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Measuring farm sustainability using data envelope analysis with principal components: The case of Wisconsin cranberry

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ABSTRACT

Measuring farm sustainability performance is a crucial component for improving agricultural sustainability. While extensive assessments and indicators exist that reflect the different facets of agricultural sustainability, because of the relatively large number of measures and interactions among them, a composite indicator that integrates and aggregates over all variables is particularly useful. This paper describes and empirically evaluates a method for constructing a composite sustainability indicator that individually scores and ranks farm sustainability performance. The method first uses non-negative polychoric principal component analysis to reduce the number of variables, to remove correlation among variables and to transform categorical variables to continuous variables. Next the method applies common-weight data envelope analysis to these principal components to individually score each farm. The method solves weights endogenously and allows identifying important practices in sustainability evaluation. An empirical application to Wisconsin cranberry farms finds heterogeneity in sustainability practice adoption, implying that some farms could adopt relevant practices to improve the overall sustainability performance of the industry.

1. Introduction

Though agricultural productivity has increased tremendously over the past decades, global food production must double between 2005 and 2050 to meet the demand of a growing population with increasing purchasing power (U.S. Department of Agriculture, 2010; Tillman et al., 2011). Agricultural intensification will be important for meeting this challenge, including continued crop genetic improvements, expansion and improvement of no-till agriculture, adoption of technologies and practices to improve nutrient and water use efficiency, and other land-sharing conservation practices on agricultural lands (Tillman et al., 2011; Ronald, 2011; Montgomery, 2007; Perfecto and Vandermeer, 2010). The concept of sustainability has been and will continue to be at the center of this debate and related efforts. Though a variety of definitions of agricultural sustainability exist, there is a general consensus that agricultural sustainability focuses on producing crops and livestock for human use while simultaneously pursuing environmental, economic, and social goals (e.g., National Research Council, 2010).

Consumers commonly express positive willingness to pay for products with sustainability attributes, but question the credibility of product claims (Blend and van Ravenswaay, 1999; Nimon and Beghin, 1999; Teisl et al., 1999; Onozaka and Mcfadden, 2011). To address this credibility problem and to begin documenting the current status of and improvements in agricultural sustainability, several sustainability indicators or standards are in various stages of development in the U.S. for different commodities.[1] These sustainability assessments or standards are typically very extensive, including many indicators for the environmental, economic, and social aspects of agricultural sustainability, such as practices or outcomes related to soil, water, nutrients, pesticides, energy, biodiversity, waste, rural community, farmer and employee welfare, and economic returns. For example, the whole farm

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[1] Examples include the Field to Market FieldPrint Calculator (http://www.fieldtomarket.org/fieldprint-calculator/), the Stewardship Index for Specialty Crops (http://www.stewardshipindex.org/) and several sustainability tools developed by the Wisconsin Institute Sustainable Agriculture (http://wisa.cals.wisc.edu/sustainability-tools).

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assessment developed by the Wisconsin Institute for Sustainable Agriculture collects information on use of over 200 practices.[2] The large number of indicators shows how comprehensive these assessments must be to describe and document the many aspects of agricultural sustainability on farms.

Given the extensive nature of most sustainability assessment tools and metrics, methods to integrate and aggregate the collected information in order to manage and to document sustainability improvements are of great interest, not only to farmers, but also to policy makers and other stakeholders. Thus, developing a composite indicator that combines information from these extensive sustainability assessments or standards seems particularly useful. At the farm-level, this composite indicator would inform individual farmers how their sustainability practices and/or outcomes compare to their peers and identify practices or outcomes that can help improve their sustainability. At the aggregate level, the properties of the distribution of all the composite indicators would describe how a farm population is performing as a whole and this performance could be tracked over time. Such information could be useful for developing and evaluating different policies and programs to help improve farm sustainability.

Some reject composite indicators because the weighting process is arbitrary (Sharpe, 2004) or because "work in data collection and editing is wasted or hidden behind a single number of dubious significance" (Saisana et al., 2005, p. 308). However, Saisana and Tarantola (2002) point out that composite indicators can summarize complex, multi-dimensional realities without dropping the underlying information base. Composite indicators are easier to interpret than a set of many separate indicators and facilitate communication with the general public and stake holders, including farmers who are primarily responsible for realizing agricultural sustainability. Moreover, concerns about the weighting process used by composite indicators and wasting or hiding data can be alleviated by choosing a non-subjective method that allows tracing a composite indicator score back to the original data.

Sustainability indicators can be classified as either outcomes or practices. Practice-based metrics document farmer adoption of various practices such as integrated pest management or soil nutrient testing, while outcome-based metrics measure or estimate various outcomes or consequences of farmer production practices, such as soil erosion rates or greenhouse gas emissions. Practice-based sustainability assessments are generally more popular among farmers because surveys are easy to complete and the data collection costs are lower. Such assessments commonly ask farmers to choose categorical rankings (never, rarely, sometimes, always) or binary indicators (yes, no) to measure their degree of adoption of practices. For example, asking for subjective assessments of how often a specific practice is used or whether or not it is used, rather than what percentage of acres or how many hours were devoted to a specific practice. Several studies exist on methods for generating composite indicators for farm sustainability (e.g., Gómez-Limón and Sanchez-Fernandez, 2010; Gómez-Limón and Riesgo, 2009; Reig-Martínez et al., 2011; Rigby et al., 2001). However, many of these methods use subjective weights or are not suitable for discrete (non-continuous) data such as collected by a practice-based sustainability assessment.

Our goal here is to describe and evaluate a method for constructing a composite indicator that addresses problems commonly arising for agricultural sustainability indicators. The method not only uses a statistical model to derive weights, but also is suitable for large correlated discrete data. As an empirical illustration, we apply the method to Wisconsin farms growing cranberries (*Vaccinium macrocarpum* Ait) to measure the intensity of sustainable practice adoption for each farm. We believe that the method is the first to combine non-negative polychoric principal component analysis (PCA) with common-weight data envelope analysis (DEA) to rank the performance of individual farms in terms of agricultural sustainability.

In the remainder of the paper, Section 2 describes Wisconsin cranberry sustainability and the data we use in this study. Following, Section 3 discusses common issues arising when using data envelopment analysis to construct agricultural sustainability composite indicators. Section 4 describes a method for transforming discrete data to become continuous and then generating a composite sustainability indicator that has weights derived by a statistical model. Section 5 presents the results and discusses how the composite indicators can help farmers and policy makers identify relevant practices in sustainability evaluation. And Section 6 concludes.

2. Wisconsin cranberry sustainability and data

In 2011, Wisconsin growers harvested almost 7,300 ha of cranberries, which produced almost 195 kiloton, or 58% of U.S. cranberry production and 45% of global cranberry production (U.S. Department of Agriculture, 2011; FAO, 2012). Cranberries are Wisconsin's largest fruit crop, accounting for almost 85% of the total value of fruit production in the state and contributing nearly $300 million annually to the state's economy and supporting approximately 3,400 jobs (Wisconsin State Cranberry Growers Association, 2011a; Arledge Keene and Mitchell, 2010). The U.S. exports about 25% of its annual cranberry production, with the United Kingdom and Germany as the major importers (Wisconsin State Cranberry Growers Association, 2011b).

Environmental sustainability of cranberry production generally focuses on management practices for water, nutrients and pests. Cranberry is a unique crop because of its special need for water during harvest and for pest control and plant protection during winter. This reliance on water makes a nutrient management plan to manage the amount, source, placement, form, and timing of the application of nutrients and soil amendments especially critical for maintaining water quality (Wisconsin State Cranberry Growers Association, 2012a). A well-developed nutrient management plan helps applied nutrients match cranberry nutrient needs and thus reduce environmental risk (Colquhoun and Johnson, 2010). A cranberry nutrient management plan encourages practices such as basing fertilizer inputs on soil tests and cranberry tissue tests, timing fertilizer applications for optimum uptake, and keeping complete and accurate nutrient management records (Colquhoun and Johnson, 2010).

Besides water quality, water availability is equally important in cranberry sustainability. A good irrigation management plan helps prevent unnecessary water losses and waste while still optimizing plant health, and usually includes calculating irrigation runtimes and monitoring soil moisture to set irrigation schedules in order to efficiently utilize water resources (Wisconsin State Cranberry Growers Association, 2012b). In addition, uniformity is critical to the irrigation system's application efficiency and crop yield. Poor uniformity not only can reduce yields from water stress and water logging, but also can increase nutrient losses when excess water leaches nutrients from the plant root zone, thus increasing fertilizer and pumping costs and reducing grower returns (Ascough and Kiker, 2002; Clemmens and Solomon, 1997).

A wide range of pests affect cranberries, including insects such as the blackheaded fireworm (*Rhopobota naevana* Hübner) and the cranberry fruitworm (*Acrobasis vaccinii* Riley), diseases such as

[2] http://wisa.cals.wisc.edu/download/whole_farm/wholefarmcashgrainprotocol2-12.pdf.

cottonball (*Monilinia oxycocci* Woronin), and multiple weed species (Wisconsin State Cranberry Growers Association, 2008). Cranberry producers rely on an integration of several pest control strategies, including cultural practices, pesticides, scouting, economic treatment thresholds and biocontrol (Wisconsin State Cranberry Growers Association, 2012c).

To address customer sustainability concerns, the Wisconsin State Cranberry Growers Association funded a survey of cranberry growers in the state in 2009 to document the current sustainability status of the industry. A practice-based approach to measuring sustainability was taken, as the cost of directly measuring multiple outcomes was prohibitive. For example, the cost of assaying a single water sample for an insecticide exceeded $200.[3]

In November and December of 2009, a mail survey was sent to all members of the Wisconsin State Cranberry Growers Association, effectively including nearly all cranberry growers in the state. The survey included a variety of questions focused mostly on the environmental and social aspects sustainability. For example, the survey asked cranberry growers about their pest management, nutrient management and irrigation practices; for social aspects, the survey asked about worker safety training and payment of benefits for employees. More sensitive questions regarding farm economics were avoided due to concerns that such questions would result in low grower response. In total, 114 growers managing 5,374 ha of cranberries (about 74% of Wisconsin's harvested area) responded to the survey.

Table 1 reports the 16 survey questions used in this analysis of sustainability and summary statistics for grower responses. Survey questions focused on grower adoption of numerous sustainable cranberry production practices, especially water, nutrient, and pest management practices for environmental sustainability. Not all respondents answered all questions, so the data summarized in Table 1 include only responses from the 95 growers who answered all 16 questions analyzed here. These 95 growers operated more than 70% of Wisconsin's harvested cranberry area.

The data show that most Wisconsin cranberry growers use various components of integrated pest management, including scouting field multiple times, hiring professional scouts and using cultural practices for pest control. In terms of nutrient management, over 87% of cranberry growers base fertilizer applications on soil and plant tissue tests and 76% have written nutrient management plans. In contrast, less than half of the growers utilize soil moisture monitoring for irrigation scheduling, have on-farm weather stations, or have conservation plans. Also, around 80% of growers recycle plastics and cardboard on their farms and provide safety training for their employees, but less than 25% of growers provide health insurance and retirement benefits for their employees. On average, cranberries are transported almost 60 km to the receiving facility, though the high standard deviation indicates a large amount of variation. Because the analysis here assumes a higher level for each variable is more sustainable, grower responses for the distance travelled to the receiving facility were converted to the maximum reported distance (338 km) minus each grower's reported distance.

3. Issues with basic data envelope analysis

Data envelope analysis (DEA) is a widely used mathematical programming technique to generate a composite index of performance. DEA benchmarks the performance of individual decision

Table 1
Survey questions used for analysis and descriptive statistics (95 observations).

	Sample average	Sample standard deviation
Continuous variables		
Production area (%) scouted for pests	68.1	34.9
Average number of times scouted per season	14.3	5.42
Average km crop traveled to receiving facility	58.7	82.6
Employees (%) receive health insurance benefits	22.8	23.6
Employees (%) receive retirement benefits	20.8	25.9
Discrete variables (Yes = 1, No = 0)		
Hire a professional pest scout	0.768	0.424
Use cultural practices for pest management	0.874	0.334
Fertilizer inputs based on soil tests	0.874	0.334
Fertilizer inputs based on cranberry tissue tests	0.884	0.322
Weather stations on the marsh	0.442	0.499
Monitor soil moisture to schedule irrigation	0.389	0.490
Test uniformity of irrigation system	0.558	0.499
Have a nutrient management plan	0.758	0.431
Have a conservation plan	0.368	0.485
Recycle plastics, cardboard, etc. from the farm	0.789	0.410
Provide employees with safety training	0.832	0.376

making units (DMUs) against a frontier based on the observed practices or outcomes of other DMUs (Cooper et al., 2007). In contrast to parametric approaches, DEA does not assume a specific functional form for the frontier or a specific distribution for the distance from this frontier. Originally developed to measure various types of technological efficiency (Cooper et al., 2007), here DEA uses the efficiency score for each DMU to integrate across the many aspects of sustainability to generate a single composite index of sustainability for each DMU. DEA is particularly well-suited for constructing composite indicators of relative levels of agricultural sustainability (Reig-Martínez et al., 2011), as indicated by several applications of DEA to measure human development levels of nations and the environmental performance of firms (e.g., Despotis, 2002, 2005; Zhou et al., 2006a,b; 2007; Hatefi and Torabi, 2010).

Various problems emerge, however, when applying a traditional DEA approach to data from sustainability assessments currently in use or in development for agriculture. These agricultural sustainability assessments typically include a large number of highly correlated variables measuring farm-level adoption of sustainable practices and/or outcomes. For a constant number of DMUs, as the number of variables increases, the frontier becomes defined by a larger number of DMUs, so that an increasing number of DMUs are ranked as efficient and the power to differentiate among farms decreases (Adler and Golany, 2002; Jenkins and Anderson, 2003; Adler and Yazhemsky, 2010; Nunamaker, 1985). In addition, correlation among the variables also influences efficiency evaluations by reducing the discriminating power of DEA (Nunamaker, 1985; Dyson et al., 2001). Moreover, categorical variables commonly occur in agricultural sustainability assessments; for example, binary variables generated from questions such as “Do you hire a professional crop scout?” or “Do you base fertilizer inputs on soil tests?” When used in DEA, categorical variables create problems such as non-constant marginal productivities and uninterpretable convex combinations of these categorical variables (Banker and Morey, 1986).

Principal component analysis (PCA) transforms a set of variables to a new set of uncorrelated principal components, with the first few principal components retaining most of the variation present in the original variables (Jolliffe, 2002; Duong and Duong, 2008). PCA is one of the most commonly used selection algorithms to reduce data dimensions, remove noise, and extract meaningful information before further analysis (Jolliffe, 2002; Han, 2010).

[3] Assay costs vary depending on the active ingredient and level of accuracy, e.g., http://www.mda.state.mn.us/en/protecting/waterprotection/pesticides/testinfo.aspx.

Traditional PCA assumes that the variables follow a normal (Gaussian) distribution, at least approximately. Discrete data violate this distributional assumption and thus bias estimation results from maximum likelihood factor analysis procedures (Kolenikov and Angeles, 2009; Rigdon and Ferguson, 1991). Hence, we use polychoric PCA to address this issue before applying DEA.

4. Non-negative polychoric PCA and common-weight DEA

4.1. Non-negative polychoric PCA

Several variables for practice-based sustainability assessments are discrete, for example, indicating whether or not a specific practice is used. Because discrete variables violate the Gaussian distributional assumption of PCA and thus bias the analysis, we use polychoric PCA based on the polychoric correlation coefficient (Kolenikov and Angeles, 2009; Rigdon and Ferguson, 1991; Babakus, 1985; Olsson, 1979; Pearson and Pearson, 1922). Conceptually, the method works as follows. Let y_1 and y_2 be two ordinal variables with m_1 and m_2 respective categories, each derived by discretizing the latent continuous variables y_1^* and y_2^* according to a set of thresholds $b_{j,1}, \ldots, b_{j,m_j-1}$ for $j = 1, 2$:

$$y_j = \begin{cases} q & \text{if } b_{j,q-1} < y_j^* < b_{j,q}, \text{ for } q = 1, \ldots, m_{j-1} \\ 0 & \text{otherwise} \end{cases}. \tag{1}$$

The polychoric correlation is the correlation for the latent continuous variables y_1^* and y_2^* implied by the observed ordinal variables y_1 and y_2. Assuming a distribution for the latent variables y_1^* and y_2^* gives the likelihood function for the polychoric correlation coefficient, which can then be estimated using the observed y_1 and y_2. Typically a bivariate normal distribution is used, assuming means of zero and standard deviations of one for the latent variables (Olsson, 1979). If one of the observed variables is discrete and the other is continuous, then the polyserial correlation is calculated, which assumes only the discrete variable has an underlying latent variable. Combining pairwise estimates of the polychoric or polyserial correlations gives the overall correlation matrix for the observed data, which can then be used to conduct PCA (Kolenikov and Angeles, 2009).

Standard PCA commonly implies both positive and negative weights when calculating principal components. However, the underlying interpretation of the data and analysis may require that the weights all be positive as both positive and negative weights that are used to calculate principal components in linear combination of variables may partly cancel each other. This non-negativity requirement applies here, as the data measure farmer adoption of sustainable agricultural practices and the subsequent application of DEA requires that the inputs and outputs be positive to have real economic meanings. Hence, we impose a non-negativity constraint on the PCA weights using the algorithm described by Zass and Shashua (2007).

Let $\mathbf{X} \in R^{V \times K}$ denote a normalized[4] data matrix composed of V variables as rows and K columns of observations of each variable for each farm, and let $\mathbf{U} \in R^{V \times I}$ denote the desired principal vectors $\mathbf{u}_1, \ldots, \mathbf{u}_I$, where $I \le V$ is the number of principal components retained for analysis (i.e., $\mathbf{U}$ is the matrix of weights for constructing the I principal components from the original V variables). The optimization problem for non-negative PCA adds a non-negativity constraint on the elements of the principal vectors ($\mathbf{U} \ge 0$), which can be expressed as:

$$\max_{\mathbf{U}} \frac{1}{2}\left\|\mathbf{U}^{\mathrm{T}}\mathbf{X}\right\|_{\mathrm{F}}^2 - \frac{\alpha}{4}\left\|\mathbf{I} - \mathbf{U}^{\mathrm{T}}\mathbf{U}\right\|_{\mathrm{F}}^2 - \beta\mathbf{1}^{\mathrm{T}}\mathbf{U}\mathbf{1}, \text{ subject to } \mathbf{U} \ge 0 \tag{2}$$

where $\|\cdot\|_{\mathrm{F}}^2$ is the square Frobenius norm for a matrix, $\mathbf{1}$ is a $V \times 1$ column vector with all elements equal to one, and $\alpha > 0$ and $\beta \ge 0$ are parameters. The parameter α controls the degree of coordinate overlap among the principal vectors of $\mathbf{U}$, while β controls the amount of additional sparseness, i.e., the number of non-zero weights in $\mathbf{U}$ (Zass and Shashua, 2007). Following Deng et al. (2012), the parameter α is set at four times I (the number of extracted principal components). As discussed by Han (2010), sparseness is a direct by-product of incorporating a non-negativity constraint into the PCA, even without imposing a sparseness control, and imposing inappropriate sparse control may break the data coherence and the orthonormality of the matrix of the principal vectors ($\mathbf{U}$). Because sparseness was not an issue for the data analyzed here, β is set equal to zero, but included in the model description as this may not be the case for other empirical applications.

Following Zass and Shashua (2007), the objective for problem (2) can be written as a function $f(\cdot)$ of each non-negative element u_{vi} in the ith row of the column vector $\mathbf{u}_v$:

$$f(u_{vi}) = -\frac{\alpha}{4}u_{vi}^4 + \frac{c_2}{2}u_{vi}^2 + c_1 u_{vi} + c_0, \tag{3}$$

where $c_1 = \sum_{h=1,h\ne i}^{V} a_{ih}u_{vh} - \alpha\sum_{h=1,h\ne v}^{I}\sum_{j=1,j\ne i}^{V} u_{vj}u_{hj}u_{hi} - \beta$, $c_2 = a_{ii} + \alpha - \alpha\sum_{h=1,h\ne i}^{V} u_{vh}^2 - \alpha\sum_{h=1,h\ne v}^{I} u_{hi}^2$, c_0 is a constant term not depending on u_{vi}, and a_{ih} is an element of $\mathbf{A} = \mathbf{X}\mathbf{X}^{\mathrm{T}}$. Setting the first derivative of Eq. (3) to zero gives a cubic equation: $(\partial f(\cdot)/\partial u_{vi}) = -\alpha u_{vi}^3 + c_2 u_{vi} + c_1 = 0$. Evaluating Eq. (3) at zero, the non-negative roots of this cubic equation allow identification of the global non-negative maximum of Eq. (3) and the corresponding u_{vi} (Zass and Shashua, 2007). Use these optimal u_{vi} to construct $\mathbf{U}$ and $\tilde{\mathbf{X}} \in R^{I \times K}$, the matrix of principal components for subsequent analysis, as $\tilde{\mathbf{X}} = \mathbf{U}^{\mathrm{T}}\mathbf{X}$, so that each element of $\tilde{\mathbf{X}}$ is

$$\tilde{x}_{ik} = \sum\nolimits_{v=1}^{V} u_{vi}x_{vk}, \tag{4}$$

where $k = 1$ to K indexes each farm and x_{vk} denotes the normalized variable x_v for farm k.

4.2. Common-weight DEA

Mathematically, the basic DEA sustainability score S_k for each farm k is determined by solving the following mathematical programming model:

$$\begin{aligned} &\text{Maximize } S_k\left(\omega_{ik}\right) = \sum\nolimits_{i=1}^{I}\omega_{ik}\tilde{x}_{ik} \\ &\text{subject to}: \sum\nolimits_{i=1}^{I}\omega_{ik}\tilde{x}_{ik} \le 1 \ \ \forall\ k, \ \ \omega_{ik} \ge \varepsilon \ \ \forall\ k. \end{aligned} \tag{5}$$

Here $\tilde{x}_{ik}$ is the ith principal component for farm k obtained via polychoric non-negative PCA and ω_{ik} is the weight for the ith principal component for farm k, which must be strictly positive ($\omega_{ik} \ge \varepsilon$), where ε is the infinitesimal. Model (5) is equivalent to an input-oriented, constant returns to scale DEA model with I outputs and a single dummy input of 1 for all farms (Despotis, 2005).

Basic DEA determines the sustainability score S_k for each farm k as a weighted average of its components: $S_k = \sum_{i=1}^{I}\omega_{ik}\tilde{x}_{ik}$. Here S_k measures the radial deviation for each farm k from the origin, expressing this distance as the proportion of the radial distance from the origin to the outer envelope or frontier defined by the full

[4] PCA based on the correlation matrix normalizes each row of $\mathbf{X}$ by its standard deviation.

data set of all farms, so that $0 \le S_k \le 1$. Basic DEA identifies these farm-specific weights for the principal components so as to maximize the sustainability score for each farm individually, which puts each farm in the "best possible light" and thus treats each farm differently.

As Despotis (2002) points out, identifying inefficient units is a strength of basic DEA, while discriminating among "efficient" units is a weakness of basic DEA. Basic DEA often rates many units as efficient, although intuitively some of those units are not as efficient as others. Therefore, common-weight DEA is frequently used to improve the discriminating power of DEA (Despotis, 2002, 2005; Hatefi and Torabi, 2010; Karsak and Ahiska, 2005, 2007). Common-weight DEA chooses a single weight for each principal component that is equal for all farms, whereas basic DEA chooses a farm-specific weight for each principal component, i.e., common-weight DEA finds $\omega_i \ \forall\ i$, while basic DEA finds $\omega_{ik} \ \forall\ k$ and $\forall\ i$.

The common-weight DEA approach (Despotis, 2002, 2005) is based on the deviation of each farm's score from S_k, the basic DEA score obtained by solving model (5) for farm k. Specifically, define $z_k = S_k - \sum_{i=1}^{I} \omega_i \tilde{x}_{ik}$ as the deviation of the common-weight DEA score $\sum_{i=1}^{I} \omega_i \tilde{x}_{ik}$ for farm k from its basic DEA score S_k and $Z = \max\{z_1, z_2, \ldots, z_N\}$ as the maximum z_k over all farms. The common-weight DEA approach then finds the set of common weights ($\omega_i \forall\ i$) by solving the following mathematical programming model:

$$\begin{aligned} &\text{Minimize } h\left(\omega_i, z_k, Z\right) = t\frac{1}{K}\sum_{k=1}^{K} z_k + \left(1-t\right)Z \\ &\text{subject to}: \quad z_k = S_k - \sum_{i=1}^{I} \omega_i \tilde{x}_{ik} \ \ \forall\ k, \quad Z - z_k \ge 0 \ \ \forall\ k, \\ &\qquad\qquad\quad z_k \ge 0 \ \ \forall\ k, \quad \omega_i \ge \varepsilon \ \ \forall\ i, \quad Z \ge 0. \end{aligned} \tag{6}$$

The programming model finds the deviations $z_k \ \forall\ k$, the common weights $\omega_i \ \forall\ i$, and the maximum deviation Z over all farms to minimize the weighted sum of the average deviation of the common-weight DEA scores over all farms $((1/K)\sum_{k=1}^{K} z_k)$ and the maximum deviation (Z) of the common-weight DEA scores from the basic DEA score (S_k) among all farms, where the parameter $0 \le t \le 1$ determines the weight for the two parts of the objective function. The first constraint defines the deviation z_k, with the remaining constraints ensuring that the deviations are non-negative ($z_k \ge 0$) and do not exceed the maximum deviation ($Z - z_k \ge 0$), that the maximum deviation is also non-negative ($Z \ge 0$), and finally that the common weights are strictly positive ($\omega_i \ge \varepsilon$), where ε is the infinitesimal.

Solving model (6) while varying t between these two extremes allows examining the different sets of optimal solutions (common weights, deviations, and implied sustainability scores) that result when compromising between minimizing the average of the deviations and minimizing the maximum dispersion of the deviations. Note that each optimal solution (ω_i, z_k, Z) depends on the parameter t. For empirical implementation, t is varied in a consistent manner (e.g., from 0 to 1 with a step size of 0.01) and model (6) is solved for each value of t, so that each solution is indexed by the value of t (i.e., ω_{it}, z_{kt}, Z_t), including the sustainability score for each farm k: $\tilde{S}_{kt} = \sum_{i=1}^{I} \omega_{it} \tilde{x}_{ik}$. The final sustainability score for farm k then averages the scores over all solutions:

$$\bar{S}_k = \frac{1}{T}\sum_{t=0}^{1} \tilde{S}_{kt} = \frac{1}{T}\sum_{t=0}^{1}\sum_{i=1}^{I} \omega_{it}\tilde{x}_{ik} = \sum_{i=1}^{I} \overline{\omega}_i \tilde{x}_{ik} \tag{7}$$

where T is the total number of values used for t, which ranges from 0 to 1 with a certain step size and $\overline{\omega}_i = ((1/T)\sum_{t=0}^{1} \omega_{it})$ is the weight for principal component i averaged over all values of t.

Substitute Eq. (4) into Eq. (7) and change the order of summation to express the sustainability score for farm k in terms of the normalized variables x_v:

$$\bar{S}_k = \sum_{v=1}^{V}\sum_{i=1}^{I} \overline{\omega}_i u_{vi} x_{vk} \tag{8}$$

As x_v is normalized by standard errors, the final weight of each original variable is $\sum_{i=1}^{I} \overline{\omega}_i u_{vi}/\sigma_v$, where σ_v is the standard error of the original variable. This expression shows that the weights for each original variable depend on the PCA weights, the DEA weights, and the standard error of the original variable (σ_v) so that the final score for a farm depends on these weights and the value of the variable for that farm (x_{vk}). This expression can be used to determine how changing a specific practice would change each farm's score, while all other farms' practices remain constant. Furthermore, this method provides a theoretical and empirical basis for deriving weights to use for each practice to create a composite indicator endogenously for a group of growers, rather than subjective weights as used by most methods (e.g., Jollands et al., 2004; Gòmez-Limòn and Riesgo, 2009; Sharpe, 2004).

5. Results and discussion

The non-negative polychoric PCA was first conducted on the 16 variables summarized in Table 1. For the final analysis, 13 principal components were retained, accounting for 92.4% of the total variance. Because the number of variables for the original data was not large and the primary purpose of using PCA is to remove correlation among variables and to generate non-discrete principal components, we retained a large proportion of the principal components to account for a large proportion of variance.[5] For a data set with a large number of variables, the number of principal components to retain can be determined using the cumulative percentage of total variation captured, usually ranging from 70% to 90% depending on practical details (Jolliffe, 2002).

Table 2 reports the 13 non-negative polychoric PCA weights for each of the 16 variables (i.e., the elements of the PCA weight matrix **U**). The weights show the resulting sparseness when adding a non-negativity constraint to PCA: there are only one or two relatively significant weights for each principal component. Just as for traditional PCA, Table 2 shows that individual principal components tend to be associated with specific variables. For example, the first and second principal components largely depend on pest scouting practices, as the variables "Production area (%) scouted for pests" and "Hire a professional pest scout" have by far the largest weights in Table 2 for these principal components. Similarly, the third and fourth principal components depend mostly on the number of times scouted per season and the distance travelled to a receiving facility, the fifth on pest management, and the sixth and seventh on nutrient management. In addition, the eighth, ninth, and tenth principal components are mainly explained by irrigation practices, the eleventh by nutrient management and recycling practices, the twelfth by provision of employee benefits, and the thirteenth by providing safety training.

Basic DEA and the common-weight DEA approaches were applied to the principal components from non-negative polychoric PCA. The basic DEA solution to model (5) gave 38 of the 95 farms a sustainability score of 1; the mean score for the 95 farms was 0.997 and the minimum score was 0.974. The original data show that the

[5] Twelve principal components explained 88.0% of the total variance, while 14 explained 93.7%. Considering the increase in the proportion of total variance explained and the number of principal components, we retain 13 principal variables which explain 92.4% of total variance.

Table 2
Non-negative polychoric PCA weights and DEA weights for the thirteen principal components and final PCA-DEA weights for the original sixteen variables.

Variable	Principal component													Final weight
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	
% Production area scouted	1.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Average scouting trips	0.001	0.004	1.009	0.001	0.000	0.001	0.004	0.006	0.001	0.000	0.000	0.000	0.003	0.000
Distance crop traveled[a]	0.000	0.000	0.000	1.010	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.002
% Receive health insurance	0.000	0.010	0.000	0.000	0.000	0.008	0.008	0.000	0.002	0.000	0.000	0.718	0.000	0.028
% Receive retirement	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.718	0.015	0.024
Hire professional scout	0.000	1.009	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.016
Use cultural practices	0.004	0.004	0.000	0.000	1.010	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.115
Fertilizer based on soil tests	0.000	0.006	0.002	0.000	0.000	1.009	0.012	0.000	0.001	0.000	0.000	0.000	0.009	0.209
Fertilizer based on tissue tests	0.000	0.007	0.000	0.001	0.000	0.000	1.009	0.005	0.007	0.000	0.000	0.000	0.001	0.090
Weather stations on marsh	0.001	0.000	0.000	0.000	0.000	0.000	0.000	1.010	0.001	0.003	0.000	0.000	0.000	0.005
Monitor soil moisture	0.001	0.004	0.001	0.005	0.007	0.003	0.003	0.005	1.009	0.000	0.000	0.000	0.003	0.006
Test irrigation uniformity	0.007	0.000	0.000	0.004	0.012	0.000	0.000	0.000	0.000	0.741	0.000	0.000	0.000	0.002
Nutrient management plan	0.000	0.000	0.000	0.000	0.006	0.011	0.026	0.000	0.013	0.000	0.714	0.000	0.000	0.004
Conservation plan	0.000	0.015	0.007	0.000	0.000	0.007	0.019	0.000	0.014	0.693	0.026	0.009	0.000	0.003
Recycle on farm	0.000	0.000	0.011	0.007	0.000	0.000	0.000	0.010	0.000	0.000	0.718	0.015	0.008	0.003
Provide safety training	0.000	0.000	0.001	0.000	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.009	0.078
Common-weight DEA weights	0.036	0.006	0.001	0.086	0.038	0.068	0.029	0.002	0.002	0.000	0.000	0.008	0.029	

[a] Variable used in analysis is the reported maximum distance minus the individual reported distance.

farms evaluated as most sustainable by basic DEA are quite different. For example, some of the farms given a basic DEA score of 1.0 scouted less than 100% of their production area and scouted a fewer number of times per season than other farms also given a basis DEA score of 1.0. These results demonstrate the need to increase the discriminating power of DEA such as by using a common-weight DEA approach.

For the common-weight DEA approach as specified in model (6), the parameter t was varied from 0 to 1 with a step size of 0.01 and model solved repeatedly. Over this set of values for t, 23 unique solutions were identified for the optimal weights, with no farm achieving a score of 1.0 for all 23 unique solutions. The bottom row of Table 2 reports the average of these weights over all values of t as expressed in Eq. (7) (i.e., the $\overline{\omega}_i \ \forall i$). These weights indicate the relative importance of each principal component, with the greatest weights attached to the fourth and sixth principal components.

The right-most column in Table 2 reports the final weights for each of the original variables as expressed by equation $\sum_{i=1}^{I} \overline{\omega}_i u_{vi}/\sigma_v$. Hence, these weights indicate the specific contributions of each practice to the final farm sustainability score. For example, basing fertilizer on soil tests and using cultural practices for pest control have the greatest weights. Basing fertilizer on tissue tests and providing safety training are also important in calculating final farm sustainability score. Farms can use these weights and their current practice adoption profile to see which practices most contributed to their final score and to identify which practices they could adopt to most increase their score.

As an example, we examine the farm with a sustainability score of 0.63 which is at 10th percentile (Table 3). While this farm had 100% of its production area scouted, used cultural practices, and provided employees with safety training, it did not provide health insurance and a retirement plan for employees and fertilizer inputs were not based on either soil or tissue tests. Its irrigation was not based on soil moisture or weather forecasts, and no uniformity test was conducted. The farm also did not recycle and did not have either a nutrient management plan or a conservation plan. In addition, the average scouting trips for the farm was 10, which was lower than the average and the distance its crop traveled was 27 km, which was shorter than the average. Based on the adoption profile of this farm and the final weights for each practice in Table 2, the recommendation for this farm would be to base fertilizer applications on soil tests and tissue tests to improve its sustainability score by 0.209 and 0.09, respectively.

As another example, we examine a farm with a median sustainability score of 0.87 (Table 3). This farm did not provide employees with health insurance or a retirement plan, did not hire a professional scout, and did not provide employees with safety training. Based on the final weights in Table 2 and the values the practice variables can take, this farm's sustainability score can be increased by 0.078 if it can provide safety training for employees. In addition, hiring a professional scout could also increase the farm's sustainability score by 0.016 points.

With common-weight DEA, the average sustainability score for all 95 farms was 0.83 with a standard deviation of 0.13, compared to the average score of 0.997 with a standard deviation of 0.004 with basic DEA. These statistics show that the common-weight DEA approach is better able to discriminate among the growers and provide more information about differences in practice adoption. Fig. 1 is a histogram of the final sustainability scores for the sampled Wisconsin cranberry growers, showing the distribution between the minimum score of 0.55 and the maximum of 1.0 (technically > 0.9998). The histogram shows a clustering of scores between 0.95 and 1.0 (the mode is 0.97) and a strong skew to the left that creates a tail of lower scoring farms. Among the growers, sustainability

Table 3
Practice adoption profiles for two farms with a low and a median sustainability score.

	Farm with a sustainability score at 10% percentile	Farm with a sustainability score at 50% percentile
% Production area scouted	100	100
Average scouting trips	10	3
Distance crop traveled (km)	27.4	16.1
% Receive health insurance	0	0
% Receive retirement	0	0
Hire professional scout	0	0
Use cultural practices	1	1
Fertilizer based on soil tests	0	1
Fertilizer based on tissue tests	0	1
Weather stations on marsh	0	0
Monitor soil moisture	0	1
Test irrigation uniformity	0	1
Nutrient management plan	0	1
Conservation plan	0	0
Recycle on farm	0	1
Provide safety training	1	0

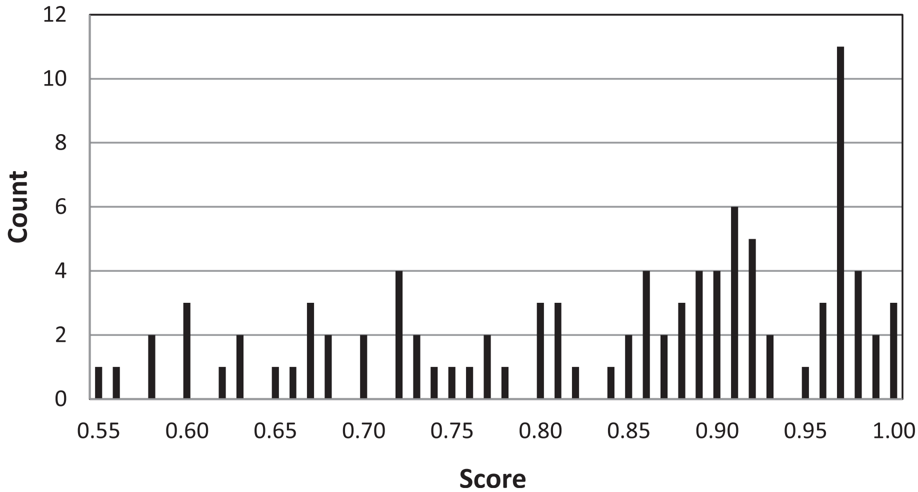

Fig. 1. Histogram of sustainability scores for Wisconsin cranberry farms, showing a clustering of sustainability leaders on the right with high scores and a long tail of lower performing farms on the left.

leaders are clustered on the right side near the maximum score 1.0, while farms with scores in the lower tail pull the group performance down. Each grower is evaluated by a sustainability score that allows growers to compare themselves to their peers. Furthermore, growers or other stakeholders can use the weights and adoption data for each farm to identify farm-specific practices for growers in the lower tail to develop priorities for practices to target for educational programing and/or incentive schemes in order to improve the performance of the growers as a group.

The empirical application to Wisconsin cranberry farms showed the heterogeneity in farmer adoption of sustainable production practices. The weights used to generate these scores can be recovered and specific practices can be identified for each farm to most improve its score. This information can then be used to set priorities for research, educational programming and/or incentive programs for targeted improvement of groups of farmers and to track their improvements over time. Thus, we believe that combining PCA and DEA with the modifications described here is a potentially useful approach for measuring agricultural sustainability at both the farm level and regionally, for both practice-based and outcome-based assessments.

The variables in the original sustainability assessment analyzed here measure practice adoption. Thus, the DEA score presented here can be interpreted as a relative measure of practice adoption intensity ranging between 0 and 1. The score is a relative measure, since the best farms in terms of the intensity of practice adoption receive a score of 1.0 and all other farms are scored relative to these farms. Thus, putting farms in appropriate peer-groups is important so that the comparisons are fair. Furthermore, the final weights for each variable in the original survey are determined endogenously by the farmer responses, so developing a complete set of appropriate practices to include in the survey is important, as is collecting data from a representative sample (or census) of farmers.

Methods to address the relative nature of the measure and to track changes over time remain to be explored. One possibility is to add to the data set a pseudo-observation for a farm that adopts all practices as an "ideal farm." This ideal farm would be on the frontier as a benchmark and all farms would then be compared to this ideal farm as a standard for comparison. To track changes over time, the survey assessment process could be repeated and the analysis repeated, pooling the practice adoption data for the new farms and the original farms. Individual farms in both data sets could be compared to see if the relative score for the farm increased or decreased over time. Also, the distribution of scores for the original farms could be compared to the distribution for the new farms to see if improvements occurred. For example, mean scores or scores for key percentiles could be compared for the new and original data sets, or histograms for the score distributions similar to Fig. 1 for both data sets could be compared visually to see if the distribution had shifted.

6. Conclusion

Improving agricultural sustainability while meeting the food and fiber demands of a growing population with increasing purchasing power has become a global challenge, even as climate change already begins to reduce crop productivity (Tillman et al., 2011; Lobell et al., 2011). An important aspect of this challenge is developing and improving methods for assessing agricultural sustainability in order to document improvements and potentially to reward or to incentivize those making gains. Indeed, extensive research exists developing and evaluating methods for assessing sustainability in agriculture and other areas (e.g., Singh et al., 2009; Van Passel and Meul, 2012). Furthermore, several agricultural sustainability assessment tools or indicators for use by farmers are in various stages of development and implementation in the US and other nations. Our focus in this paper was on a composite indicator that aggregated and integrated across the large number of discrete and correlated variables that are commonly included in agricultural sustainability assessments. In this paper, we described and empirically evaluated a composite indicator that builds on a combination of PCA and DEA.

The method described here first uses non-negative polychoric principal component analysis (PCA) to pre-process the data, and then applies common-weight data envelope analysis (DEA) to determine a score for each farm. Data collected as part of agricultural sustainability assessments commonly include many variables with high degrees of correlation, with many of the variables also discrete; each of these qualities create difficulties for DEA. Non-negative polychoric PCA reduces the number of variables, removes correlation, transforms discrete variables to continuous principal components, and ensures that all elements of the principal components are non-negative. Moreover, the sparseness in the non-negative polychoric PCA helps overcome the difficulty generally encountered in the interpretation of principal components in traditional PCA.

Some studies have used only PCA to generate composite indicators (e.g., Jollands et al., 2004; Gòmez-Limòn and Riesgo, 2009).

While principal components are used in those studies as composite indicators for each sub-section, the final aggregate composite indicator is a weighted sum of these principal components, with the weights decided subjectively. Our method applies DEA instead to decide weights endogenously, to let the data "speak" for themselves.

As an empirical illustration to evaluate the method, we analyze data from a sustainability assessment completed by 95 Wisconsin cranberry farms. For this specific case, the application of non-negative polychoric PCA reduced the 16 original variables, of which 11 were discrete, to 13 continuous principal components that accounted for 92% of the total variance. Applying basic DEA to the resulting principal components scored 40% of the farms as fully sustainable, showing the need for common-weight DEA to better discriminate among these farms. The results not only rank each grower in terms of sustainability practice adoption by the composite indicators, but also identify specific practices for growers to most improve their performance.

In practice, an individualized report would be generated for each farm to give each farm its score and clear feedback on specific practices to adopt to most improve its score over time. Summarizing these reports would identify priority practices for the grower population as a whole, to help set research and outreach priorities to improve the sustainability of the growers as a group. Finally, the initial score for each farm and the distribution of scores for the whole industry can also be used as a baseline and the evaluation process repeated to track sustainability improvements of growers over time.

This sustainability assessment process provides a method for farmer organizations to begin assessing the sustainability of their members. Developing a complete set of appropriate practices is crucial for correctly and thoroughly evaluating farm sustainability, as is delineating an appropriate peer group for farms. Measuring farmer adoption of a set of practices that is poorly connected with sustainable outcomes is not useful, hence selecting a set of practices with science-based evidence for producing more sustainable outcome is important. Also, a regional approach seems appropriate, since a set of sustainable practices must be defined that are applicable to the cropping systems used by most farmers in the region, otherwise the process loses credibility with farmer respondents. Some issues that remain to be examined include the potential for defining an "ideal farm" to make the measure less relative and difficulties that may arise when tracking performance over time. Also, this method could be applied to sustainability outcome data (e.g., greenhouse gas emissions, nutrient losses, soil erosion) or a mix of outcome and practice adoption data, as well as to data for multiple crops or the whole farm. Finally, though theoretically possible, the practical logistics for efficiently creating individualized farm reports and communicating them anonymously to farmer respondents might be difficult to manage for major crops with thousands of growers in a region.

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