Chapter 1 Data Envelopment Analysis as a Tool for Sustainable Foodstuff Consumption

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1 Data envelopment analysis and foodstuffs

As many different methods for measuring the environmental effects of foodstuffs are readily available, it is appropriate to ask if we have any use for one more. Ecological Footprint, Material Flow Accounting, Life-Cycle Assessment and Material Input per Service unit are all measures of interest for environmentally inclined decision making. What does the method discussed in this paper, Data Envelopment Analysis (DEA), offer that the other measures do not provide?

Methodologically DEA modelling is based on mapping of inputs and outputs into the dimension of efficiency. This type of models can be used in an attempt to bring externalities back to economical analysis, and to make ecological effects part of economical decision making (Luhmann, 1990:104-106). As DEA models discuss efficiency, taking into account all variables that are of interest, we can easily integrate economic and ecological factors into the same efficiency score. Even if we should disagree on the matter of DEA modelling being the right method of integration, we should note that the consideration of the problem has already shifted to the consideration of the method. DEA modelling is one possibility for continuing the discussion.

In this study DEA modelling is used for solving the overall efficiency for different foodstuffs. For successful modelling, taking all the relevant factors into account is necessary. Here, the problem is approached from the point of view of the consumer and his or her choice, by posing the following question: what has an effect on a particular consumer's choice of a particular foodstuff? In the context of DEA modelling we can approach the problem by introducing different inputs and outputs (or costs and payoffs) which may have an effect on the consumer choice. Inputs may include both monetary values, such as purchasing cost, and environmental values, such as material input. Outputs can include a number of values such as subjective taste and

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religious views, but also nutrition and environmental effects. All these factors are not easy to measure.

The aim of this study is to provide sustainability scores for Finnish foodstuffs. ‘Sustainability score’ refers here to long-term efficiency. The scenario (Hukkinen 2006) of dematerialization presented by the material input indicator is therefore of particular interest, and material input data can be used in this context as an input. Additionally, as this is most likely to be of interest to the consumers, the purchasing cost of foodstuffs is modelled as an input for some of the DEA models. Nutritional values are used as outputs, as they provide consumer information which is both measurable and useful. To sum up, Finnish data on material inputs and the purchasing cost of foodstuffs are used as inputs and foodstuffs’ nutritional values are used as outputs in all of the following DEA models.

Particular environmental effects, like CO_2-emissions or acidification can be included in the same DEA model with the other variables, as undesirable outputs. In addition to these, models of individual consumer interest can also be built by the inclusion of different variables of taste, although the usual problems of inquiry on subjective taste have to be dealt with. However, for practical reasons (degrees of freedom in DEA model, see eg. Cooper et al., 2007, 283) all the variables of interest cannot yet be included into the same model; the environmental effects and material inputs are known for too few Finnish foodstuffs. More extensive DEA models can be discussed as more diversified data becomes available. With data on 100 different foodstuffs, all the variables mentioned above could already be included in the analysis.

In this study we offer the DEA models of Charnes-Cooper-Rhodes (CCR), Banker-Charnes-Cooper (BCC) and Charnes-Cooper-Rhodes Assurance Region (CCR-AR). These DEA models can be implemented through the many DEA modelling tools available. In this study DEA Solver, software compatible with Excel, was used for implementation. The resulting DEA models were checked using Matlab 6.5. In addition to the models themselves, the relationship between the DEA models was studied with help of Domination matrix (e.g. Tuomaala, 2002). Results from the DEA models were compared to foodstuffs’ Total material requirement (TMR). Chapter 2 gives both the data used and the possible user groups for the DEA modelling conducted. Chapter 3 introduces some of the theory of DEA modelling and the Domination matrix. Chapter 4 gives the main results, which are discussed in Chapter 5.

2 Valid user groups and information needed

Results shown in this paper can be of interest to a user group if the information used in forming the DEA model is appropriate for the decision making in that particular group. Here we briefly discuss the following user groups and their interests in different types of information.

1. The state; agricultural sector
2. Federation of municipalities
3. Foodstuff manufacturers
4. Institutional kitchens
5. Private consumers

The state, or its agricultural sector, may need information on how to develop forms of governmental control that can be justified on the grounds of sustainable development. It can be argued that it is possible to develop sustainability on a state level with the help of general indicators such as material input (see eg. Hoffrén 2001). Controlling decisions made by the state can be seen as more justified if they take into account the nutritional values of the foodstuffs affected, as decisions can have a positive impact on the health of the population. If need be, costs for the state caused by different means of control can also be included in the analysis.

A federation of municipalities may also be concerned about sustainable development. They can seek to address sustainability e.g. of food supply by promoting local food production. As is well-known (e.g. Lähteenoja et al., 2006), local food consumption often has a smaller material input than similar food delivered from a distance. Again, the federation can seek to combine the concern for the environment with concern for its inhabitants, including the nutritional value of different food products, in the analysis. In addition, it might be of interest for the municipalities to analyse their local food production by including some specific environmental indicators in the analysis, in order to address specific problems found within the federation's area.

Firstly, both foodstuff manufacturers and institutional kitchens can endeavour to acquire a competitive edge on a highly competitive market (where the purchasing costs for the producer and the selling prices to the consumer have already been minimized) by introducing a sustainability score for the services offered. Well-marketed, this creates an image of a healthy and sustainable service. Secondly, it can be argued that the production of food which is environmentally inefficient has poorer prospects in the future than food that is environmentally efficient (Pinstrup-Andersen and Pandya-Lorch 1998). Foodstuff manufacturers may attempt to find new markets through the suitable analysis of healthy and sustainable food products.

Individual consumers are a varied group with different needs and wants. In order to analyse foodstuff consumption for individual consumers in general, some measurable quantities can be used. These include environmental effects, material input, purchasing costs and nutrition. Even different (sometimes local, sometimes global) environmental effects and absolute or relative costs are of differing importance to different consumers. When offering advice for specific individual consumers, one has to resort to a more traditional analysis of decision making. This includes weights for taste, ethical views and the like. However, some general level analysis may help individual consumers interested in environmental issues to change their habits for more sustainable ones. Of the factors discussed here, the data on material input and nutritional values can be used to this end.

.2.1 Data on purchasing cost, material input and nutritional values

Table 1 and Table 2 give the data used in the DEA models. Table 1 presents the material inputs of different foodstuffs, studied by Kauppinen et al. in the FIN-MIPS Household project (2008, to appear). Also consumer prices, acquired from the Statistical Yearbook of Finland (2005) are shown in Table 1. These are used as inputs in the DEA models. Respectively, nutritional values provided by the Finnish National Public Health Institute (2008) are used as outputs in the DEA models (Table 2).

Material input data shown in Table 1 are MIPS figures. Material Input per Service unit (MIPS) measures the total material input (MI) per given service (S) through its whole life-cycle. Here the service unit is one kilogram of foodstuff. Material input is divided into 5 different categories: abiotic (non-liveable), biotic (liveable), water, air and erosion.

Table 1: Data used as inputs in DEA modelling

Product group	Purchasing Cost & MIPS (input)					
	Price (€/kg)	Abiotic (kg/kg)	Biotic (kg/kg)	Water (kg/kg)	Air (kg/kg)	Erosion (kg/kg)
Milk	0.73	1.1	3.0	31	0.09	0.3
Butter	4.88	9.8	25.1	208	0.67	2.6
Spreadables, rapeoil	2.90	7.6	19.2	162	0.68	2.0
Spreadables, soyoil	2.90	8.3	19.7	168	0.56	2.2
Cheese	7.67	11.3	28.9	260	1.13	3.0
Beef	9.92	12.0	30.6	439	0.99	3.2
Pork	10.64	8.3	10.2	240	1.91	2.8
Fish	8.29	2.8	4.7	271	0.83	0.2
Poultry meat	10.47	7.0	4.6	228	1.52	1.2
Eggs	2.45	5.7	4.0	141	1.01	1.1
Soy	3	1.3	1.4	157	0.92	0.4
Lager	3	1.5	0.3	280	0.51	0.1
Potato	0.60	0.3	1.7	52	0.02	0.1
Sugar	1.05	3.1	1.6	24	0.80	0.4
Wheat bread	3.00	1.1	1.3	20	0.14	0.3
Rye bread	3.18	1.6	0.8	111	0.21	0.3
Mixed bread	3.06	1.3	1.1	99	0.21	0.3
Barley bread	3.06	1.1	1.4	21	0.15	0.4
Tomato	3.14	8.0	1.4	793	4.50	0.0
Cucumber (average)	3.14	7.0	1.4	570	4.13	0.0
Cucumber (aty)	3.14	13.8	1.4	2481	6.99	0.0
Apple	2	0.7	1.0	7	0.01	0.3
Cloudberry	10	2.0	1.0	17	0.19	0.0
Strawberry	5	1.1	1.0	17	0.15	0.6

Two different cucumbers given in Table 1 and Table 2 refer to different methods of growing. The average cucumber is Finnish national average of all cucumber production, which, as an average, takes place around 9 months per year. On the other hand, ‘aty’-cucumber refers to production which takes place around the year. Otherwise Table 1 and Table 2 should be self-explanatory. However, “Fats” refers only to non-saturated fats, and “Minerals and traces” do not include salt or sodium (Table 2).

Table 2: Data used as outputs in DEA modelling

Product group	Nutritional values (output)					
	Energy (kJ/kg)	Carbo-hydrates (g/kg)	Proteins (g/kg)	Fats (g/kg)	Minerals and traces (g/kg)	Vitamins (g/kg)
Milk	1580	51	38	2	4425	24
Butter	30350	4	12	220	789	28
Spreadables, rapeoil	26020	2	5	468	217	132
Spreadables, soyoil	26020	2	5	468	217	132
Cheese	14640	3	250	74	14450	83
Beef	6390	0	193	23	5228	93
Pigmeat	9140	0	183	87	4572	81
Fish	4500	0	109	42	5434	94
Poultry meat	7340	0	175	69	3507	123
Eggs	5970	3	125	45	4140	70
Soy	14420	257	581	3	37342	158
Lager	1780	41	4	0	762	9
Potato	2640	132	16	2	4894	95
Sugar	16980	999	0	0	28	0
Wheat bread	10570	490	73	46	2127	50
Rye bread	8580	407	67	5	7662	34
Mixed bread	9913	463	71	32	3954	45
Barley bread	8200	387	56	9	4063	46
Tomato	840	35	6	2	3405	200
Cucumber (average)	400	14	6	2	3184	92
Cucumber (aty)	400	14	6	2	3184	92
Apple	1330	71	2	2	1102	125
Cloudberry	1750	78	14	3	2523	1 040
Strawberry	1800	84	5	2	2566	613

3 Using Data envelopment analysis

Technically the DEA model is a non-parametric method of measuring the efficiency of decision making units (DMUs). DEA modelling has been developed since Farrell (1957), and the models discussed here have been discovered during the last thirty years. Charnes, Cooper and Rhodes (1978) introduced the CCR model; Banker, Charnes and Cooper (1984) first studied the BCC model; and the CCR-AR model was developed by Thomson, Singleton, Thrall and Smith (1986). In this study only input-oriented models are used: they enable us to study sustainability scores that consider providing individuals with a proper amount of nutrients while minimizing the material inputs (and in some models, monetary assets).

A few words on the notation used would seem appropriate (see also Cooper et al., 2006). Every foodstuff is a decision-making unit (DMU), consisting of a pair of positive input and output vectors $(\bar{x}_j, \bar{y}_j)$, $j = 1,\dots,n$, respectively. X is a $n \times m$ matrix, consisting of all input vectors $\bar{x}_j$. Y is a $n \times s$ matrix, consisting of all output vectors $\bar{y}_j$. Moreover, we define $\theta \in \Re$, e as a row vector in which all elements are equal to 1 and a non-negative vector $\bar{\lambda} = (\lambda_1,\dots,\lambda_n)^T$. In the general case then, presented in Table 1 and Table 2, we have $n = 24, m = 6$ (Table 1) and $n = 24, s = 6$ (Table 2). Otherwise the notation above is used to present the dual form of the DEA models. For further discussion on formulating the primal and dual problems, see e.g. Cooper et al., 2006, 445.

As mentioned in the introduction, due to an excess of degrees of freedom, all the variables shown in Table 1 can not be included in a single DEA model. Through testing it was found that all the output variables can be included in a model if only three or four of the input variables are used. Therefore we have $m = 3$ or $m = 4$. It was decided to include only abiotic, biotic, erosion and price data in the main analysis. This was partly because the total material requirement of a product (TMR) can be calculated using the following formulation.

$$TMR = abiotic + biotic + erosion \tag{1}$$

As we shall see, it is interesting to compare the DEA models formed using TMR data to TMR data alone. Further, other material inputs are discussed alongside the main results.

.3.1 CCR model

For simplicity, we begin by presenting the CCR DEA model. The CCR model is formed by allowing only constant returns to scale, creating a constantly increasing efficiency frontier. The dual of the input-oriented CCR model is given as follows (Cooper et al., 2006, 43).

$$\begin{aligned}
&\min_{\theta,\lambda} \theta \\
&s.t. \\
&\theta x_0 - X\overline{\lambda} \geq 0 \\
&Y\overline{\lambda} \geq 0 \\
&\overline{\lambda} \geq 0.
\end{aligned} \tag{2}$$

Here the optimal solution for θ is denoted by $\theta*$, and we have $0 \leq \theta* \leq 1$, where $\theta*$ is the sustainability score for DMU_0 by the duality theorem of linear programming (Cooper et al., 2006, 445). By solving the LP problem (2) for every DMU *j*, sustainability scores for all *n* DMUs are acquired. As these scores are solved by optimizing the weights for every DMU, they all receive a sustainability score which is as close to 1 as possible.

.3.2 BCC model

Unlike the CCR model, the BBC model allows for increasing, decreasing and constant returns to scale, creating a piecewise-linear efficiency frontier. The dual of the input-oriented BCC model is given as follows (Cooper et al., 2006, 91).

$$\begin{aligned}
&\min_{\theta_b,\lambda} \theta_b \\
&s.t. \\
&\theta_b \overline{x}_0 - X\overline{\lambda} \geq 0 \\
&Y\overline{\lambda} \geq \overline{y}_0 \\
&e\overline{\lambda} = 1 \\
&\overline{\lambda} \geq 0.
\end{aligned} \tag{3}$$

We find that the dual of the BCC model differs from the dual of the CCR model only by the condition $e\overline{\lambda} = 1$. Together with the last condition given in (3), a convexity condition is formed. This allows for more variation in the type of DMUs given a sustainability score of 1, as the DMUs themselves define the piecewise-linear efficiency frontier.

.3.3 CCR-AR model

The CCR-AR model is the most restrictive of the three models described here. In addition to the constant returns to scale assumption we are using expert knowledge to further scale down the number of foodstuffs defined as sustainable and healthy. The dual of the input-oriented CCR-AR model is given as follows (Cooper et al., 2006, 179).

$$
\begin{aligned}
&\min_{v,u,\pi,\tau} \theta \\
&s.t. \\
&\theta x_0 - X\overline{\lambda} + P\overline{\pi} \geq 0 \\
&Y\overline{\lambda} + Q\overline{\tau} \geq 0 \\
&\overline{\lambda} \geq 0, \overline{\pi} \geq 0, \overline{\tau} \geq 0.
\end{aligned}
\qquad (4)
$$

We can see that, compared to the CCR model (2), additional coefficients have been added to the constraints. Matrices *P* and *Q* enable the utilization of expert knowledge. Relative weights for this knowledge are given by non-negative multiplier vectors $\overline{\pi}$ and $\overline{\tau}$, respectively. The weights are still defined so as to optimize every DMUs sustainability score.

In the CCR-AR model nutritional recommendations are added as an assurance region for the definition of the sustainability. No assurance region for inputs is given: thus, matrix *P* is a zero matrix. Matrix *Q* on the other hand is formed by ratios of different nutrients in nutritional recommendations. As only ratios of nutrients are studied, the assurance region used is defined as a suitable general diet for an average adult (i.e. for someone who is not ill, physiologically impaired or suffering of foodstuff strictures).

The minimum and maximum for ratios between some nutrients *a* and *b*, for which the minimum and maximum recommended intake per day is known, can be solved as follows:

$$
\min \frac{a}{b} = \frac{\min a}{\max b}, \max \frac{a}{b} = \frac{\max a}{\min b} \qquad (5)
$$

The ratios can be used as an assurance region by appropriate substitutions for matrix *Q*, as described in the theory (Cooper et al., 2006, 178).

.3.4 Domination matrix

Next we discuss the concept of domination matrix in relation to DEA models (as in Tuomaala, 2002). To form a domination matrix, pairwise comparisons between DMUs k and l for all models $z=1,\dots,Z$ are made. If for sustainability scores E_k and E_l it holds that

$$[(E_k / E_l) - 1] \geq 0, \qquad (6)$$

we say that DMU k dominates l in model z, and write $D_k^z(l) = 1$. Otherwise we have $D_k^z(l) = 0$. By making the comparison between all DMUs k and l with every model z, we end up with the number of times k dominates l in all models z. This number can be divided by Z, giving the ratio (the percentage score) of cases where k dominates l.

This type of analysis can be applied to a group of DEA models. In Chapter 4 we give the results of this sort of model comparison with different material inputs, models that have ("with") or do not have ("w/o") prices included, and models that are formed using BCC, CCR or CCR-AR modelling.

4 Results

After an observable modelling effort, the following models were formed. Material inputs are varied so that the material input data on abiotic and erosion is always included, and only the third type of material input is varied.

1. 18 DEA models altogether, in the following manner.
    a. BCC, CCR, and CCR-AR models used.
        i. Third material input was varied using all the 3 different models available; water, air or biotic as the third MI.
        ii. Every model was formed with and without price as input.
2. A domination matrix, based on these 18 DEA models was formed.

Here the key results are discussed, with the emphasis on the comparison of the sustainability scores different models provide. TMR figures are also used in order to further elaborate the differences between a traditional TMR measure and the sustainability scores found through DEA modelling. Interpretation of the results received using the domination matrix is also discussed. Table 3 shows the most prominent models, including all the CCR-AR models. The column averages of the domination matrix are also given for every foodstuff. This can be interpreted as an average percentage of other foodstuffs dominated by the foodstuff in question.

Comparing columns in Table 3, we can see that CCR-AR models provide only two foodstuffs with a sustainability score of 1, while the CCR model has seven and the BCC model fifteen of them. This is a common trend in the results: CCR-AR models provide the strictest measure for the sustainability score, CCR models slacken it, while BCC models provide two thirds of foodstuffs with the highest sustainability score.

We can also note that the third material input used has only a small effect on sustainability scores compared to the effect of the model. This said however, some foodstuff's sustainability score may be changed drastically by changes in material input. For example, the sustainability score of cucumber decreases notably when air is included in material inputs. In the same manner, the sustainability score of milk increases when water, and not air or biotic MI is used in the DEA model.

Price seems to have its own prominent effect on the sustainability scores. In Table 3 it can be seen that almost every product's sustainability score increases when the price is taken into account. This may well be because the problem of excess degrees of freedom discussed earlier realises itself with four or more inputs, when only 24 DMUs are used.

Table 3: Sustainability scores given by different DEA models and the results from the domination matrix

Model	CCR-AR				CCR	BCC	18 models, domination average (%)
3rd MI	Biotic	Biotic	Air	Water	Biotic	Biotic	
Product group	w/o price	with price	w/o price	w/o price	w/o price	w/o price	
Milk	0.130	0.416	0.192	0.324	0.174	0.468	0.36
Butter	0.162	0.472	0.229	0.326	0.485	1.000	0.62
Spr., soyoil	0.181	0.591	0.251	0.360	1.000	1.000	0.86
Spr, rapeoil	0.167	0.564	0.236	0.336	0.958	0.972	0.75
Cheese	0.087	0.219	0.119	0.192	0.177	0.183	0.18
Beef	0.034	0.074	0.048	0.060	0.071	0.078	0.06
Pork	0.064	0.104	0.081	0.112	0.254	0.342	0.10
Fish	0.414	0.440	0.414	0.414	1.000	1.000	0.83
Poultry meat	0.101	0.101	0.113	0.134	0.456	0.594	0.17
Eggs	0.100	0.227	0.117	0.154	0.349	0.366	0.19
Soy	1.000	1.000	1.000	1.000	1.000	1.000	1.00
Lager	0.361	0.361	0.266	0.266	0.547	1.000	0.40
Potato	0.711	0.789	1.000	0.711	1.000	1.000	0.95
Sugar	0.623	1.000	0.652	1.000	1.000	1.000	0.98
Wheat bread	0.531	0.531	0.713	1.000	1.000	1.000	0.93
Rye bread	0.733	0.733	0.664	0.547	1.000	1.000	0.70
Mixed bread	0.541	0.541	0.597	0.575	0.993	0.996	0.51
Barley bread	0.421	0.421	0.567	0.871	0.787	0.885	0.59
Tomato	0.577	1.000	0.213	0.213	0.846	1.000	0.81
Cucum. (ave[1])	0.479	0.961	0.198	0.198	0.826	1.000	0.76
Cucum. (aty[2])	0.502	1.000	0.103	0.103	0.878	1.000	0.75
Apple	0.118	0.118	0.452	0.444	0.465	1.000	0.67
Cloudberry	1.000	1.000	1.000	1.000	1.000	1.000	1.00
Strawberry	0.142	0.142	0.151	0.333	1.000	1.000	0.77

The question now arises, regarding how we should interpret the results. Cloudberry and soy seem to have a prominent sustainability score in all the models used, while beef and pork, along with cheese, have the lowest sustainability scores. But what does the sustainability score indicate? In Section 4.1 we move on to a comparison of the results acquired through the different methods of DEA modelling, Domination matrix and TMR measurements. The aim is to develop a sensible interpretation for the sustainability scores based on the research on Total material requirement and its uses as an indicator.

.4.1 Comparison of DEA models, Domination matrix and TMR data

The most straightforward method of studying the similarities between TMR measures, domination matrix and DEA models is to calculate the correlation between the results acquired. In Table 3, the correlations between

[1] Average of Finnish cucumber production.

[2] Around the year values for Finnish cucumber production.

these measures are given. 'Data (ratio scale)' refers to the data used as it is shown above, on ordinary scale of ratios. Correlation was calculated using Pearson correlation. 'Ranking (ordinal scale)' refers to the data ranked on an ordinal scale: every foodstuff was given a ranking from 1 to 24 for every measure used, so that the highest sustainability score was given the number-one ranking. Modified data was then used for the calculation of Spearman correlations, as is appropriate for this sort of data with only a few equal rankings.

While the TMR measures have a negative correlation using the ratio scale (as they should, when an increasing TMR is considered 'bad' for the environment, while increasing sustainability score is considered 'good' for it), correlations on the ordinal scale show positive correlations. This is because the ranking order for the TMR data was reversed compared to the order used for sustainability scores, explained above.

As we can see in Table 4, correlations on the ratio scale produce very few sensible results. It seems that CCR and BCC models correlate strongly with the domination matrix used. Every type of DEA model has some version with over 50% absolute correlation with the TMR measure. It seems that when DEA models have many DMUs with a sustainability score close to 1, they are in a slightly better position to form a high correlation with both domination matrix and TMR. The exceptions seem to be the CCR-AR models without price included. We next discuss the reasons for this phenomenon.

Table 4: Correlation of measures using ratio scale and ordinal scale

Models Used			Correlation (Pearson)		Correlation (Spearman)	
			Data (ratio scale)		Ranking (ordinal scale)	
			Dom. (%)	TMR	Dom. (%)	TMR
Domination (%)			1.000	-0.457	1.00	0.34
TMR			-0.457	1.000	0.34	1.00
CCR-AR	Biotic	w/o price	0.720	**-0.563**	0.79	**0.51**
	Biotic	w price	0.757	-0.326	0.78	0.14
	Air	w/o price	*0.673*	**-0.556**	0.72	**0.68**
	Air	w price	0.810	-0.189	0.78	0.12
	Water	w/o price	*0.676*	**-0.523**	0.73	**0.62**
	Water	w price	0.826	-0.442	0.81	0.28
CCR	Biotic	w/o price	0.882	**-0.507**	0.88	0.43
	Biotic	w price	0.898	**-0.521**	**0.90**	0.29
	Air	w/o price	0.736	-0.390	0.75	0.48
	Air	w price	**0.940**	-0.399	**0.90**	0.29
	Water	w/o price	0.720	-0.467	0.75	**0.52**
	Water	w price	**0.926**	-0.499	0.88	0.27
BCC	Biotic	w/o price	0.859	**-0.560**	0.80	0.48
	Biotic	w price	0.811	**-0.643**	0.81	0.40
	Air	w/o price	**0.926**	-0.375	0.86	0.27
	Air	w price	0.886	-0.473	0.86	0.27
	Water	w/o price	**0.907**	-0.467	0.83	0.31
	Water	w price	0.864	**-0.514**	0.78	0.27

Domination matrix has been defined to give both DMUs domination over each other when they have the same sustainability score. When models are included in the domination matrix with a large number of DMUs having a sustainability score of 1, the domination matrix will have many DMUs with domination percentages close to 100%. As this is the case here (see Table 3), the correlation between the DEA scores and the domination matrix is partly a measure of the number of DMUs with a perfect sustainability score presented by the DEA model in question (see Table 4).

Many TMR measures have a value between 0 and 5, while some are higher than 40. All the DEA models react to the highest TMR figures, as those of the beef, pork and cheese (see Table 3). However, it is the DMUs with small TMR figures that have different sustainability scores depending on the model used. We can note that if all these DMUs are given values closer to 1, the correlation produced will be higher than when these figures are given values between 0 and 1. Therefore the TMR measure has trouble differentiating between the models on ratio scale.

For these reasons the ordinal scale is used for the further analysis. As the ordinal scale is well-founded in the statistical theory, the rescaling of sustainability scores, TMR measures and domination percentages is statistically valid. However, the level of precision is impaired when shifting to the use of ordinal scale. Here the ordinal scale is used to dispose of problems found in the use of ratio scale. In the process, the ordinal scale produces results that are more easily comparable.

When we look at the last two columns in Table 4, we find that the rankings of the CCR sustainability scores correlate more strongly with the rankings of the domination matrix, compared to the rankings of the CCR-AR and BCC sustainability scores. This is because of the definition of average percentage, effectively revealing the CCR models being closest to the average DEA model. However, all the DEA model rankings appear to have a correlation of over 70% with the ranking of the domination matrix. This indicates relatively small variation between the results.

In general it can be noted that dominance matrix (ranking or otherwise) does not have a significant correlation with the TMR measure. This provides further indication that it is not irrelevant which DEA model is used when having to produce a ‘sustainability score’ for the different DMUs in question.

We can note that different CCR-AR models without price included have a high correlation with TMR-figures, comparing the ranking given by sustainability scores with the ranking given by TMR measure. The sustainability scores of foodstuffs in an input-oriented CCR-AR DEA model correlate from 50 to 70% with the TMR scores of foodstuffs on the ordinal scale. Next we take a look at different CCR-AR models without price included, domination matrix and TMR figures. Figure 1 shows a chart diagram of the ranking of these groups for further mutual comparison.

In Figure 1 it is visually obvious that the domination matrix gives very different ranking and thus has very little to do with the TMR measure. However, the different CCR-AR models have a closer relation to TMR. It can be seen that the ranking of at least two of the three different CCR-AR models follows the ranking given by the TMR measure with the following foodstuffs: beef, pork, poultry, eggs, fish, tomato and cucumber. A clearly higher ranking compared to the TMR measure are received by cloudberry and soy. Because of their high energy content sugar and butter are also higher up in the ranking through the sustainability score. Spreadables have a large dose of unsaturated fats, giving them a higher ranking in sustainability scores as well. Foodstuffs with a clearly lower ranking in sustainability scores than in the TMR measure are apple, lager and strawberry. This is most likely because of their relatively low nutrition content.

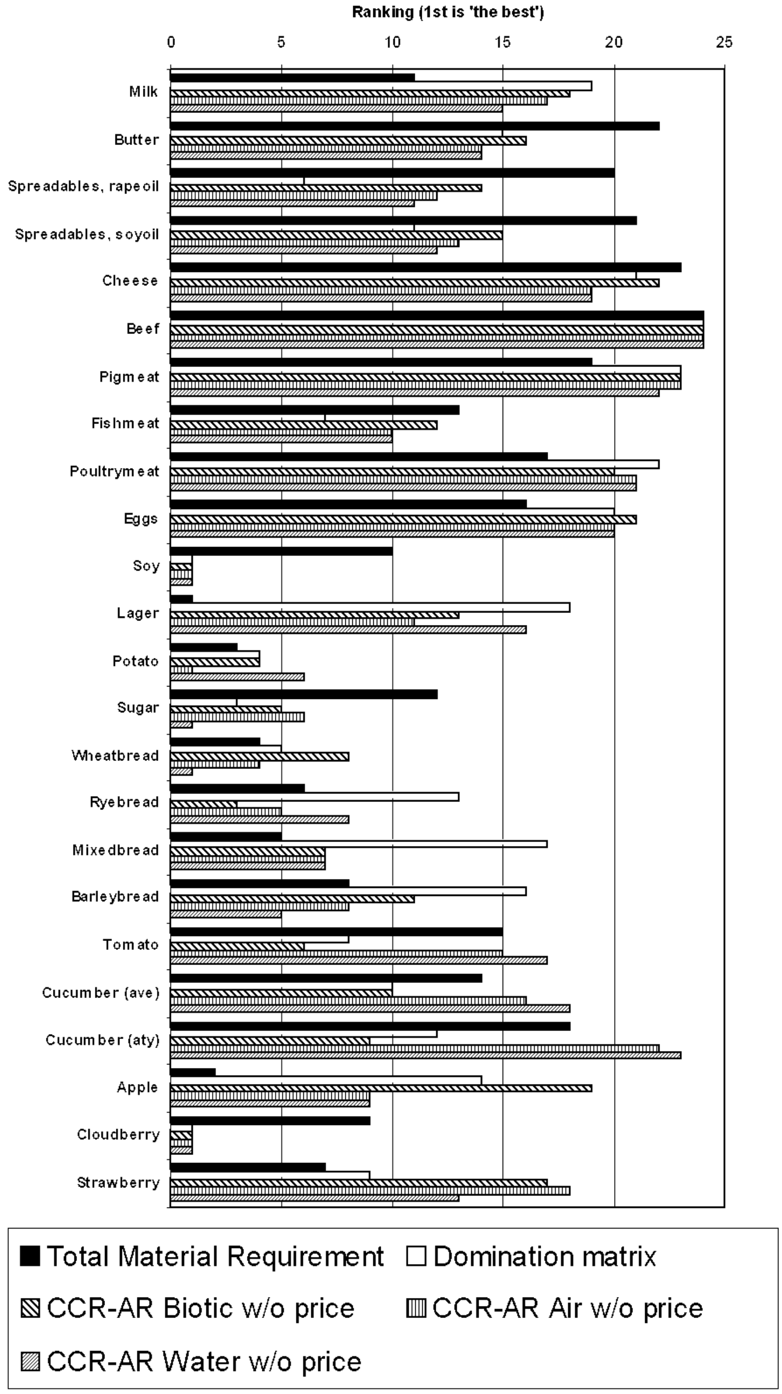

Figure 1: TMR figures, prominent DEA models and Domination matrix column averages on an ordinal scale.

5 DEA models, TMR measurements and user groups

The CCR-AR models seem to be able to differentiate between low material input and healthy foodstuffs and those that are lacking in the other respect: foodstuffs that are either relatively unhealthy, or relatively high on material inputs. Apples are a good example. Apple is healthy, but at the same time inefficient in delivering nutrients compared to its material input. Therefore apple is not as sustainable foodstuff as cloudberry, and has a lower sustainability score. On the other hand, lager is low on material inputs, but as it is not nutritious, its sustainability score is low as well. Both the DEA model and the TMR figures agree on the relatively non-sustainable foodstuffs: beef, pork, cheese, and to some extent on the greenhouse cucumber.

In Chapter 2 we discussed different user groups which could benefit from using DEA modelling in relation to foodstuffs. In this study we have been able to show that suitable a CCR-AR DEA model reacts to material inputs as inputs and nutritional values as outputs coherently. If we include more inputs (and more DMUs to avoid problems with degrees of freedom) this is not likely to change. Thus, user groups can add their own interests (e.g. costs) as additional inputs in the model. Additional outputs can be added as well, including undesirable outputs like CO_2-emissions.

The state can benefit from the use of DEA models in governmental control to justify actions promoting sustainable development. By the use of suitable inputs, the state can add the costs of changes in taxation and so forth to the model and find sustainability scores which are appropriate to the situation. Again, the results given here can be used as a starting point, with emphasis not on the costs, but on health and the environment. Federations of municipalities mentioned can act in the same manner, adding suitable inputs or undesirable outputs, as deemed appropriate. On both the state and municipal levels it can be valuable to be able to take the public health into account, in the indicator of sustainability and in the decision making.

The main user group for the DEA modelling discussed are foodstuff manufacturers and institutional kitchens. The results of CCR-AR DEA models, with similar inputs and outputs as in this study, can be used directly in the marketing of products: a sustainability score of from 0 to 1 can be transformed into a percentage score of from 0 to 100%. From the consumer's perspective, a high sustainability score could mean a healthy and environmentally conscious product. This association is backed up by the results of this study. In addition, sustainability scores can be used in decision making inside the foodstuff companies for seeking products, which have better prospects of thriving in increasingly environment and health conscious food markets.

Last but not least individual consumers are a varied group with an obvious use for an indicator that can be modified according to individual needs. Consumers could use this kind of indicator as an Internet service, adding suitable inputs and outputs through different questionnaires. The basic CCR-AR DEA model with material inputs as inputs and nutritional values as outputs could also be used as a general indicator alongside others, such as the TMR indicator, to help customers make sustainable decisions considering their consumption. More basic Internet services of this kind are already under construction (e.g. Tuotewiki 2007, in Finnish).

Although we have received evidence for the CCR-AR DEA models ability to encapsulate a large amount of information into a one sustainability score, we should remain aware that choosing the inputs and outputs for the DEA model has to be done carefully. In this study, for example the (unhealthy) saturated fats were left out of the analysis to reduce the number of variables. The analysis conducted gives a slightly biased ranking for the different spreadables, as only the unsaturated fats are taken into account. To improve the results in this respect, we should build a model that takes the saturated fats into account as undesirable outputs. This, however, requires more DMUs for the analysis.

Already with a hundred DMUs a total of ten input and ten output variables could be included into a DEA model. These variables could include costs, material inputs and/or ethical views as inputs, while direct environmental effects (received through life cycle analysis, LCA) could be included as undesirable outputs. In addition, nutritional values and different tastes could be included as desirable outputs. Even with this sort of extended amount of variables, a suitable DEA model can offer a coherent set of sustainability scores for the foodstuffs evaluated. As the set of variables can be chosen freely, different actors' interests can be modelled by careful choice of variables as inputs and different type of outputs. Thus, DEA modelling gives efficient decision making aid concerning foodstuffs for the user group in question.

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