Nonradial Technical Efficiency and Chemical Input Use in Agriculture

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Radial and nonradial measures of technical efficiency are calculated empirically for Florida vegetable farms using DEA (data envelopment analysis) techniques. Use of the nonradial measures to calculate overuse of chemical inputs by inefficient farmers is demonstrated and the potential for reduced environmental loading of pesticides and fertilizers by improving efficiency is evaluated.

Over the last four decades, pesticides and fertilizers have played an integral role in the technological advances that have doubled total factor productivity in U.S. agriculture (USDA, 1990). The use of these chemical inputs, however, has also raised health and environmental concerns (Cooper and Loomis; Hallberg; Harper and Zilberman; Mott). In particular, concern over the safety of our food supply and the quality of groundwater has motivated economists to examine ways for farmers to reduce their dependence on these chemicals, without a detrimental impact on consumers budget or on farmers profitability.

In his seminal paper, Farrell noted in 1957 that in addition to its theoretical importance, determination of efficiency is valuable for the economic policy maker because it provides information on how much a firm or industry can increase output "by simply increasing its efficiency, without absorbing further resources." Equivalently, technically inefficient firms can be brought towards the frontier (which describes the minimum amount of inputs required to produce some desired output level) by cutting back overused inputs. The improvement in the effectiveness of input use, particularly in the case of fertilizers and pesticides, can increase farm profitability as well as alleviate health and environmental concerns. In this regard, the efficiency of fruit and vegetable production is especially important because of its intensive use of chemical inputs. For example, in 1990, pesticide expenditures per acre by fruit and vegetable growers were about $100, nearly seven times the agricultural average (USDA, 1990; Gianessi and Puffer). Also, food safety concerns about pesticide residues are especially pertinent in fruits and vegetables which are often consumed with little post-harvest processing (National Academy of Sciences).

Florida is one of the nation's largest fruit and vegetable producing states, with over 358,600 acres of vegetable crops planted in 1990 (USDA, 1991). Moreover, Florida offers unique features: Approximately 89 percent of its vegetable acres are treated with nitrogen fertilizers, 92 percent with insecticides, about 75 percent with herbicides, and nearly 100 percent with fungicides (USDA, 1991). Florida is also a large producer of tomatoes, which rank first among foods in terms of risk of exposure to pesticides in the daily diet (National Research Council). Furthermore, nearly the entire state of Florida is highly vulnerable to groundwater contamination by pesticides and nitrates (EPA), and several large urban centers lie above those vulnerable areas.

Efficiency issues are critical for winter vegetable farms (tomatoes, peppers, cucumbers), which produce a large share of Florida's vegetable output, because their survival depends on their ability to compete with Mexican vegetable farms. The North American Free Trade Agreement (NAFTA) is likely to enhance this competition, bringing negative repercussions on less efficient farms. At the same time, a shift in winter vegetable production from Florida to Mexico is likely to reduce fertilizer and pesticide use in Florida because of the decreased production and the drop in input use per unit of output, as the remaining farms in Florida are likely to be the more efficient. From this perspective, NAFTA may have a beneficial environmental impact for Florida.

Previous empirical studies have been limited by

Economic Research Service, U.S. Department of Agriculture. The views expressed in this paper are those of the author and do not necessarily represent views or policies of the U.S. Department of Agriculture. I would like to thank Agapi Somwaru for her help with GAMS programming, and Steve Payson, Sharon Jans, Wen Huang, the Editor, and two anonymous reviewers for helpful comments.

the use of radial measures of efficiency. These measures are restrictive because they imply that an inefficient farm can only be brought toward the frontier by shrinking all inputs equiproportionately (input mix being constant along a ray in input space). The use of radial efficiency to calculate input overuse presents serious drawbacks because it implicitly assumes that a technically inefficient farm will have the same degree of input overuse for all variable inputs. Using a nonradial measure, on the other hand, one can shrink each component of the observed input vector as much as possible until the frontier is reached.

The objectives of this paper are: (i) To determine farm-level technical efficiencies using nonradial and radial measures for winter vegetable farms in Florida, (ii) to project the inefficient farms onto the frontier, calculating the degree of input overuse and the savings in chemical inputs that could be obtained without sacrificing output, and (iii) to evaluate the degree of association between technical efficiency and farm characteristics or production practices. This paper provides the first empirical results of technical efficiencies for vegetable farms reported in the literature, to our knowledge. More importantly, it shows the general applicability of nonradial measures for addressing issues of input overuse and the potential for reduction of environmental loadings in agriculture.

Theoretical Background

DEA (data envelopment analysis) refers to nonparametric techniques (in the sense of not requiring the specification of a particular functional form) that have been extensively used in agricultural economics. Introduced by Farrell in 1957, this methodology has been developed independently by Färe, Grosskopf and Lovell, and by Charnes and Cooper. In addition, Banker and Morey generalized the model to allow for fixed and exogenous factors, while Banker and Banker and Thrall further developed the use of returns to scale in DEA models. Other approaches to measure technical efficiency include those pioneered by Afriat and developed by Richmond and Greene.

To review the theoretical framework, consider J farms (observations), each using N variable inputs and K fixed inputs in the production of M outputs. Let $x = (x_1 \ldots x_N)' \in \Re^N{}_+$ denote the vector of variable inputs; $y = (y_1 \ldots y_M)' \in \Re_+{}^M$ the vector of variable outputs; and $z = (z_1 \ldots z_k)'$ the vector of nonnegative quasi-fixed inputs. In addition, let the matrix of observed inputs of dimension $N \times J$ be represented by X and the matrix of observed outputs of dimension $M \times J$ be represented by Y.

In the presence of fixed inputs, the input set (which yields at least output y) satisfying variable returns to scale (V) and strong disposability of inputs and outputs (S) is given by (Färe, Grosskopf, and Lovell):[1]

$$L(y|V,S) = \left\{ x\colon Y\alpha \geq y,\ X\alpha \leq x,\ Z\alpha \leq z, \right.$$

$$\text{(1)} \qquad \left. y \in \Re_+{}^M,\ \sum_{j=1}^{J} \alpha_j = 1,\ \alpha_j \geq 0 \right\}$$

where $\alpha = (\alpha_1 \ldots \alpha_J)'$ is the input utilization rate or intensity vector (also interpreted as the vector of weights associated with each observation) that forms the convex combinations of the observed input and output vectors. Nonincreasing returns to scale are imposed by relaxing the constraint on the intensity vector to $\Sigma\alpha_j \leq 1$ and constant returns to scale are imposed by eliminating the constraint altogether. A farm is technically efficient in the production of an output bundle y if, and only if, the inputs used belong to the efficient subset, defined by

$$\text{(2)} \qquad Eff\, L(y|V,S) = \{x{:}x \epsilon L(y|V,S),\ \hat{x} > x \rightarrow \hat{x} \notin L(y \mid V,S)\}$$

The input-based radial technical efficiency is defined as:

$$\text{(3)} \qquad E_R(V,S) = Min_{\theta,\alpha}\, \{\theta{:}\theta x \epsilon L(y \mid V,S)\}$$

where $L(.)$ is given by equation 1 and θ is a scalar ($0 \leq \theta \leq 1$). The radial technical efficiency of a farm with observed inputs and outputs (x^o, y^o) may be interpreted as the ratio of observed inputs to potential inputs (located in the frontier).[2] It is radial in the sense that for each observed point, the corresponding frontier point has the same input mix and thus the ratio of observed to potential inputs is the same for all inputs. An inefficient farm can be made more efficient by projecting it into the frontier through proportional reduction of all inputs keeping output constant, i.e., the input levels are reduced (shrunk) along a ray until the frontier is reached. Thus, an inefficient point (x,y) projected to the frontier becomes $(\theta x,\ y)$.

The notion of radial efficiency has some advantages such as its duality relationships (the radial efficiency is the inverse of the distance function) and its cost interpretation, but it can lead to an overstatement of the "true" technical efficiency of an input vector (Lovell and Schmidt). In addition, the use of radial efficiency to calculate input overuse presents serious drawbacks, because it is not realistic to expect that a technically inefficient farm will show the same degree of input overuse for all variable inputs.

To overcome these difficulties one can use the nonradial (or Russell) measure of technical efficiency (Färe and Lovell; Färe, Lovell and Zieschang). The nonradial overall efficiency of a farm is obtained by shrinking each component of the observed input vector as much as possible until the frontier is reached. The nonradial overall (input side) measure is defined as:

$$E_{NR}(V,S) = Min_{\theta,\alpha}\left\{\sum_{n=1}^{N} \theta_n/\tilde{N}: (\theta_1 x_1, \ldots, \theta_n x_n, \ldots, \theta_N x_N) \in L(y|V,S)\right\} \tag{4}$$

where $\tilde{N}$ is the number of nonzero inputs (varies for each farm), $\theta = (\theta_1, \ldots \theta_n, \ldots, \theta_N)$ is a vector and each component θ_n provides a measure of the efficiency in the use of that input.[3] The nonradial efficiency reduces to the radial case when $\theta_1 = \theta_2 = \ldots = \theta_n = \ldots = \theta_N = \theta$ for all n that correspond to $x_{jn} > 0$. Färe and Lovell also establish several properties of the nonradial efficiency. In particular, they show that for $x \in L(x)$ and $x > 0$, the radial measure is greater than or equal to the corresponding nonradial measure. Intuitively, since the nonradial measure shrinks the input bundle at least as much as the radial measure, it follows that the ratio of the "shrinked" input vector to the original vector, or input-based technical efficiency, should be larger (or equal) in the radial case than in the nonradial case.

Figure 1 illustrates the radial and nonradial efficiency measures for a simple case with 2 variable inputs (fertilizer and pesticides) and 5 observations (A, B, C, D and E where the first 3 determine the efficient frontier ABC). Point D can be made radially efficient by shrinking both inputs proportionaly until the frontier is reached at D′. On the other hand, point E (or any point outside the cone LOL′) can not be made radially efficient because E′ does not belong to the efficient subset. However, point E can be brought nonradially to a point such as F, which belongs to the efficient subset.

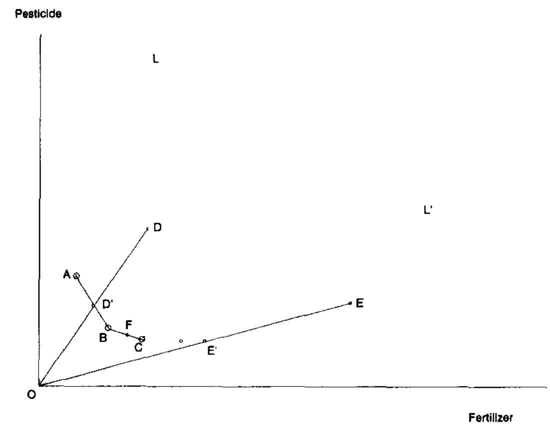

Figure 1. Radial and Nonradial Technical Efficiency

Returns to Scale

As Chavas and Aliber note, multiproduct returns to scale can be characterized from the production technology as well as from the cost function. Because of data considerations, we use the first characterization.[4] [5] In either the radial or nonradial case, one can estimate three sets of efficiencies. First, the more restrictive condition on the weights ($\Sigma\alpha_j = 1$), corresponds to the general case of variable returns to scale (VRTS). Next, relaxing the restriction to $\Sigma\alpha_j \leq 1$ imposes non-increasing returns to scale (NIRTS). Finally, the elimination of the condition on $\Sigma\alpha_j$ leads to the most restrictive case with regard to returns to scale: it only allows constant returns to scale (CRTS). These calculations enable us to classify each farm in terms of its returns to scale as either increasing, constant or decreasing. The method employed has been outlined by Ferrier and Lovell and is based on the notion that the efficiencies calculated under a NIRTS technology must be less than or equal to the efficiencies calculated in the more general case (VRTS). Similarly, the efficiency calculated under the CRTS constraint is less than or equal to the efficiency calculated under NIRTS. The reason is that the CRTS frontier cannot envelop the data more closely than the NIRTS can. Intuitively, the data points are closer to the isoquant, and thus, are more efficient in the NIRTS case. For the same reason, the NIRTS frontier can not envelop the data more tightly than the VRTS frontier.

The procedure for classifying each of the farms in terms of returns to scale is as follows: For each farm one compares the technical efficiency calculated under the VRTS frontier to the efficiency calculated under NIRTS. If they are not equal, one classifies the farm as operating under increasing returns to scale (IRTS). If they are equal, one compares the efficiency based on the NIRTS technology to the efficiency calculated under CRTS. If these two efficiencies are equal, one classifies the farm under CRTS; otherwise, the farm must be operating under decreasing returns to scale (DRTS).

Data and Empirical Issues

The data were obtained from the Agricultural Chemical Use Survey and its Economic Follow-On for vegetables, administered by the National Agricultural Statistics Service of the U.S. Department of Agriculture in several states including Florida. This survey employs a two-frame probability sample: a list frame and an area frame. The list frame is based on all known commercial growers of fresh and/or processed vegetables, strawberries, or melons. In order to be included in the list, the growers are required to have at least a tenth of an acre of production. By comparison, the area frame is taken from the 1990 Agricultural Survey Tracts, and used only to provide additional information (USDA, 1991).

A stratified sampling technique was used, where each stratum was a mutually exclusive set of the commodities of interest. Farms were partitioned so that each farm would be associated with one, and only one, stratum. After observations with missing values were excluded, 87 usable observations of winter vegetable Florida farms were available for analysis.

The model is specified with six output categories (tomatoes, peppers, cucumbers, squash, "other vegetables," and "other outputs"). Four variable inputs (fertilizer, pesticides, labor, and "other variable inputs") and three categories of quasi-fixed factors (land, capital, and "other fixed factors" such as soil conservation improvements, drainage, irrigation improvements, fences, etc) are also considered. Outputs are expressed in physical units (e.g. pounds), except the category "other vegetables," which is expressed as an index calculated from the production of each of the other vegetables (asparagus, broccoli, celery, etc) in physical units weighted by their value shares, calculated using average prices for each of those vegetables. Among the variable inputs, fertilizer, pesticides, and "other" are expressed as expenditures, while labor is expressed in hours. Finally, among the quasi-fixed factors, land is measured in acres and capital and "other fixed factors" are expressed in dollars.[6] Table 1 presents the means, standard deviation, minimum and maximum value for each of the most important variables used.[7]

The radial efficiency is obtained as the solution to the following linear programming (LP):

$$(5) \qquad Min_{\theta,\alpha}\ \theta^0$$

$$s.t. \quad \sum_{j=1}^{J} \alpha_j y_{mj} \geq y_m^0, \qquad m = 1, \ldots, M$$

$$\sum_{j=1}^{J} \alpha_j x_{nj} \leq \theta^0 x_n^0, \qquad n = 1, \ldots, N$$

$$\sum_{j=1}^{J} \alpha_j Z_{kj} \geq z_k^0, \qquad k = 1, \ldots, K$$

$$\sum_{j=1}^{J} \alpha_j = 1, \alpha_j \geq 0 \qquad j = 1, \ldots, J$$

The nonradial efficiency is obtained as the solution of the following *LP* problem:

Table 1. Data Summary—Winter Vegetable Florida Farms—1990

Variable	Sample average	Standard deviation	Minimum	Maximum
Tomatoes, thousand pounds	1492	6410	0	54000
Cucumbers, thousand pounds	416	2035	0	16500
Peppers, thousand pounds	622	2871	0	18480
Squash, thousand pounds	60.0	169	0	945
Other Vegetables, index	69.1	197	0	434
Other, index number	14.3	59.4	0	518
Fertilizers, thousand $	57.0	218	0	1800
Pesticides, thousand $	75.9	223	0	1400
Labor, thousand hours	53.0	67.8	6.4	555
Other variable inputs, thousand $	255	692	380	3623
Land, acres	371	746	5	5765
Capital, thousand $	297	495	5	2525
Percent of farms located in the southern counties	19.5	39.9	0	100
Percent of farms using IPM	37.9	48.8	0	100

$$(6) \qquad Min_{\alpha,\theta} \sum_{n=1}^{N} \theta_n^0 / \tilde{N}^0$$

$$s.t. \quad \sum_{j=1}^{J} \alpha_j y_{mj} \geq y_m^0, \qquad m = 1, \ldots, M$$

$$\sum_{j=1}^{J} \alpha_j x_{nj} \leq \theta_m^0 \, x_n^0, \qquad n = 1, \ldots, N$$

$$\sum_{j=1}^{J} \alpha_j Z_{kj} \leq z_k^0, \qquad k = 1, \ldots, K$$

$$\sum_{j=1}^{J} \alpha_j = 1, \alpha_j \geq 0 \qquad j = 1, \ldots, J$$

where $J = 87$, the matrix X is 4×87, the matrix Y is 6×87, the matrix Z is 3×87, the vector α is 87×1, x^0, y^0, z^0 represent the (input/output) vectors for the farm under examination. The radial (nonradial) technical efficiency for all the farms is calculated by solving 87 linear programming problems, each represented by Equation 5 (Equation 6), with the farm under evaluation defined by (x^0, y^0, z_0) changing for each problem. All LP problems are formulated and written in GAMS (General Algebraic Modeling System) (Brooke, Kendrick and Meeraus).

A critical issue to be addressed when working with DEA models is the selection of outputs and inputs to be included. As Seiford and Thrall note, since DEA relies on extremal points, the results can be very sensitive to model specification. In particular, the model's ability to discriminate among firms decreases as the numbers of outputs (M) and inputs (N) increase. Seiford and Thrall observe that, given enough factors, all or most of the firms will be regarded as efficient. Thus, the key factor is the dimensionality of the input/output space ($N + M$) relative to the number of observations (J). While there are some ways to deal with these difficulties by restricting the efficient set, such as the "assurance region" (Thompson et al.) and the "cone ratio" (Charnes et al.) methods, perhaps the best rule of thumb is for one to have a dimensionality ratio $J/(N + M)$ large enough for good discrimination, e.g., larger than 5. In this study with 87 farms, six outputs, and four variable inputs, the dimensionality ratio is 8.7 (In addition, land, capital and "other" are included as quasi-fixed factors).

In order to understand what factors or farmer attributes might be associated with technical efficiency, several regressions of efficiency on farmer attributes are estimated. Ordinary least squares estimation methods are inappropriate because of the characteristics of the survey data and the nature of the dependent variable. Unlike simple random sampling, the selection of an individual farm for the survey is not equally likely across all farms on the list because the sample was stratified. Some farms have a higher probability of selection than others. Differences in the probability of selection introduce bias in simple ordinary least squares estimates of the parameters and their variances. Thus, weighted least squares estimation methods are used, where the weights are equal to the inverse of the probability of selection.

In addition, a "two-limit tobit" regression framework (Maddala) is used, since the dependent variable is bounded between zero and one. The two-limit model can be expressed as $\theta_n{}^* = X'\beta + \epsilon$, where the matrix X represents the factors or farmer attributes associated with technical efficiency, ϵ is a normally distributed error term with zero mean and variance σ, and the dependent variable is the latent variable $\theta_n{}^*$, which can be expressed in terms of the observed variable (technical efficiency) θ_n as follows:

$$\begin{aligned} \theta_n &= 1 \text{ if } \quad \theta_n^* \geq 1 \\ \theta_n &= \theta_n^* \text{ if } 0 > \theta_n^* < 1 \\ \theta_n &= 0 \text{ if } \quad \theta_n^* \leq 0 \end{aligned}$$

Several researchers have attempted to explain technical efficiency differences between firms. For example Page, Timmer, Hall and LeVeen, Bagi, Grisley and Mascarenhas, Bailey et al., Tauer and Belbase, Garcia et al., Bravo-Ureta and Rieger, Chavas and Aliber. In general, the single most important predictor of efficiency (excluding input factors) appears to be firm size and has been used extensively (Page, Bailey et al., Grisley and Mascarenhas, Garcia et al., Bravo-Ureta and Rieger). A relationship between firm size and technical efficiency is to be expected when there are economies of scale in the physical production function, while a positive relationship between allocative efficiency and firm size might indicate that relative prices are such that increasing size reduces costs (Hall and LeVeen). Other firm attributes often used as predictors of technical efficiency are education, age, and experience of the entrepreneur, managerial structure of the firm, characteristics of the labor force, including part-time farming (Ekanayake and Jayasuriya), degree of specialization (Aly et al. (1990), Tauer and Belbase), financial ratios (Grisley and Mascarenhas, Tauer and Belbase, Chavas and Aliber). Locational factors, such as soil fertility, rainfall, and temperature, can also affect technical efficiency because they can cause differences among farms in yields, directly through increased fertility, and indirectly through influence on pests. Thus, in agriculture it is important to include land productivity effects using regional dummies as proxies (e.g. Grisley and Mascarehas, Tauer and Belbase, Ekanayake and Jayasuriya, Chavas and Aliber). In this paper both input-use and overall nonradial efficiencies are regressed on farm attributes and locational factors. The following factors or attributes are included:

1. LAND: Farm acres (in thousands), used as a proxy for farm size.
2. OFFARM: Dummy variable equal to 1 if the operator worked off-farm (including part time work) 0 otherwise.
3. UNFAMLAB: Amount of unpaid work carried out by the operator's family, expressed in thousands of hours per year.
4. PARTNER: Dummy variable equal to 1 if the operator had a partner involved in management, 0 otherwise.
5. Locational dummies: Two regions are considered for Florida, the south includes the 10 southern counties (SOUTHD = 1). Although precipitation differences between the south and north are minor, temperature differences have caused Florida's fresh winter vegetable production to be located primarily in the south.
6. IPM: Dummy variable equal to 1 if the farm used integrated pest management (IPM) techniques, 0 otherwise.[8]
7. IPMLAND: Interaction variable equal to IPM times LAND.
8. Crop variables: Binary indicator variable for each of the main crops grown in the state: TOMATOD for tomatoes, MELOND for melons, etc. The binary variable equals 1 if the given crop is grown on that farm.

Results

A comparison of the overall results for the radial and nonradial measures of technical efficiency is provided in Table 2. As expected from the theoretical discussion, the nonradial measures are smaller than the corresponding radial measures of efficiency, under all three cases of scale economies imposed in the technology and the differences between the means of the technical efficiency based on the radial and nonradial frameworks are significant at the 5 percent level. Average radial efficiencies are 20 to 25 percent higher than the corresponding nonradial efficiencies and about a third of the farms are efficient in the nonradial case whereas more than forty percent of the farms are radially efficient. While we are not aware of other studies of technical efficiency in vegetable farms, and few studies in agriculture report the percent of efficient farms, our finding that between one third and forty percent of the farms are efficient appears reasonable. Our results lie between the results reported by Grisley and Mascarenhas (6 to 19 percent of farms efficient) and Chavas and Aliber (between 32 and 100 percent of farms efficient in the short run and between 44 and 100 percent in the long run). Differences in results among researchers may arise because of differences in methodology, types of farms evaluated (e.g., vegetable farms may tend to be more efficient than other farms due to their higher per acre value), measurement error, etc.

With respect to scale economies, Table 3a shows that, using the traditional concept of radial efficiency, 52 percent of the small farms (less than 50 acres), about 45 percent of the medium farms (between 50 and 600 acres), and only 18 percent of the large farms are operating at increasing returns to scale (IRTS). The rest of the farms are operating at either constant or decreasing returns to scale. The results for returns to scale based on the nonradial concept follow the same tendency, the percent of farms operating at IRTS decreasing as farm

Table 2. Comparison of Average Radial and Nonradial Technical Efficiency of Florida Vegetable Farms

	Variable Returns to Scale	Nonincreasing Returns to Scale	Constant Returns to Scale
Radial Efficiency			
Average percent efficiency	71.9	65.3	64.2
Percent of farms that are efficient	47.1	42.1	41.4
Nonradial Efficiency			
Average percent efficiency	59.2	52.1	52.1
Percent of farms that are efficient	38.4	32.0	32.0

Table 3. Economies of Scale of Florida Vegetable Farms (percent of farms of the given size range which belong to the given category)

a. Using Radial Efficiencies

Acres	Increasing Returns to Scale	Constant Returns to Scale	Decreasing Returns to Scale	Total
0 to 50	51.7	44.8	3.5	100.0
51 to 300	48.2	37.0	14.9	100.0
301 to 600	40.0	40.0	20.0	100.0
More than 600	18.2	45.5	36.4	100.0
All	43.7	41.4	14.9	100.0

b. Using Nonradial Efficiencies

Acres	Increasing Returns to Scale	Constant Returns to Scale	Decreasing Returns to Scale	Total
0 to 50	84.2	15.8	—	100.0
51 to 300	81.8	18.2	—	100.0
301 to 600	76.5	23.5	—	100.0
More than 600	63.6	36.4	—	100.0
All	78.3	21.7	—	100.0

size increases. However, absolute number of farms operating at IRTS is higher (table 3b).

Table 4 reveals that pesticide and fertilizer-use inefficiencies (obtained by solving LP problem 6) are the most important contributors to overall technical inefficiency, confirming the expectation of chemical input overuse. Pesticide-use, averaged over all farms in the sample, is lowest with about 50 percent, indicating that the average farm is applying twice as much pesticide as it could if it were on the production frontier. Regarding the other inputs, average input-use efficiencies range from 53 percent for fertilizer-use to 64 percent for labor-use. These results indicate that, on average, it would be possible to reduce pesticide and fertilizer use on these farms by almost half of the amounts by increasing technical efficiency. Other variable inputs use could also be reduced, but to a somewhat lesser extent. These results should be interpreted with caution and not extrapolated to farms different from those in the sample because results are sensitive to measurement error and calculated efficiencies may be somewhat imprecise due to the nature of DEA models, which do not allow for stochastic errors. Still, the advantages of DEA models (notably, their nonparametric nature) are believed by many (see Färe, Grosskopf and Lovell) to outweigh their disadvantages.

Table 4. Nonradial Technical Efficiencies of Florida Vegetable Farms

	Average (percent)[1]	Percent of Farms that Are Efficient
Overall Efficiency	59.2	36.8
Fertilizer-Use Efficiency	53.1	36.8
Pesticide-Use Efficiency	50.1	36.0
Labor-Use Efficiency	64.4	34.5
Other Inputs-Use Efficiency	55.5	37.0

[1]Variable returns to scale technology.

As shown in Table 5, there is a high correlation (between 0.80 and 0.90) among the different input-use (nonradial) efficiencies and also between each of the input-use measures and the overall nonradial efficiency (0.88 to 0.96). The correlation between the radial efficiency and nonradial efficiencies is also very high, ranging from 0.90 to 0.95. This can be interpreted as an indication that, on average, farms on our sample overusing a certain input are also likely to overuse all the other inputs to a similar extent.

The regression results of nonradial efficiencies (input-use and overall) on farm attributes and locational factors are provided in Table 6. The log likelihood ratio test indicates that in every case the covariates (excluding the intercept) are significant at the one percent level of significance. In general, technical efficiency appears to be positively related to size, to location in the southern portion of the state, and to a more formal organizational structure (i.e., partnerships), while it is negatively related to off-farm work carried out by the operator, to the use of unpaid family labor, and to melon production.

From a theoretical perspective, a positive relationship between farm size and technical efficiency is expected to exist because of physical economies of scale, and on average, smaller firms will tend to be less efficient and lie farther away from the efficient frontier in input space (Hall and LeVeen). Efficiency is also found empirically to be posi-

Table 5. Correlation Coefficients Between Technical Efficiencies

	Nonradial Efficiency				
	Fertilizer-Use Efficiency	Pesticide-Use Efficiency	Labor-Use Efficiency	Other inputs Use Efficiency	Overall Efficiency
Radial Efficiency	0.901	0.904	0.910	0.929	0.952
Nonradial Efficiency					
Fertilizer-Use Efficiency		0.871	0.836	0.899	0.946
Pesticide-Use Efficiency			0.803	0.912	0.948
Labor-Use Efficiency				0.819	0.878
Other Inputs-Use Efficiency					0.957

tively correlated with size by Aly et al., (1987) for a sample of Illinois grain farms, Bagi for Tennessee grain and mixed farms, Hall and LeVeen for a sample of California farms, by Grisley and Mascarenhas for Pennsylvania dairy farms, and by Tauer and Belbase for New York dairy farms. Still, Bravo-Ureta and Rieger find that efficiency of New England dairy farms is not markedly affected by farm size and Garcia et al. find that small Illinois grain farms were just as efficient as larger farms. Finally, it should be noted that it is also plausible, as Feder, Just, and Zilberman caution us, that farm size may be a surrogate for other factors, such as wealth and access to credit, scarce inputs, or information.

The notion that efficiency is negatively related to off-farm labor also makes intuitive sense since off-farm labor is inversely related to operator labor. By reducing the amount of time that the operator dedicates to managerial activities, off-farm employment presents a constraint to technical efficiency. Similar considerations justify the association of efficiency with more formal types of organizational structures associated with "high-tech" farms. Among the crop production variables, only melon production had a significant effect. Given that melons are a relatively simpler crop to produce, the negative and very significant coefficient for melons may only indicate that, unlike melon producers, growers specializing in the

Table 6. Two-Limit Tobit Regression Results of Nonradial Efficiencies on Characteristics for Florida Vegetable Farms[1]

	Overall Efficiency	Fertilizer Efficiency	Pesticide Efficiency	Labor Efficiency	Other inputs Efficiency
Intercept	0.873***	0.877***	0.819***	0.873***	0.863***
	(0.062)	(0.065)	(0.070)	(0.055)	(0.065)
SOUTH	0.166**	0.180**	0.183**	0.076	0.138*
	(0.068)	(0.072)	(0.078)	(0.060)	(0.071)
LAND	0.199**	0.148*	0.188**	0.094*	0.169**
	(0.078)	(0.078)	(0.084)	(0.057)	(0.077)
IPM	−0.282***	−0.354***	−0.249***	−0.202***	−0.281***
	(0.071)	(0.069)	(0.073)	(0.060)	(0.068)
IPMLAND	0.217*	0.276**	0.245*	0.278**	0.251*
	(0.129)	(0.127)	(0.129)	(0.120)	(0.132)
MELOND	−0.390***	−0.370***	−0.379***	−0.159***	−0.359***
	(0.066)	(0.065)	(0.070)	(0.056)	(0.064)
UNFAMLAB	−0.195***	−0.166***	−0.173***	−0.126***	−0.157***
	(0.031)	(0.027)	(0.029)	(0.023)	(0.027)
PARTNER	0.277***	0.192	0.109	0.045	0.190**
	(0.100)	(0.097)**	(0.104)	(0.082)	(0.096)
OFFARM	−0.0476	−0.038	−0.039	−0.012	−0.029
	(0.059)	(0.060)	(0.064)	(0.050)	(−0.34)
−2 Log-likelihood function for covariates[2]	111.0***	128.6***	115.4***	83.6***	115.8***

[1]Asymptotic standard error in parentheses.
[2]$-2 \log L_0/L_1$, where L_1 is the maximized log likelihood function for the intercept plus the covariates and L_0 is the maximized log likelihood value of the intercept only.
*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

more difficult, but higher-priced, crops tend to be more efficient farmers.

With respect to integrated pest management (IPM), it is interesting to note that farms using IPM techniques tend to be more efficient than farms not using IPM, except for smaller farms (less than 120 acres) which make up approximately less than a third of our sample size (table 1).[9] One reason for this is that large farms may adopt productivity-improving innovations earlier than small farms. Just, Zilberman, and Rauser show that given the uncertainty, and the fixed transaction and information costs associated with innovations, there may be a critical lower limit on farm size, which prevents smaller farms from adopting.

Concluding Comments

Nonradial measures of technical efficiency have useful empirical applications in production economics. Unlike radial measures of efficiency, which are restrictive because they imply that an inefficient farm can only be brought towards the frontier by shrinking all inputs equi-proportionately, the nonradial measures allows one to shrink each component of the observed input vector as much as possible until the frontier is reached. Thus, in the context of input overuse, nonradial efficiency measures overcome a serious drawback of radial efficiency measures, because they do not implicitly assume that a technically inefficient farm will overuse all variable inputs to the same degree.

The average radial efficiencies of winter vegetable Florida farms in the sample are between 20 to 25 percent higher than the corresponding nonradial efficiencies. Approximately one third of the farms are efficient in the nonradical case while more than forty percent of the farms are radially efficient. There is a high correlation (between 0.80 and 0.96) among the different input-use and overall measures of nonradial efficiency and between radial and nonradial efficiencies. This can be interpreted as an indication that, on average, farms on our sample overusing a certain input are also likely to overuse all the other inputs to a similar extent.

It may be possible for the average farm to reduce pesticide and fertilizer use by almost 50 percent by increasing technical efficiency. The use of other variable inputs could also be reduced, but to a lesser extent. These results should be interpreted with caution because they may be sensitive to measurement error and calculated efficiencies may be somewhat imprecise due to the nature of DEA models, which do not allow for stochastic errors.

Efficiency appears to be positively related to size, to location in the southern portion of the state and to a more formal organizational structure (as opposed to family farms) and is negatively related to off farm work carried out by the operator and by use of unpaid family labor. Farms using IPM techniques tend to be more efficient than those not using IPM, but this tendency is reversed for smaller farms.

While one must be cautious against extrapolating these results to all Florida vegetable farms, the general tendencies found regarding input overuse are confirmed by conversations with farmers and with extension professionals. Thus, it is likely that improving technical efficiency of Florida's winter vegetable farms would not only be beneficial for farm profitability and improve their chances of survival vis a vis competition with Mexican farms, but would be environmentally beneficial as well.

Notes

1. Since we are focusing on the input side, this paper uses input-based measures. A parallel development exists for output-based efficiency measures (see Färe, Grosskopf and Lovell).

2. In fact, in their first DEA model, Charnes, Cooper and Rhodes start with a fractional (nonlinear) program minimizing efficiency, $E = \text{Min}\ \{u'y^0/v'x^0\}$ subject to $u'y_j/v'x_j \leq 1$ for $j = 1, \ldots J$, where the vectors u and v are called the virtual multipliers. After transforming the fractional programming problem into a LP program, a version of the dual of (3) is obtained.

3. Of course, the nonradial measure is not free from some drawbacks; for example, its cost interpretation is not straightforward (Kopp).

4. Given the production possibility set $T = \{(x,y)|y \text{ can be produced from } x\}$ and the usual regularity conditions, the degreee of multiproduct returns to scale for a competitive firm measures the maximal proportionate rate of increase in outputs (y) as all inputs (x) are expanded proportionally (keeping the mix constant) (Baumol, Panzar and Willig). More formally:

$$\tilde{S}_N = \text{Sup}\ \rho\ \{\rho \mid \exists \delta > 1 \text{ such that } (\lambda x, \lambda^\rho y) \in T \\ \textit{for } 1 \leq \lambda \leq \delta\}$$

Local returns to scale can be described by $\tilde{S}_N$, which behaves as the local degree of homogeneity of the production set (Baumol, Panzar and Willig). Moreover, returns to scale at point (x,y) are defined to be increasing if $\tilde{S}_N > 1$; constant if $\tilde{S}_N = 1$; or, decreasing if $\tilde{S}_N < 1$.

5. In addition to the concept of economies of scale, which addresses the efficiency of firm size, it is sometimes useful to understand why some

firms produce more than one output. These type of issue can be analyzed using the concept of economies of scope (Fernandez-Cornejo et al. (1992), Chavas and Aliber). Lack of data does not allow calculation of scope economies in this paper.

6. Using expenditures instead of physical units assumes that all farmers in the sample are facing the same prices. This assumption has often been made for outputs and inputs due to a lack of data. This study is less restrictive in that we are assuming that Florida vegetable farmers face similar prices only for three of the variable inputs.

7. As can be inferred from the minimum values from table 1, some of the farms did not produce all of the outputs and, in some rare occasions, some of the farms did not use all the variable inputs. This means that we have some "zeros in the data," as this problem is called in the DEA literature Older DEA models, such as Charnes, Cooper and Rhodes, in fact did not allow for zeros in the data. More recent DEA models (Charnes, Cooper and Thrall; Seiford and Thrall) relax the requirements that all the inputs and outputs must be positive.

8. For a definition of IPM and its use by vegetable growers see Fernandez-Cornejo et al.

9. The sign of the IPM dummy is negative, indicating that IPM adopters are less efficient than nonadopters at smaller (land) sizes. The positive sign of the coefficient of the interaction term (IPMLAND) indicates that (in a efficiency versus size graph) the slope for IPM adopters is greater than that of nonadopters. At a farm size of about 120 acres IPM adopters become more efficient than nonadopters.

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