivars in county t that have a smaller carbon footprint than that of the cultivar with the highest net return. Note that the necessary carbon price (CP_{kt}) reported is the minimum price required across all of the cultivar comparisons in a particular county.

Should carbon prices remain negligible, companies could pay a premium to entice producers to change cultivars in counties where a lesser-emitting

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[9] ERS reports prices in dollars per hundredweight; we converted them to dollars per bushel. The ERS prices also include both medium and short grain varieties. The majority of medium grain rice produced is forward-contracted so the market price for medium grains is more nebulous than the price for long grains.

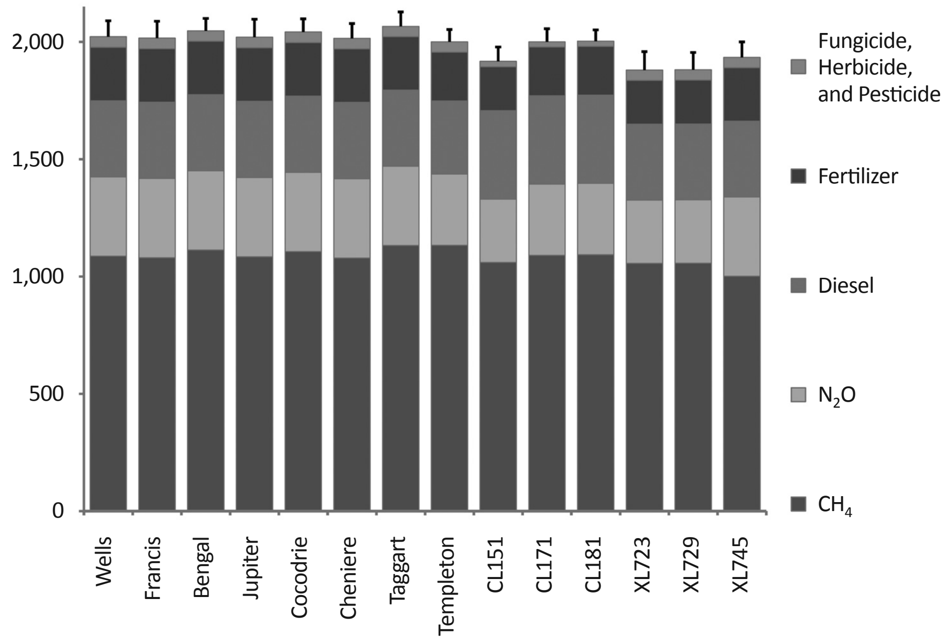

Figure 1. Carbon Equivalent Emissions: Average and 90-percent Upper Limit by Cultivar in Pounds per Acre

cultivar is not the profit-maximizing cultivar. The price premium per bushel for lesser-emitting cultivars, PP_t, in county t would thus be

(5) $$PP_t = \left(\pi_t^{\pi_{max}} - \pi_{kt}\right)/Y_{kt} \ \forall \ CF_{kt} < CF_t^{\pi_{max}} \ \in \ N_t$$

where Y_{kt} is the yield per acre of any cultivar with a smaller carbon footprint than the cultivar that provides the greatest net return in county t; the other variables and procedures are as previously described.[10]

Results

Cultivar Differences in Emissions and Yield-based Sequestration

Table 5 and Figure 1 show that, aside from methane emissions, nitrogen-fertilizer-associated N_2O emissions and emissions from diesel fuel used for flooding the field accounted for the majority of GHG emissions per acre. Clearfield lines were estimated to require more diesel fuel (Table 2) than the other cultivars because they need more water. Consequently, diesel fuel accounted for an average of 49 percent of the carbon footprint for Clearfield cultivars versus approximately 41 percent for other cultivars. Conversely, since Clearfield lines require less nitrogen fertilizer than conventional varieties (Table 2), the role of fertilizer and N_2O in GHG emissions was smaller for Clearfield cultivars than

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[10] Note that the minimum per-acre carbon footprint also coincided with the minimum per-bushel carbon footprint in all counties. The ranking of cultivars from least emission to most emission per acre is not the same as the ranking by per-bushel carbon footprint.

for conventional varieties. Methane emissions represented nearly half of total emissions for all of the cultivars (Table 6 and Figure 1). Hybrid cultivars had the fewest days on flood (Table 2) and so had the lowest amount of methane emission. Table 6 presents the average yield per acre for each of the cultivars in all of the test plots. The hybrid cultivars yielded an average of 9,421 pounds (209 bushels) per acre, the conventional cultivars 7,969 pounds (177 bushels) per acre, and the Clearfield cultivars 7,803 pounds (173 bushels) per acre. The amount of carbon sequestered is associated with a cultivar's yield. The hybrid cultivars sequestered the most carbon at 813 pounds CE per acre, followed by conventional cultivars at 690 pounds, and Clearfield cultivars at 673 pounds (Table 5). The hybrid cultivars' relatively small use of diesel, applied nitrogen, and days on flood and relatively large yields resulted in less emission per bushel, as illustrated by Figure 2. The hybrid lines also had the smallest variance of emission per bushel on average with a 90 percent confidence interval range of 2.03 pounds per bushel. The Clearfield and conventional line variances were 2.40 and 4.83 pounds per bushel, respectively.

GHG Emissions per Acre and per Bushel of Rice Produced

Differences in the carbon footprint (pounds of CE) per acre and per bushel are shown in Table 7 and in Figure 3. They indicate a large degree of spatial variation across test plot locations and within cultivars. In Arkansas County, for example, XL729 generated the least net pounds of CE per bushel (4.92) while Taggart generated the most (9.17). As illustrated in Figure 3, the hybrid lines produced

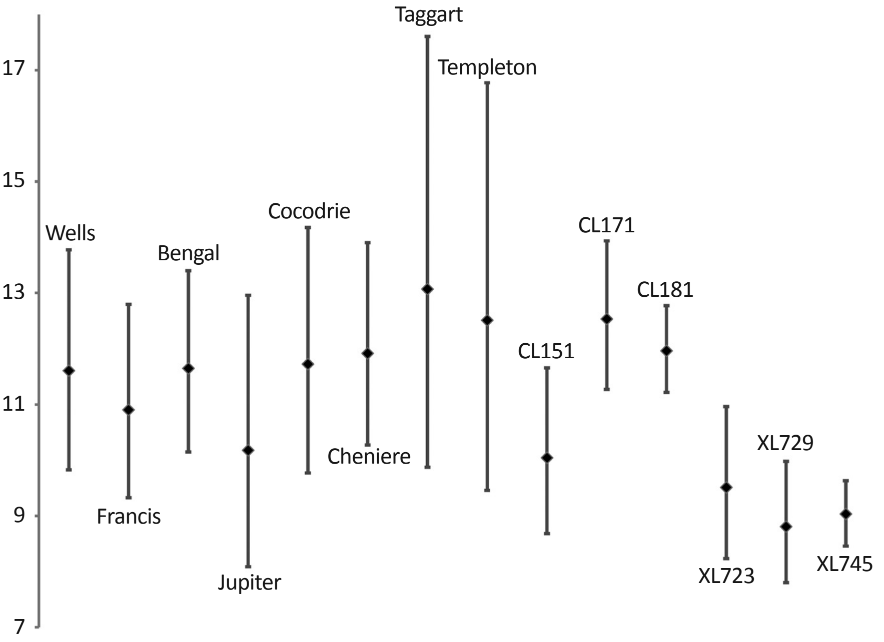

Figure 2. Carbon Equivalent Emissions: Averages and 90-percent Confidence Intervals by Cultivar in Arkansas County, Arkansas, in Pounds per Acre

Table 7. Varietal Carbon Footprints for Counties with Arkansas Rice Performance Test Plots

	Cultivar Yield in Pounds per Acre (Carbon Footprint in Pounds of Carbon per Bushel)													
County	**Wells**	**Francis**	**Bengal**	**Jupiter**	**Cocodrie**	**Cheniere**	**Taggart**	**Templeton**	**CL151**	**CL171**	**CL181**	**XL723**	**XL729**	**XL745**
Arkansas	1,336[a] (7.71)	1,289 (7.01)	1,357 (7.75)	1,230 (6.28)	1,355 (7.83)	1,351 (8.02)	1,431 (9.17)	1,357 (8.61)	1,171 (6.16)	1,378 (8.65)	1,352 (8.08)	1,108 (5.63)	1,048 (4.92)	1,102 (5.15)
Clay	1,192 (5.73)	1,210 (5.97)	1,265 (6.36)	1,219 (5.98)	1,355 (7.94)	1,226 (6.10)	1,431 (9.17)	1,357 (8.61)	NA	1,153 (5.48)	NA	891 (4.50)	NA	NA
Desha	1,363 (8.37)	1,308 (7.44)	1,374 (8.30)	1,336 (7.70)	1,421 (9.38)	1,415 (9.26)	1,407 (8.47)	1,415 (9.64)	1,404 (10.66)	1,562 (14.50)	1,531 (12.96)	1,189 (6.95)	1,287 (8.45)	1,476 (12.56)
Jackson	1,207 (5.92)	1,165 (5.47)	1,287 (6.88)	1,092 (4.75)	1,267 (6.51)	1,234 (6.36)	1,361 (7.63)	1,504 (13.06)	NA	1,497 (11.61)	NA	920 (3.99)	NA	NA
Mississippi	1,286 (7.21)	1,259 (7.03)	1,388 (8.67)	1,336 (8.26)	1,416 (9.26)	1,322 (7.76)	1,441 (9.30)	1,284 (7.01)	1,313 (8.63)	1,371 (8.48)	1,351 (8.05)	1,166 (6.75)	958 (4.07)	1,260 (7.46)
St. Francis	1,272 (6.70)	1,191 (5.70)	1,318 (7.34)	1,252 (6.55)	1,368 (8.27)	1,298 (7.13)	1,404 (8.35)	1,419 (9.58)	1,282 (7.85)	1,500 (12.02)	1,438 (9.90)	1,161 (6.39)	1,094 (5.44)	1,238 (6.93)

[a] Carbon footprint (emissions – sequestration) is measured in pounds of carbon equivalent per acre.

Notes: NA indicates that yield data for the corresponding cultivar and county were not available via the Arkansas Rice Performance Test Plots.

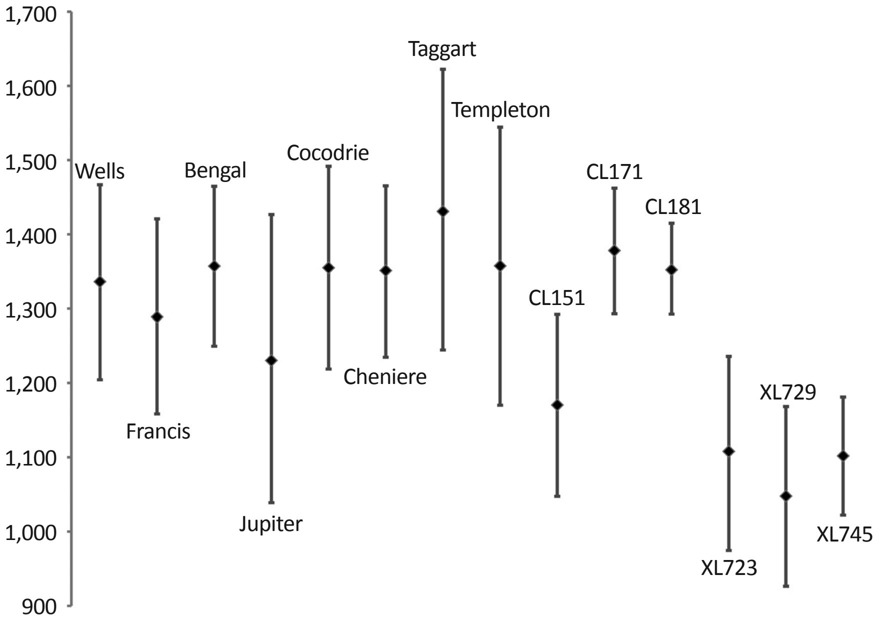

Figure 3. Net Emissions (Emissions – Sequestration): Average and 90-percent Confidence Interval by Cultivar in Arkansas County, Arkansas, in Pounds per Acre

the smallest net emissions in Arkansas County; however, the Clearfield lines demonstrated the least variance of net emissions on average with a 90 percent confidence interval range of 178 pounds of CE per acre. Variances for the hybrid and conventional lines were 221 and 483 pounds per acre, respectively. Because of their high yields and associated levels of soil carbon sequestration, the hybrid lines offered the greatest GHG efficiency ratio (the lowest carbon footprint per bushel) across all counties. Although the Clearfield lines (CL151, CL171, and CL181) used 62 percent less herbicide on average than the hybrid cultivars, the Clearfield lines typically yielded less (21 percent on average). Thus, the benefit of Clearfield's reduced need for herbicide applications is overshadowed by its smaller yields, and hybrid rice emerges as the leader in GHG efficiency.[11] That being said, more than 60 percent of Arkansas' rice acres are infested with red rice, which makes Clearfield rice an important line. Thus, Clearfield rice is important for increasing the efficiency of inputs on those acres and for reducing GHG emission per bushel of rice produced on those acres. Further, if we assume that changes in input prices are consistent across rice production regions and that the price received for rice does not vary significantly across cultivars, then the largest driver in dollars per pound of carbon footprint across cultivars would be yields.

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[11] Here we assume that producers have identical supply elasticities and we do not consider preferences for hybrids versus conventional, preferences for medium grain versus long grain rice, the need for Clearfield technology, or other cultivar characteristics. We also assume that all cultivars possess identical end-use qualities for milling, puffing, parboiling, etc. This often is not the case.

The Carbon Price or Price Premium Needed to Reduce the Carbon Footprint

As shown in Table 8, the conventional cultivar Jupiter generated greater net returns than the other cultivars included in Arkansas, Desha, Jackson, Mississippi, and St. Francis counties. Jupiter is a medium grain cultivar. In the 2008 marketing year, medium grain cultivars earned $0.99 more per bushel than long grain cultivars. The hybrid cultivar XL723 produced the greatest net return and lowest emissions per acre in Clay County. Therefore, planting XL723 in Clay County would maximize the producer's profit while also minimizing the fields' GHG emissions relative to the other rice cultivars considered. Hence, a producer in Clay County would have no incentive to switch cultivars. The GHG emissions are already minimized and would not qualify for a carbon-offset credit. In Arkansas, Desha, Jackson, Mississippi, and St. Francis counties, however, producers could respond to the provision of carbon-offset credits by switching cultivars if the carbon price was high enough because the profit-maximizing cultivars do not minimize emissions. Nonetheless, the carbon price (equation 4) would have to be at least $3,231 per ton for a CER credit to cause producers in Arkansas County to switch from Jupiter, the profit-maximizing cultivar, to one that emits less, in this case XL729.[12]

Across all of the counties that qualified for carbon-offset credits, varieties with the smallest carbon footprint also minimized the carbon price necessary to induce a change in cultivars. The minimum carbon price per ton necessary to induce a change in cultivar was $2,884 to switch to XL729 in Desha County, $2,767 to switch to XL723 in Jackson County, $26 to switch to XL729 in Mississippi County, and $4,063 to switch to XL729 in St. Francis County. These prices are significantly greater than current prices for carbon. Hence, it is unlikely that an offset policy would influence producers' cultivar decisions. Such high carbon prices likely would induce producers to significantly reduce the number of acres planted to rice if cross-commodity comparisons were performed.

Upstream pressure from food processors and retailers may yet become the driving force behind producers choosing to plant lower-emitting cultivars and the premiums thus earned by producers would not affect other commodities. If companies compensated producers for switching cultivars, the smallest price premium per bushel (equation 5) that would induce a switch from the most profitable cultivar to a lesser-emitting cultivar was $1.36 to switch to XL723 in Arkansas County, $0.78 to switch to Francis in Desha County, $0.96 to switch to XL723 in Jackson County, $0.02 to switch to XL723 in Mississippi County, and $1.58 to switch to XL729 in St. Francis County. Note that these price premiums do not lead to a switch to the least-emitting cultivars in Arkansas and Desha counties. In Arkansas County, XL729 would reduce the amount of emissions by an additional 60 pounds of CE per acre compared to XL723 by earning only $0.01 per bushel ($23 per acre) more. In Desha County, for XL723 to be chosen over Francis, the premium for XL723 would have to be $1.19 per bushel higher ($69 for an added 119 pounds of CE). Note that these price premiums do not reflect additional identity-preservation charges that may be incurred for separate storage of the lower-emitting rice. Furthermore, processors may

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[12] Note that this is mostly a function of the discrepancy in prices for long and medium grain rice. Given the volatility in the medium grain market relative to the long grain market, the payment could easily be much smaller in a given year.

Table 8. Varietal Net Return and Estimated Standard Deviation for Counties with Arkansas Rice Performance Test Plots

	Cultivar Yield in Bushels per Acre													
County	**Wells**	**Francis**	**Bengal**	**Jupiter**	**Cocodrie**	**Cheniere**	**Taggart**	**Templeton**	**CL151**	**CL171**	**CL181**	**XL723**	**XL729**	**XL745**
Arkansas	451 (94)	504 (93)	635 (92)	789 (177)	451 (104)	419 (81)	394 (146)	405 (147)	427 (87)	259 (53)	298 (36)	518 (88)	495 (79)	474 (42)
Clay	646 (131)	610 (115)	783 (97)	808 (98)	450 (131)	587 (74)	394 (146)	405 (147)	NA	556 (159)	NA	812 (190)	NA	NA
Desha	415 (139)	478 (135)	607 (174)	620 (93)	361 (150)	332 (58)	426 (98)	327 (99)	119 (38)	17 (106)	62 (91)	408 (147)	179 (49)	–20 (31)
Jackson	626 (137)	671 (132)	747 (190)	1,011 (198)	569 (117)	577 (149)	488 (94)	207 (167)	NA	102 (46)	NA	773 (232)	NA	NA
Mississippi	518 (181)	545 (218)	585 (195)	619 (239)	369 (151)	458 (153)	380 (130)	505 (48)	240 (100)	268 (31)	299 (18)	439 (185)	614 (98)	265 (114)
St. Francis	538 (96)	637 (98)	697 (182)	755 (167)	433 (151)	490 (82)	430 (77)	322 (55)	280 (36)	98 (100)	185 (35)	446 (109)	434 (78)	295 (47)

Notes: Standard deviations for yield over time and across plots in a county are reported in parentheses. NA indicates that yield data for the corresponding cultivar and county were not available via the Arkansas Rice Performance Test Plots.

source from low-GHG-footprint regions rather than pay the premiums, which could then alter their transport costs. Hence, the premiums merely provide a guideline for how large the per-bushel incentive must be to induce producers to change cultivars and how the premiums might differ across areas of the state.

To put the carbon price CP_{kt} and the price premium PP_t in relative terms, the price premiums for switching to the least-emitting cultivars (as much as $1.58 per bushel) are similar to the $0.99-per-bushel premium for medium grain rice over long grain whereas the difference in the carbon-offset price needed to induce a switch to the least-emitting cultivars (as much as $4,058 per ton of CE) is much larger than current market prices for carbon (less than $1 per ton). Hence, the industry may well play a larger role in GHG reductions than adoption of a carbon offset market like the one modeled here.

Conclusions

This study estimated the net carbon footprint of the fourteen commonly produced rice cultivars in Arkansas using yield data from six locations across the state's rice-growing region. Methane emissions, modeled as a function of days on flood by cultivar variety, contributed nearly half of total GHG emission for each cultivar. Nitrogen fertilizer was the second largest component of total GHG emission while diesel fuel used for irrigation ranked third. Carbon sequestration in the soil, on the other hand, was a function of yield so higher-yielding cultivars would be preferable from an environmental perspective. Therefore, the ideal cultivar in terms of net GHG emission would have a short growing season so that there would be fewer days on flood, a large increase in yield in response to nitrogen, the ability to grow successfully with shallower floods so the stems would be more resistant to fungi, and high yields. Hybrid cultivars embody many of these traits and thus provide an environmentally friendly alternative to conventional and Clearfield cultivars by maximizing the GHG efficiency and yield—albeit at a greater cost for seed.

For a CER credit to cause producers to switch from profit-maximizing cultivars that produce unfavorable quantities of emissions, the carbon price per ton must be many times greater than what current carbon markets offer because the price premium granted to medium grain varieties played a significant role in this analysis. Additionally, the effects of yields on switching from profit-maximizing to least-emitting cultivars were positive; the least-emitting cultivars always had higher yields than the profit-maximizing alternative in counties in which profit-maximization was not yield-maximizing or least-emitting. Consequently, rice buyers' concerns about reductions in supply under GHG incentives, at least from the perspective of cultivar selection, were not supported by this analysis. However, cross-commodity impacts and quality concerns may still be an issue.

Future research highlighting the effects of changes in production practices (e.g., measuring yield effects generated by modifying the level of irrigation and/or irrigation methods such as intermediate flooding) on the leading hybrid cultivars should provide additional answers. Also of interest would be measured differences (rather than estimated differences) in methane emissions across production methods and leading cultivars. The answer to that question so far has been cost prohibitive because a large number of these tests would be needed to generalize the findings across the state and the weather data needed for biophysical simulation is not readily available. Other research questions of interest include how risk aversion would affect cultivar selection and whether producers would switch to cultivars with smaller net carbon footprints without a profit incentive. Overall, given the results of this study, information on net GHG emissions per bushel and per acre may not drive the cultivar selection process but may very well contribute to it. Finally, industry signals transmitted through cultivar-specific price premiums are perhaps more likely than carbon markets to lead to efforts to reduce GHGs given the comparatively large change in carbon-offset price needed to modify producer behavior.

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