# Assessing the regional efficiency of Swedish agriculture under the CAP – a multidirectional efficiency approach

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**Abstract**
The regional dimension is central when designing structural reforms for rural areas. In this study we implement the multidirectional efficiency analysis approach in a regional, rural development context, with the aim of analysing the regional efficiency of agricultural resource use. The efficiency patterns of each input and output were observed over three Common Agricultural Policy (CAP) periods. The results show the largest improvements in the efficiency of diversified output and labour, especially when concerns about environmental conditions and rurality were included in CAP, 2008-2013. Further improvements in regional efficiency could be achieved by creating possibilities for diversified output and structural changes in assets.

**Keywords:** Common Agricultural Policy (CAP), Multidirectional Efficiency Analysis (MEA), regional efficiency, rural development, Sweden

## 1. Introduction

Inefficient farm structures, where agricultural resources are not fully utilised, are problematic for rural areas (Anania, *et al.*, 2003). Improving the potential for utilising the agricultural resources has been found to support farm development and to facilitate rural development (Ezcurra, *et al.*, 2011). In the European Union (EU), balanced development across the EU rural areas is maintained by the Common Agricultural Policy (CAP), covering areas such as: farming and forestry, land use, management of natural resources and economic diversification in rural communities (European Commission, 2016). To provide a sound background for decision making on agricultural policy and thus contribute to rural development, a number of empirical studies have analysed the efficiency of the agricultural sector (Barnes, 2008, Gorton and Davidova, 2004, Manevska-Tasevska, *et al.*, 2016, Sipilainen, *et al.*, 2008). **In most of these studies, assumptions about the characteristics of regional efficiencies in the agricultural sector are based on farm-level efficiency analysis, where single efficiency estimates are presented as the average for sample firms operating in the region/sector/industry.**

Rather than farm-level analysis, **regional-level analysis is suggested to be better suited to decision-making processes relating to rural development policy** and thus more comprehensive regional efficiency analyses updated in line with agricultural policy reforms are needed (Ezcurra, *et al.* (2011). The regional dimension is central when designing structural reforms for rural areas (Crescenzi, *et al.*, 2015, Marsden and Sonnino, 2008), and the regionalisation of agricultural policy is promoted both for the first- and the second (rural development) pillar of the (CAP) (Trouvé and Berriet-Solliec, 2010). Even the distribution of CAP support (e.g. direct payments, Less Favoured Area (LFA) payments, payments to environmentally sensitive regions) is designed to fit regional potential and rurality, but not the costs of individual farms (Manevska-Tasevska, *et al.*, 2016, Marsden and Sonnino, 2008, Nilsson, *et al.*, 2008). Furthermore, research findings show that **the arithmetic/geometric average of farm-level efficiencies by region does not necessarily reflect the efficiency of the corresponding region**, unless the size and performance of the firms included in the analysis are uncorrelated (Karagiannis, 2015). For example, the average efficiency is lower than the aggregate efficiency, i.e. group (regional, industry, etc.) efficiency, when larger units are more efficient than smaller ones, and *vice versa* (Karagiannis, 2015). Even the use of weights, as suggested by Farrell (1957), cannot *a priori* guarantee that the weighted averages of the estimated technical efficiency (TE) of individual farms/firms are consistent measures of the aggregate efficiency (Färe and Karagiannis, 2017).

**Regional efficiency studies have been conducted previously on other sectors**, e.g. the use of infrastructure and human capital in Germany (Schaffer, *et al.*, 2011) and private output and capital (Albert, 1998) and on the intra-sector efficiency of the major productive sectors in Spain (Maudos, *et al.*, 2000), the tourist industry in Italy (Suzuki, *et al.*, 2011), research and development in Korea (Han, *et al.*, 2016), the Greek economy (Tsekeris and Papaioannou, 2017). However, findings from other industries cannot be generalised and applied to the agricultural sector, since both the inputs consumed and outputs produced differ. Moreover, **in the majority of regional efficiency studies the efficiency of the regions is estimated as a single aggregated indicator**, where a best practice threshold is established based on the most feasible input-output combination representing the most efficient regions. However, ranking the regions against an overall efficiency measure does not provide information about how they are performing with respect to each individual input and output. Individual estimations would give better insights into the use of agricultural resources and production of outputs in the regions, providing information about the importance of each input and output for further improvements in efficiency. Estimating the efficiency potential improvement of each input and output was first suggested/introduced by Bogetoft and Hougaard (1999), and initially implemented by Asmild, *et al.* (2003) in order to measure the efficiency of Danish dairy farms. In applications in the agricultural sector, the approach has been used recently by Labajova, *et al.* (2016) to estimate the efficiency of Swedish pig farms and by (Asmild, *et al.*, 2016) to estimate the efficiency of Lithuanian family farms. However, in all applied studies to date, only farm-level analysis has been conducted and the regional aspect has not been considered.

In the present study, we moved beyond the existing literature by implementing the multidirectional efficiency analysis approach (MEA) (Asmild, *et al.*, 2003) in a regional, rural development context, with the aim of analysing the regional TE of agricultural resources. Moreover, we assessed the TE of regions in a combined input-output orientation, simultaneously providing estimates of the ability of different regions to reduce their use of agricultural resources and increase their production of multiple (agricultural, other diversified and social) outputs. This is an acceptable approach in evaluation situations and when implementing policies for simultaneous input reductions and output improvements without prioritising some resources and outputs over others (Wang, *et al.*, 2013). We applied the method to the empirical case of agriculture in Sweden, using panel data from the Swedish Farm Accounting Data Network (FADN) for the period 1998-2013. Following the standard NUTS 3 regional division, there are 21 Swedish territorial units (counties). Due to huge differences in agricultural production condition and potential between the Swedish regions, Sweden is one of the highest contributors to RDPs in the EU (Manevska-Tasevska, *et al.*, 2016), employing measures designed to achieve both sector growth and rural development. In this study, the efficiency patterns of the Swedish regions were determined, statistically tested and discussed in relation to changes in the CAP over the last three CAP programmes: i) the period 1998-2002 (denoted CAP 1), which covers the coupled income support and agri-environmental payments provided to farmers who voluntarily complied with ecological practices; ii) the period 2003-2007 (CAP 2), starting with the Luxembourg CAP reform in 2003 when the single farm payments dependent on cross-compliance were introduced; and iii) the period 2008-2013 (CAP 3), when concerns about environmental conditions and rurality were included in RDPs.

The contribution of this study is twofold. First, contributing to the existing efficiency literature we show how MEA can be used for evaluating the regional improvement potential for the use of agricultural resources and the production of multiple outputs. Second, we contribute to the possibilities of making sound policy recommendations, by promoting regional efficiency estimation to be used as a ground for ex-post CAP evaluations, and for further geographical differentiation of policy.

The rest of the paper is structured as follows: Section two describes the model framework and data, the empirical results are presented and discussed in section three and some conclusions are presented in section four.

## 2. Model framework

### *2.1. Data and variables*

For the present analysis, data from the Swedish Farm Accounting Data Network (FADN) provided by the Swedish Board of Agriculture for the period 1998-2013 (17,188 observations, representing 2,397 farms) were aggregated to fit the regional approach. In total 21 Swedish counties were studied, following the NUTS 3 regional division (as in Schaffer, *et al.*, 2011). See Appendix 1 for more details. FADN data have been aggregated by Esposti (2007) and Shucksmith, *et al.* (2005) to create regional (NUTS 2 and NUTS 3 level, respectively) series of CAP payments. To generate a variable for the aggregate output of the Spanish region, Maudos, *et al.* (2000) aggregated the output originating from each sector of the region. Indeed, the data collection procedure for the FADN follows a methodology aiming to reflect the heterogeneity of farming and to provide representative data covering different regions, economic sizes and types of farming (i.e. a three-way stratification). Therefore, regional aggregation of the FADN data was considered appropriate for the present analysis. Eurostat's regional data from agricultural accounts could be used as an alternative data source, but these data are available only at NUTS 2 level, distinguishing between eight territorial units, instead of the 21 NUTS 3 territorial units.

In this study, the aggregate values of the outputs and inputs of each county were obtained as a sum of the corresponding outputs and inputs of each farm belonging to the county. This means that the aggregate values do not reflect the total use of inputs and production of inputs in the county, but a share which, because of the three-way stratification used to collect the FADN data, can be taken to be representative of the county.

Output selection followed the multifunctional aspect of agricultural activity in the counties. Three outputs were included: i) agricultural output (AO), representing the total revenue (expressed in thousand SEK = Swedish krona, ) from sales of agricultural products in the counties; ii) diversified output (DO), representing the total revenue (expressed in thousand SEK) from on-farm activities outside conventional agriculture such as farm shops and tourism and renting out machinery, buildings and livestock for insemination, or where farm products are processed on-farm using agricultural resources (such as land holdings, buildings, machinery and labour) (Barnes, *et al.*, 2015). In Sweden, diversified output is produced at around 70% of the larger Swedish farms, with an average contribution of 12-15% of the total revenue, most often for processing and sale on the farm, shops, tourism and contractual work (Hansson, *et al.*, 2010). iii) and social output (SO), proxied by the total amount of subsidies (expressed in thousand SEK) paid under Pillar I, provided as socioeconomic income support, and Pillar II, to compensate for regional differences in potential for agriculture and environmentally orientated output-reducing production practices (European Commission, 2016) in the counties.

For each county, inputs were represented by: i) variable costs (VC), containing the total specific costs of plant and animal production (expressed in thousand SEK); ii) fixed costs (FC), representing depreciation, rents, and interests (expressed in thousand SEK); iii) labour (L), considering the total hours of unpaid and paid labour engaged (expressed in thousand working hours); and iv) assets value (A), reflecting the size of the opportunity costs of the capital not covered in FC, and including the total asset value of land, machinery, buildings, breeding and non-breeding livestock (expressed in thousand SEK). Sustainable agricultural production and rural development are related to both positive and negative externalities. However, as this study was based on farm accounting data, the efficiency in the generation of negative externalities could not be observed. The means of the input and output variables at sample and county level are given in Table 1.

**Table 1.** Means of input and output variables across the whole study period 1998-2013, for the whole sample and for all counties individually. kSEK = thousand Swedish krona

| | **Variable costs, kSEK** | **Fixed costs, kSEK** | **Labour, thous. hours** | **Assets value, kSEK** | **Agricultural output, kSEK** | **Diversified output, kSEK** | **Social output, kSEK** |
|---|---|---|---|---|---|---|---|
| **Sample means** | 62128 | 29297 | 184 | 313469 | 74632 | 8388 | 21296 |
| **County means** | | | | | | | |
| Blekinge | 19854 | 10104 | 70 | 105341 | 24996 | 3171 | 4859 |
| Skåne | 268327 | 136917 | 712 | 1530086 | 349003 | 35142 | 74783 |
| Halland | 100895 | 41246 | 259 | 455687 | 122108 | 10449 | 18874 |
| Västra Götaland | 220206 | 110278 | 634 | 1211595 | 274790 | 31302 | 74765 |
| Gotland | 68681 | 30883 | 205 | 330859 | 81294 | 7153 | 22509 |
| Jönköping | 80405 | 33404 | 270 | 319901 | 98019 | 9592 | 21589 |
| Kalmar | 84994 | 37710 | 232 | 375854 | 106796 | 9549 | 22928 |
| Kronoberg | 27541 | 11548 | 96 | 136976 | 31550 | 4303 | 9185 |
| Östergotland | 91930 | 49038 | 262 | 546118 | 108293 | 15823 | 41835 |
| Stockholm | 14106 | 8495 | 49 | 62645 | 18236 | 3432 | 7611 |
| Södermanland | 37646 | 20467 | 131 | 243379 | 40286 | 6691 | 20376 |
| Uppsala | 28077 | 14167 | 91 | 149289 | 34023 | 7335 | 13350 |
| Västmanland | 35627 | 18409 | 97 | 174596 | 40243 | 7585 | 16754 |
| Värmland | 34218 | 14129 | 100 | 153866 | 34973 | 3879 | 14569 |
| Örebro | 41699 | 22151 | 119 | 236979 | 49545 | 5846 | 14045 |
| Dalarna | 12524 | 5459 | 49 | 52347 | 14159 | 975 | 5150 |
| Gävleborg | 31102 | 11162 | 119 | 125963 | 29082 | 4407 | 13290 |
| Jämtland | 21295 | 7301 | 78 | 68049 | 20907 | 2253 | 10698 |
| Västernorrland | 30305 | 11156 | 99 | 108706 | 29227 | 3330 | 13988 |
| Norrbotten | 14782 | 5570 | 50 | 49272 | 15593 | 1697 | 6201 |
| Västerbotten | 40468 | 15636 | 147 | 145342 | 44153 | 2237 | 19849 |

*2.2. Estimating the multidirectional regional efficiency of Swedish agriculture*

As at micro level, a region's achievement of higher efficiency relies on that region's ability to use the available resources and generate output in an efficient way (Schaffer and Siegele, 2009). The MEA, which simultaneously provides multi output/multi input efficiency estimates, was used in this study and variable returns to scale (VRS) were considered in order to allow for economies of scale. Regional efficiency studies have been conducted using both constant returns to scale (CRS) and VRS (e.g. Han, *et al.*, 2016, Martić and Savić, 2001, Maudos, *et al.*, 2000). Gerdessen and Pascucci (2013) assessed the sustainability of regional agricultural systems and showed that the results are not very sensitive to assumptions concerning CRS and VRS, and are barely affected by choosing a input- or output-orientated model. In this study, VRS was still considered theoretically more appropriate because inputs such as agricultural land are only available in a certain amount (as part of the total asset value) in each region. Pooled data for the period 1998-2013 were used to facilitate direct comparisons of efficiency scores between periods and to boost the sample size, thereby strengthening the discriminatory power of the method (Asmild, *et al.*, 2016, Martić and Savić, 2001, Wang, *et al.*, 2013). In estimation of MEA TE scores, we considered the set of 21 territorial units – counties $(c = 1, \dots, 21)$ in the dataset observed in each study year t, where $(t = 1, \dots, 15)$. A county $c$ in year $t$ uses four production inputs $x_{j,c}^{t} (j = 1, \dots, 4)$ to produce three outputs $y_{i,c}^{t} (i = 1, 2, 3)$. Linear programming equations used for calculating the VRS-MEA TE scores (equations 1 to 4) were solved using the benchmarking package in the R programme. First, for a given time=t, for each input $j = 1, \dots, 4$ and each county $(x_{jc_0}^{t}, y_{ic_0}^{t})$ we solved:

$$min_{\lambda_c, a_{j,c_0}^t} \; a_j^t \text{ s.t.}$$
$$\sum_c \lambda_c \, x_{j,c}^t \; \leq \; a_{j,c_0}^t$$
$$\sum_c \lambda_c \, x_{-j,c}^t \; \leq \; x_{-j,c_0}^t \qquad (1)$$
$$\sum_c \lambda_c \; y_{i,c}^t \; \geq \; y_{i,c_0}^t \quad i = 1, 2, 3$$
$$\sum_c \lambda_c \; = 1$$
$$\lambda_c \geq 0$$

In equation (1), $(-j)$ denotes all inputs except input $j$.

Second, for a given time=t, for each output $i = 1, 2, 3$ and each county $(x_{j,c_0}^t, y_{i,c_0}^t)$ we solved:

$$max_{\lambda_c, \alpha_{i,c_0}^t} \; \alpha_i^t \text{ s.t. } .$$
$$\sum_c \lambda_c \, x_{j,c}^t \; \leq \; x_{j,c_0}^t \quad j = 1, \ldots, 4$$
$$\sum_c \lambda_c \; y_{i,c}^t \; \geq \; a_{i,c_0}^t$$
$$\sum_c \lambda_c \; y_{i,c}^t \; \geq \; y_{-i,c_0}^t$$
$$\sum_c \lambda_c \; = 1 \qquad (2)$$
$$\lambda_c \geq 0$$

In equation (2), $(-i)$ denotes the outputs except output $i$. The solutions to equations 1 and 2 resulted in an ideal reference point $(a_{1,c_0}^{t*}, \ldots, a_{4,c_0}^{t*}, \alpha_{1,c_0}^{t*}, \ldots, \alpha_{3,c_0}^{t*})$ for county $(x_{c_0}^t, \; y_{c_0}^t)$. The values $(a_{1,c_0}^{t*}, \ldots, a_{4,c_0}^{t*})$ refer to the solutions to the input minimisation problems and the values $(\alpha_{1,c_0}^{t*}, \ldots, \alpha_{3,c_0}^{t*})$ refer to the solutions to the output maximisation problems. Next, we used the ideal reference point for $(x_{c_0}^t, \; y_{c_0}^t)$ calculated in the first step to solve the following programme:

$$max_{\lambda_c, \beta_{c_0}^t} \; \beta_{c_0}^t \quad \text{ s.t.}$$
$$\sum_c \lambda_c \, x_{j,c}^t \; \leq \; x_{j,c}^t - \; \beta_{c_0}^t \left( x_{j,c_0}^{\,t} \; - \; a_{j,c_0}^* \right), \; j = 1, 2, 3, 4$$
$$\sum_c \lambda_c \; y_{i,c}^{\,t} \; \geq \; y_{i,c}^{\,t} + \beta_{c_0}^t \left( \alpha_{i,c_0}^* - \; y_{i,c_0}^{\,t} \right), \qquad i = 1, 2\,, 3$$
$$\sum_c \lambda_c \; = 1 \qquad (3)$$
$$\lambda_c \geq 0$$

Finally, we used the solution $(\lambda_C^*, \beta_{c_0}^{t*})$ to determine the vector of relative variable-specific MEA efficiencies scores for county $(x_{c_0}^t, \; y_{c_0}^t)$ as:

$$\left( \frac{x_{1,c_0}^{\,t} - \beta_{c_0}^{t*}\left( x_{1,c_0}^{\,t} - a_{1,c_0}^{t*} \right)}{x_{1,c_0}^{\,t}}, \ldots, \frac{x_{4,c_0}^{\,t} - \beta_{c_0}^{t*}( x_{4,c_0}^{\,t} - a_{4,c_0}^{t*})}{x_{1,c_0}^{\,t}}, \frac{y_{1,c_0}^{\,t}}{y_{1,c_0}^{\,t} + \beta_{c_0}^{t*}( a_{1,c_0}^{t*} - y_{1,c_0}^{\,t})}, \ldots \frac{y_{3,c_0}^{\,t}}{y_{3,c_0}^{\,t} + \beta_{c_0}^{t*}( a_{3,c_0}^{t*} - y_{3,c_0}^{\,t})} \right)$$
(4)

MEA TE scores take a value between zero for totally inefficient and 1 for totally efficient regions.

*2.3 Exploring the patterns of technical efficiency scores*

The patterns within the MEA TEs were explored both visually and statistically. First, to visualise the changes in the MEA TE scores across the CAP periods, non-parametric kernel-based density functions were used**.** Kernel-based density functions are becoming a popular tool for visual representation of results obtained from nonparametric efficiency analysis, and are favoured over the commonly used histograms as they provide smoother density estimates and do not depend on the width and number of bins (Baležentis, *et al.*, 2014, Mugera and Langemeier, 2011).

Second, to identify the presence of statistically significant differences between the medians of each MEA TE score across the three CAP periods for the sample and each county separately (as the assumption of normality was not met)[1], the Kruskal-Wallis test (Kruskal and Wallis, 1952) was applied as a nonparametric alternative to one-way ANOVA, i.e. as a one-way ANOVA on ranks. The conclusions from the Kruskal-Wallis test was that the medians of at least two CAP periods were different, but does not provide information on which specific CAP periods groups were statistically significantly different from each other. Since we have defined three groups, one for each CAP period, determining which of these groups differed from each other was important. For that purpose, we used the post hoc Dunn's test (Dunn, 1964), which is suggested to be an appropriate procedure following the Kruskal-Wallis test (Dinno, 2015). Because the decision to reject the null hypothesis in rank tests depends both on the p-values of each pairwise test and the rank, the Holm adjustment (Holm, 1979) was specified to identify the significance.

Finally, in order to observe how regions are clustered with respect to the MEA TEs over the CAP periods, we employed the Ward agglomerative error sum of squares hierarchical clustering method Ward (1963). In essence, there are no rules-of-thumb about the sample size necessary for cluster analysis (Dolnicar, 2002). However, the choice of method for conducting cluster analysis depends on the size of the data, among other things, and hierarchical clustering is being characterised as appropriate for small datasets (Huang, 1997). With the Ward method, the error sum of squares begins at zero, because at the beginning, every object (i.e. county) is in its own cluster which then grows as clusters merge. The Ward method joins the two objects, and then clusters those that result in the least increase in error.

## 3. Empirical results and discussion

### *3.1 Multidirectional technical efficiency scores*

Table 2 presents the average MEA TE scores for the overall sample and for each of the counties included in the analysis, for each of the three CAP periods. Considering the whole sample means (see Table 2), the average MEA TE of the inputs ranged from 0.90 for TE of assets ($TE_A$) in CAP 2 & 3 and 0.90 for TE of labour ($TE_L$) in CAP 1 to 0.97 for fixed costs ($TE_{FC}$) in CAP 3. The sample means for the TE of outputs ranged from 0.76 for the diversified output ($TE_{DO}$) to 0.90 for the social output ($TE_{SO}$) and 0.97 for the agricultural output ($TE_{AO}$). There were only small differences in $TE_{VC}$, $TE_{FC}$ and $TE_{AO}$ (with sample means of 0.96), indicating that production practices such as use of materials, managing fixed costs and agricultural output are rather well harmonised at regional level. The potential for further improvements in regional efficiency was greatest for $TE_{DO}$ and $TE_A$, which might be an indication that future regional efficiency, and thereby regional growth, can be expected to be driven by improvements in the efficiency of diversified output and that further structural changes in terms of capital use are needed. In that regard, more research investigating the regional specifics of agricultural assets and diversified outputs that drive/restrain regional efficiency could provide more insights for better strategic planning and development of rural areas.

[1]The normality of MEA TEs was tested using both skewness and kurtosis tests and the Shapiro-Wilks W test for normal data. Results are available upon request.

**Table 2.** Mean technical efficiency (TE) of inputs and outputs: variable costs (VC), fixed costs (FC), labour (L), assets (A), agricultural output (AO), diversified output (DO) and social output (SO), for each region, over the three CAP periods.

| | | CAP 1: 1998-2002 | | | | | | | CAP 2: 2003-2007 | | | | | | | CAP 3: 2008-2013 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | INPUTS | | | | OUTPUTS | | | INPUTS | | | | OUTPUTS | | | INPUTS | | | | OUTPUTS | | |
| | | VC | FC | L | A | AO | DO | SO | VC | FC | L | A | AO | DO | SO | VC | FC | L | A | AO | DO | SO |
| **Sample (country level ) means** | | **.96** | **.94** | **.90** | **.91** | **.96** | **.76** | **.91** | **.96** | **.95** | **.93** | **.90** | **.96** | **.82** | **.89** | **.96** | **.97** | **.96** | **.90** | **.97** | **.89** | **.92** |
| **County means** | | | | | | | | | | | | | | | | | | | | | | |
| Syd | Blekinge | .94 | .92 | .88 | .85 | .95 | .70 | .64 | .96 | .95 | .92 | .88 | .97 | .88 | .75 | .93 | .91 | .92 | .81 | .93 | .76 | .68 |
| | Skåne | .99 | .97 | .95 | .96 | .99 | .95 | .97 | .99 | .99 | .98 | .97 | .99 | .99 | .96 | .99 | .99 | .97 | .93 | .99 | .97 | .98 |
| Väst | Halland | .95 | .92 | .86 | .82 | .96 | .66 | .79 | .96 | .94 | .90 | .83 | .97 | .84 | .74 | .98 | .99 | .97 | .94 | .99 | .95 | .92 |
| | Väst. Götaland | .99 | .98 | .95 | .97 | .99 | .93 | .97 | .99 | .97 | .96 | .95 | .99 | .97 | .93 | .99 | .99 | .98 | .96 | .99 | .97 | .99 |
| Syd-ost | Gotland | .97 | .97 | .88 | .89 | .98 | .73 | .92 | .95 | .93 | .90 | .85 | .96 | .74 | .87 | .95 | .96 | .93 | .82 | .96 | .83 | .88 |
| | Jönköping | .96 | .95 | .86 | .85 | .98 | .82 | .84 | .96 | .95 | .88 | .83 | .97 | .85 | .83 | .99 | .99 | .98 | .95 | .99 | .97 | .98 |
| | Kalmar | .96 | .95 | .88 | .87 | .97 | .81 | .87 | .96 | .94 | .90 | .84 | .96 | .85 | .85 | .98 | .98 | .97 | .93 | .99 | .90 | .93 |
| | Kronoberg | .95 | .92 | .86 | .86 | .96 | .71 | .78 | .95 | .93 | .89 | .86 | .94 | .85 | .81 | .96 | .96 | .93 | .85 | .97 | .85 | .88 |
| | Östergotland | .99 | .97 | .96 | .98 | .99 | .96 | .98 | .99 | .97 | .97 | .95 | .98 | .98 | .96 | .96 | .96 | .97 | .89 | .97 | .92 | .93 |
| S | Stockholm | .99 | .98 | .98 | .99 | .99 | .99 | .99 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | .97 | .97 | .99 | .95 | .98 | .94 | .97 |
| Västerås | Södermanland | .96 | .91 | .88 | .90 | .92 | .85 | .94 | .94 | .93 | .91 | .96 | .93 | .85 | .88 | .93 | .93 | .92 | .80 | .94 | .82 | .86 |
| | Uppsala | .98 | .97 | .93 | .96 | .98 | .91 | .98 | .99 | .98 | .98 | .97 | .98 | .98 | .96 | .98 | .99 | .97 | .93 | .98 | .97 | .95 |
| | Västmanland | .99 | .96 | .95 | .97 | .98 | .93 | .97 | .97 | .96 | .96 | .91 | .96 | .93 | .89 | .97 | .98 | .99 | .96 | .98 | .98 | .97 |
| | Värmland | .94 | .89 | .88 | .98 | .93 | .53 | .89 | .92 | .91 | .91 | .85 | .93 | .66 | .86 | .93 | 95 | 94 | .84 | .95 | .84 | .92 |
| | Örebro | .96 | .94 | .91 | .86 | .97 | .58 | .89 | .94 | .91 | .92 | .82 | .95 | .68 | .79 | .94 | .93 | .96 | .87 | .95 | .85 | .84 |
| Mitt | Dalarna | .99 | .97 | .97 | .98 | .99 | .86 | .98 | .97 | .93 | .91 | .89 | .97 | .50 | .85 | .93 | .93 | .93 | .86 | .95 | .63 | .87 |
| | Gävleborg | .91 | .90 | .82 | .86 | .88 | .63 | .89 | .94 | .94 | .86 | .87 | .94 | .81 | .90 | .93 | .97 | .92 | .87 | .95 | .92 | .92 |
| | Jämtland | **.97** | .96 | .90 | .96 | .96 | .67 | .97 | .98 | .98 | .96 | .98 | .98 | .85 | .98 | **.95** | .97 | .95 | .91 | .97 | .87 | .92 |
| | Västernorrland | .90 | .88 | .83 | .84 | .85 | .52 | .86 | .93 | .91 | .87 | .87 | .93 | .71 | .89 | .96 | .98 | .97 | .93 | .98 | .92 | .97 |
| Norr | Norrbotten | 1 | .99 | .98 | .99 | 1 | .88 | .99 | .99 | .98 | .98 | .98 | .99 | .89 | .98 | .96 | .97 | .97 | .95 | .97 | .84 | .95 |
| | Västerbotten | .94 | .91 | .85 | .91 | .94 | .38 | .93 | .94 | .92 | .88 | .90 | .95 | .52 | .93 | .99 | .99 | .99 | .97 | .99 | .89 | .98 |

Note: CAP 1, CAP 2 and CAP 3 represent the period 1998-2002, 2003-2007 and 2008-2013, respectively. Colours and regions correspond to those in Figure A1 in the appendix.

Schaffer, *et al.* (2011) concluded that improvements in regional efficiency are driven by growing outputs rather than decreasing inputs. Among the different agricultural outputs, diversified output has been identified as one of the most important for efficiency at regional level, especially in regions where farm growth is restricted (Lakner, *et al.*, 2014). However, in both those studies, efficiency was observed as aggregated output-orientated efficiency estimates, which prevents the efficiency potential of inputs being observed.

Across the Swedish counties (see Table 2), overconsumption of inputs, particularly $TE_L$ and $TE_A$, and underproduction of outputs, mainly $TE_{DO}$, were found for central and northern Sweden (see regions 'Mitt' and 'Norr' in Figure A1 in the appendix), especially during CAP 1, when coupled income support was the main subsidy provided to farmers. Counties such as Gävleborg, Västernorrland and Västerbotten, which are often recognised as disadvantaged for agricultural activities, were among the worst affected. Findings for specific counties also showed low efficiency, but not exclusively in disadvantaged/environmentally sensitive regions, as has been found in the majority of studies analysing the efficiency of the agricultural sector at farm level (Barnes, 2008, Gorton and Davidova, 2004, Manevska-Tasevska, *et al.*, 2016, Sipilainen, *et al.*, 2008). Low MEA TE values, particularly $TE_{DO}$, were also found for counties such as Värmland and Örebro, both belonging to the Västerås region, which is not characterised as a disadvantaged region, especially before environmental conditions and rurality were included in RDPs (i.e. in CAP 1 and CAP 2). Previous research shows that the need for specific food and fibre commodities and non-food and fibre commodity outputs may differ between regions (Lankoski, 2000, Nilsson, *et al.*, 2008). For instance, Lakner, *et al.* (2014) found that multifunctional farming is typical for regions with relatively low or marginal agricultural production potential. Since other non-disadvantaged regions were found to have relatively high $TE_{DO}$, that could not be confirmed in the present study.

*3.2 Changes in technical efficiency scores between CAP periods*

Figures 1 and 2 show the kernel density estimates of the MEA TE scores over the three CAP periods. As can be seen, changes in terms of improvements in mean efficiency were largest and continuous for $TE_L$ and $TE_{DO}$; $TE_{FC}$ improved mostly in CAP 3, when concerns about environmental conditions and rurality were included in RDPs. The distribution of the other two inputs, i.e. $TE_{VC}$ and $TE_A$, and of social output ($TE_{SO}$) followed the distribution of $TE_{AO}$, which points to their direct connection with the production of agricultural outputs.

Results from the analysis of variance in MEA TEs across the three CAP periods at sample and county level are given in Table 3 and Table 4, respectively. In the tables, the Kruskal-Wallis test is represented by $Chi^2$ and p-values (statistical significance at $p<0.05$). Dunn's test (with Holm adjustment) is represented by z-values (statistical significance at $p<0.05$). Dunn's test shows the stochastic dominance among multiple pairwise comparisons, but the z-values and the corresponding p-values do not provide information on the magnitude, and the effects of external factors cannot be controlled.

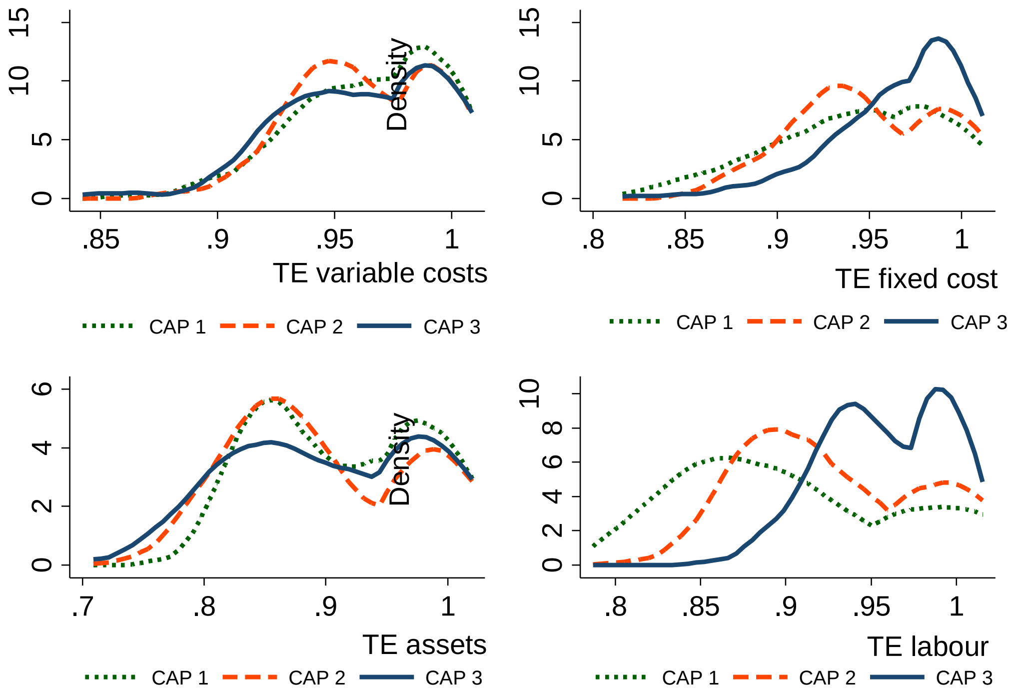


**Figure 1.** Kernel density estimates of the technical efficiency (TE) of inputs over the three CAP periods: 1998-2002; 2003-2007 and 2008-2013.

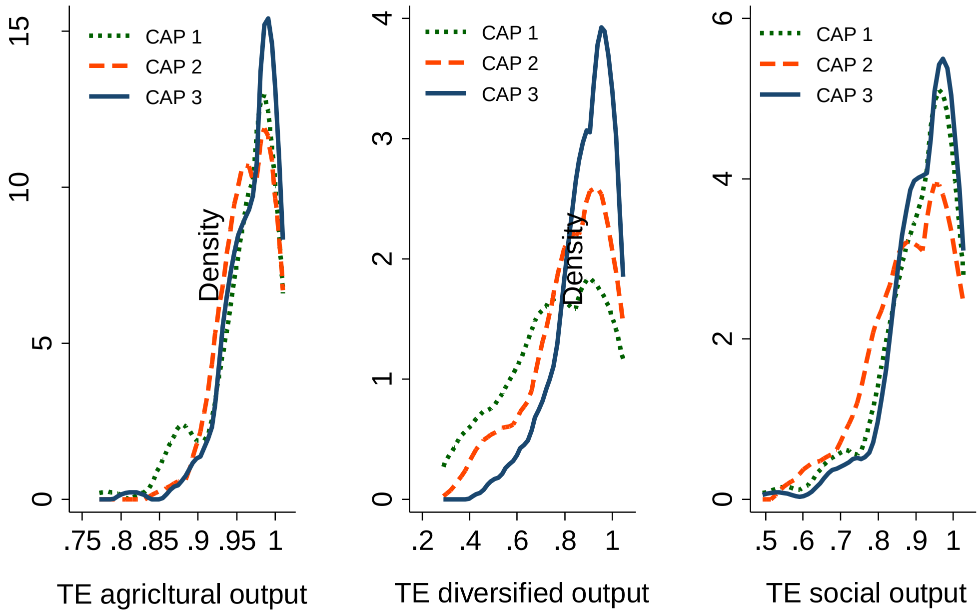


**Figure 2.** Kernel density estimates of the technical efficiency (TE) of outputs over the three CAP periods: 1998-2002, 2003-2007 and 2008-2013.

In line with the findings from the kernel density function, at sample level the Kruskal-Wallis and Dunn's tests indicated statistically significant differences between the median MEA TE scores for $TE_L$ and $TE_{DO}$ in all pairwise comparisons and $TE_{FC}$ in CAP 3 relative to CAP 1 and CAP 2 (see Table 3). Since 2010, Sweden has been working continually on strengthening the roles of the regions, through supporting agriculture and diverse entrepreneurial activities by focusing on region-specific assets and labour services (OECD, 2017). Therefore the relative improvements observed for CAP 3, mostly relative to CAP 1, can be expected to be due to changes in implementation of RDPs and the CAP. However, as the present study was based on panel data for 16 years, improvements in $TE_L$ might also be associated with technological change to some extent, although due to the model specifications this could not be observed. The recently proposed MEA Malmquist approach (Asmild, *et al.*, 2016), which allows efficiencies to be disaggregated into technological and efficiency change, could be used to rectify this in future studies

T**able 3.** Kruskal-Wallis and Dunn's post-test of multiple comparisons of the technical efficiency (TE) of inputs and outputs, at sample (country) level, over the three CAP periods.

| **MEA TE** | **Kruskal-Wallis** | | **Dunn's test** | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | **CAP 2 vs CAP 1** | | **CAP 3 vs CAP 1** | | **CAP 3 vs CAP 2** | |
| | **Chi2 with ties** | **p-value** | **Z** | **p-value** | **z** | **p-value** | **z** | **p-value** |
| **Inputs** | | | | | | | | |
| TE VC | .57 | .7530 | .57 | .5811 | .73 | .7022 | .15 | .4407 |
| TE FC | 16.44 | .0003* | -.33 | .3703 | -3.62 | .0004 | -3.27 | .0011 |
| TE Labour | 53.54 | .0001* | -2.64 | .0042 | -7.20 | .0000 | -4.44 | .0000 |
| TE Assets | 1.82 | .4022 | 1.29 | .2931 | 1.00 | .3167 | -.35 | .3627 |
| **Outputs** | | | | | | | | |
| TE Agr. out | 3.40 | .1828 | .09 | .4650 | -1.52 | .1273 | -1.62 | .1590 |
| TE Div. out | 21.682 | .0001* | -2.08 | .0187 | -4.64 | .0000 | -2.47 | .0137 |
| TE Soc. out | 5.20 | .0744 | 1.44 | .1486 | -.75 | .2268 | -2.26 | .0359 |

Note: For the Kruskal-Wallis Chi2 statistics, * indicates significance at $p<0.05$ at least. For the Dunn's pairwise z-values, where figures are underlined, the hypothesis is rejected. CAP 1, CAP 2 and CAP 3 represent the period 1998-2002, 2003-2007 and 2008-2013, respectively.

At county level (see Table 4), statistically significant differences between the means of all MEA TE scores across the three CAP periods were found for the counties in western and south-eastern Sweden (especially Halland, Jönköping and Kalmar) and central and northern Sweden (Dalarna, Gävleborg, Västernorrland and Västerbotten). In general, it was found that the TEs of both inputs and outputs improved, except for Dalarna (relative decrease in $TE_{VC}$, $TE_A$, $TE_{AO}$, $TE_{DO}$ and $TE_{SO}$). Gotland showed a relative decrease in $TE_A$ but increase in $TE_L$ The most common improvements were in $TE_L$ and $TE_{FC}$, especially in CAP 3 compared with CAP 1. Among the regions, the largest improvements were in Halland, Jönköping, Gävleborg, Västernorrland and Västerbotten.

T**able 4.** Kruskal-Wallis and Dunn's post-test of multiple comparisons of the technical efficiency (TE) of inputs and outputs, by county, over the three CAP periods

| | | Syd | | Väst | | Syd-ost | | | | | Stoc | Västerås | | | | | Mitt | | | | Norr | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Blek | Skan | HalL | V.Go | Gotl | Jonk | Kalm | Kron. | O.go. | Stock | Sod | Upp | Väst | Varm | Oreb | Dalar | Gavl | Jaml | V.no. | N.bot | V.bo |
| TE VC | **Kruskal-Wallis (Chi2)** | 4.12 | 1.85 | **6.42*** | .06 | 4.88 | **6.54*** | **6.06*** | .74 | 3.71 | 5.47 | .97 | 1.12 | .44 | 2.99 | 2.02 | **11.08*** | 5.09 | 2.05 | **7.99*** | 2.81 | **7.68*** |
| | Dunn: CAP 2 vs CAP 1 | -1.46 | -.85 | -.40 | .07 | 1.86 | .53 | .60 | .40 | .23 | -.99 | -.13 | -.72 | .64 | 1.73 | 1.26 | 2.07 | -2.13 | -.70 | -1.33 | .43 | .53 |
| | Dunn: CAP 3 vs CAP 1 | .44 | .46 | -2.34 | .24 | 1.99 | -1.86 | -1.72 | -.44 | 1.75 | 1.29 | .76 | .34 | .52 | .81 | 1.21 | 3.31 | -1.76 | .70 | -2.82 | 1.61 | -2.04 |
| | Dunn: CAP 3 vs CAP 2 | 1.96 | 1.35 | -1.93 | .16 | .05 | -2.41 | -2.35 | -.86 | 1.51 | 2.33 | .90 | 1.09 | -.13 | -.99 | -.10 | 1.15 | .46 | 1.43 | -1.43 | 1.16 | -2.60 |
| TE FC | **Kruskal-Wallis (Chi2)** | 5.42 | .69 | **8.54*** | .15 | 5.23 | **10.66*** | **6.39*** | 4.27 | 1.67 | 4.81 | .233 | .879 | .65 | **7.99*** | 1.46 | 3.52 | **8.37*** | .51 | **10.76*** | .70 | **10.11*** |
| | Dunn: CAP 2 vs CAP 1 | -2.06 | -.78 | -.73 | .15 | 2.19 | .07 | .40 | -.93 | .77 | -1.15 | -.20 | -.852 | .14 | -.80 | 1.13 | 1.60 | -1.26 | -.70 | -.930 | -.21 | -.40 |
| | Dunn: CAP 3 vs CAP 1 | -.15 | -.17 | -2.80 | -.23 | .59 | -2.75 | -1.92 | -2.06 | 1.29 | 1.00 | -.47 | -.113 | -.60 | -2.73 | .22 | 3.67 | -2.88 | -.23 | -3.17 | .58 | -2.90 |
| | Dunn: CAP 3 vs CAP 2 | 2.00 | .65 | -2.02 | -.38 | -1.70 | -2.82 | -2.34 | -1.09 | .48 | 2.19 | -.27 | .777 | -.75 | -1.90 | -.96 | .00 | -1.27 | .50 | -2.20 | .80 | -2.48 |
| TE Labou | **Kruskal-Wallis (Chi2)** | **6.50*** | 1.35 | **11.39*** | .21 | **7.99*** | **12.25*** | **10.78*** | **11.32*** | .55 | 4.54 | .86 | 1.846 | 1.57 | **9.71*** | 3.12 | 4.56 | **13.35*** | **7.28*** | **12.18*** | .34 | **11.93*** |
| | Dunn: CAP 2 vs CAP 1 | -2.19 | -.99 | -1.12 | -.29 | -.80 | -1.27 | -.93 | -1.99 | -.64 | -1.22 | -.53 | -1.33 | -.14 | -1.06 | -.33 | 2.13 | -1.66 | -2.49 | -1.26 | -.07 | -1.13 |
| | Dunn: CAP 3 vs CAP 1 | -2.25 | .01 | -3.32 | -.46 | -2.73 | -3.44 | -3.17 | -3.35 | -.66 | .85 | -.93 | -.46 | -1.14 | -3.05 | -1.65 | 1.21 | -3.64 | -2.18 | -3.43 | .46 | -3.37 |
| | Dunn: CAP 3 vs CAP 2 | .04 | -1.04 | -2.06 | -.15 | -1.90 | -2.12 | -2.20 | -1.27 | .01 | 2.13 | -.37 | .93 | -.99 | -1.94 | -1.31 | -1.02 | -1.91 | .42 | -2.12 | .53 | -2.19 |
| TE Assets | **Kruskal-Wallis (Chi2)** | 4.69 | 2.20 | **8.04*** | .19 | **6.38*** | **10.35*** | **7.66*** | 1.29 | 4.25 | **5.87*** | **9.23*** | 2.60 | .85 | 3.30 | 1.18 | **11.25*** | .40 | 2.05 | **6.32*** | 2.11 | **6.86*** |
| | Dunn: CAP 2 vs CAP 1 | -.66 | -.51 | .20 | .37 | 1.46 | 1.53 | 1.20 | -.33 | .77 | -.92 | 1.13 | -.58 | .62 | 1.00 | 1.00 | 1.80 | -.60 | -.70 | -1.06 | .43 | .20 |
| | Dunn: CAP 3 vs CAP 1 | 1.41 | .92 | -2.31 | -.01 | 2.52 | -1.61 | -1.50 | .75 | 2.03 | 1.43 | 3.00 | .980 | -.25 | 1.82 | .15 | 3.35 | -.50 | .70 | -2.50 | 1.41 | -2.12 |
| | Dunn: CAP 3 vs CAP 2 | 2.10 | 1.45 | -2.52 | -.40 | .99 | -3.21 | -2.75 | 1.10 | 1.23 | 2.39 | 1.82 | 1.59 | -.91 | .78 | -.89 | 1.47 | .13 | 1.43 | -1.34 | .96 | -2.33 |
| TE Ag. ou | **Kruskal-Wallis (Chi2)** | 3.94 | .89 | **6.93*** | .01 | 4.41 | **6.90*** | **6.06*** | 2.85 | 2.43 | 4.81 | .76 | .88 | .21 | 1.67 | .99 | **7.80*** | **9.72*** | 1.54 | **10.34*** | 1.50 | **9.32*** |
| | Dunn: CAP 2 vs CAP 1 | -1.74 | -.72 | -.33 | .00 | 1.73 | .80 | .60 | .93 | .50 | -1.15 | -.07 | -.85 | .07 | -.07 | 1.00 | 1.53 | -2.59 | -1.23 | -1.33 | .64 | -.20 |
| | Dunn: CAP 3 vs CAP 1 | -.07 | .15 | -2.40 | .10 | 1.92 | -1.72 | -1.72 | -.72 | 1.52 | 1.00 | -.78 | -.11 | -.35 | -1.15 | .52 | 2.66 | -2.83 | -.50 | -3.19 | 1.22 | -2.70 |
| | Dunn: CAP 3 vs CAP 2 | 1.73 | .90 | -2.05 | .10 | .12 | -2.55 | -2.35 | -1.69 | 1.00 | 2.19 | -.71 | .78 | -.42 | -1.08 | -.52 | 1.06 | -.13 | .78 | -1.80 | .56 | -2.49 |
| TE Div. ou | **Kruskal-Wallis (Chi2)** | **5.82*** | 1.64 | **12.11*** | .26 | 4.32 | **8.36*** | .46 | 4.46 | 4.49 | 5.12 | .05 | 1.35 | 1.04 | **8.37*** | 5.11 | **8.98*** | 9.12 | 3.60 | **10.82*** | .48 | **11.63*** |
| | Dunn: CAP 2 vs CAP 1 | -2.39 | -1.13 | -1.87 | -.51 | .27 | -.60 | -.20 | -1.93 | -.64 | -1.07 | -.07 | .99 | .00 | -1.26 | -.93 | 3.00 | -1.33 | -1.43 | -1.26 | .00 | -1.53 |
| | Dunn: CAP 3 vs CAP 1 | -.97 | -.07 | -3.48 | -.27 | -1.62 | -.2.73 | -.66 | -1.75 | 1.39 | 1.14 | .15 | .01 | -.90 | -2.88 | -2.23 | 1.57 | -3.01 | -1.81 | -3.25 | .59 | -3.40 |
| | Dunn: CAP 3 vs CAP 2 | 1.53 | 1.11 | -1.53 | .27 | -1.90 | -2.10 | -.45 | .27 | 2.06 | 2.26 | .22 | 1.04 | -.87 | -1.56 | -1.27 | -1.57 | -1.62 | -.32 | -1.93 | .59 | -1.79 |
| TE Soc. ou | **Kruskal-Wallis (Chi2)** | 2.15 | 1.16 | **5.95*** | .21 | 2.06 | **10.66*** | 5.27 | 5.53 | 2.06 | 4.81 | 4.96 | 1.84 | .56 | .86 | 1.59 | **9.78*** | 1.80 | 1.44 | **7.13*** | 2.39 | 7.414 |
| | Dunn: CAP 2 vs CAP 1 | -1.46 | -.51 | .47 | .29 | 1.33 | -.07 | .27 | -.66 | .44 | -1.15 | 1.39 | -.44 | .62 | .53 | 1.26 | 2.73 | -.33 | -.76 | -.60 | .35 | -.13 |
| | Dunn: CAP 3 vs CAP 1 | -.86 | .54 | -1.80 | -.15 | 1.16 | -2.82 | -1.81 | -2.29* | 1.39 | 1.00 | 2.21 | .86 | -.06 | -.37 | .66 | 2.73 | -1.28 | .39 | -2.53 | 1.47 | -2.39 |
| | Dunn: CAP 3 vs CAP 2 | .67 | 1.07 | -2.29 | -.46 | -.23 | -2.75 | -2.08 | -1.60 | .94 | 2.19 | .75 | 1.32 | -.71 | -.93 | -.66 | -.13 | -.94 | 1.19 | -1.91 | 1.10 | -2.25 |

Note: For the Kruskal Wallis Chi2 statistics, * indicates significance at p<0.05 at least. For the Dunn's pairwise z-values, underlining indicates significance at p<0.05 at least. CAP 1, CAP 2 and CAP 3 represent the period 1998-2002, 2003-2007 and 2008-2013, respectively. Colours and regions correspond to those in Figure A1 in the appendix.

*3.3. Clustering of regions*

Within each CAP period, the counties were clustered based on the MEA TEs in order to identify similarities and differences between groups (clusters) of counties. Based on the 'stability', which involved multiple repetitions of the clustering procedure with varying numbers of clusters (Dolnicar, 2002) and visual presentations, i.e. dendrograms, the counties were classified into three clusters (two clusters in CAP 3). Descriptive statistics on the MEA TEs of clusters can be found in Table A1 in the appendix. Details on allocation of counties based on the hierarchical cluster analysis are given in Table A2 and presented graphically in Figure 3.

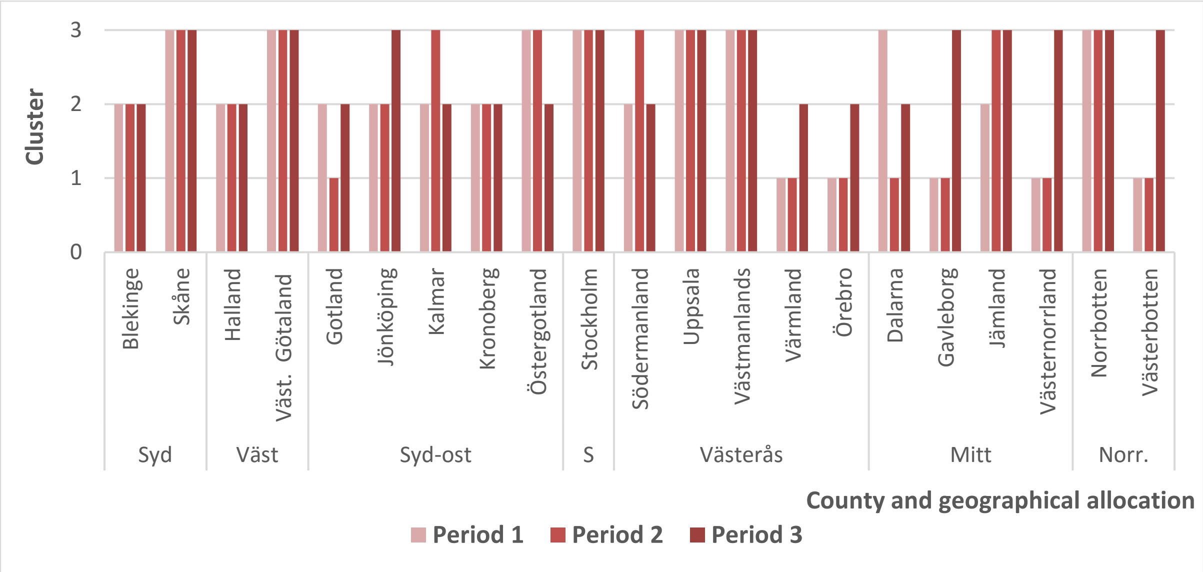


**Figure 3.** Ward *hierarchical clustering* of counties over the three CAP periods: CAP 1 = 1998-2002, CAP 2 = 2003-2007, CAP 3 = 2008-2013. Cluster 1, Cluster 2 and Cluster 3 group counties with lowest (below the mean), around the mean and highest (above the mean) MEA technical efficiency (TE) values, respectively.

The best-performing regions, i.e. those with the highest average MEA TEs (above the sample mean) across the CAP periods made up Cluster 3; those with MEA TEs around the sample mean value made up Cluster 2; and those with the lowest MEA TEs made up Cluster 1. In CAP 3, only two clusters were defined: Cluster 2 containing regions with MEA TEs around the sample mean and Cluster 3 with regions where MEA TEs were above the sample mean. Cluster 1 disappeared due to decreased difference between the regions' MEA TEs, i.e. higher mean values, likely as a result of the better use of resources and better redistribution of the CAP funds.

According to Trouvé and Berriet-Solliec (2010), without proper redistribution of resources and CAP support, regionalisation of the CAP may increase the inequalities between rich and poor regions, which in our case would imply lowering the mean values of the MEA TEs. Trouvé and Berriet-Solliec (2010) have also found that besides the resources, the success of the CAP also depends on the regions' engagement into the agricultural politics. In Germany, economically powerful regions have traditionally engaged in an active agricultural policy. Similarly, based on the findings from the cluster analysis, over the three CAP periods the best-performing counties were those in the most productive agricultural areas and those containing large cities (i.e. Skåne, Västra Götaland, Värmland, Stockholm, Uppsala all belonging to Cluster 3). Interestingly, Norrbotten and Jämtland, which are typically recognised as environmentally sensitive, were also found to fall within Cluster 3. Unfortunately, information about regions engagement into the agricultural policy was not available for this study. Over the three CAP periods, the largest improvements were in environmentally sensitive regions in central and northern Sweden (regions 'Mitt' and 'Norr' in Figure 3). These regions belonged to Cluster 1 in CAP 1 and CAP 2, and joined Cluster 3 in CAP 3. This result is in line with recent OECD reports on growth of the Swedish regions, and northern, sparsely populated areas (OECD (2017, 2017), which after 2010 show low territorial disparities in Sweden and potential for high productivity and productivity growth in low-density areas. The counties Gotland and Dalarna showed the lowest efficiency performance during CAP 2, when both counties belonged to Cluster 1. Last but not the least, the spatial distribution of the efficiency values indicated that regions with similar values and trends in TE, and regions with statistically significant impacts of the CAP changes, tended to be clustered together.

## 4. Conclusions

Individual assessment of the efficiency patterns of agricultural resource use for creation of multiple (agricultural, diversified, and social) outputs is important for rural development, but has not been performed in previous regional efficiency studies. Moreover, previous studies have used aggregated estimates of regional agricultural efficiency based on farm-level efficiency, an approach recently criticised as being inappropriate.

This study analysed the regional technical efficiency and efficiency patterns of the agricultural sector in Sweden in a novel way involving implementation of the MEA approach in a regional, rural development context. MEA allows for assessment of the TE of each input and output used in the production process, enabling both the resource use efficiency and the efficiency of the production of a multidimensional vector of outputs within the agricultural sector to be studied. In most commonly used efficiency approaches (parametric and non-parametric) aggregated estimates of input- or output-orientated efficiency are estimated, and as a result important differences in input/output efficiencies can be hidden. Individual assessment of regional efficiency is of great value for policy makers creating and evaluating rural development policy schemes where strategies for efficiency improvements in different resources and outputs are among the priorities.

The MEA TE scores for each input and output in 21 Swedish counties and efficiency patterns were considered and compared between three CAP periods. The results showed small differences in $TE_{VC}$, $TE_{FC}$ and $TE_{AO}$, indicating harmonised agricultural practices in use of production materials and fixed costs, and production of agricultural outputs at county level. The lowest TE scores were found for $TE_{DO}$ and $TE_{A}$, indicating that further improvements in the regional efficiency of the agricultural sector in Sweden could be driven by farm diversification (i.e. activities where farm resources are also used for on-farm activities outside conventional agriculture) and structural changes in assets. Over the CAP periods studied, the TE of both inputs and outputs improved, particularly $TE_{DO}$ and $TE_{L}$. Among the counties, the most obvious improvements were in counties lying in environmentally sensitive regions in central and northern Sweden (Västernorrland, Gävleborg and Västerbotten) and in the neighbouring counties of Halland and Jönköping in western and south-eastern Sweden. Improvements were especially marked in CAP 3, when concerns about environmental conditions and rurality were included in RDPs. Consistently high TE scores were found for counties in the plains region of Sweden, which have good conditions for agricultural activities, and in counties containing large cities, such as Skåne, Västra Götaland, Värmland, Stockholm and Uppsala.

Further work is needed on the multidimensional efficiency of regions in terms of their multiple outputs, including negative externalities (i.e. environmental and climate), while taking into account efficiency change as well as technical change. Moreover, since the potential for further improvements in TE was found here to be largest for assets and diversified output, more research is needed on the regional specifics of agricultural assets and diversified output that drive/restrain regional efficiency, in order to provide more insights for better strategic planning and development of rural areas. Last but not least, the spatial distribution of efficiency values indicated that regions with similar values and TE development, and regions with statistically significant impacts of the CAP changes, tended to be clustered together. Extensive analysis, incorporating MEA and spatial models, is needed to further explain that finding.

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## Appendix 1

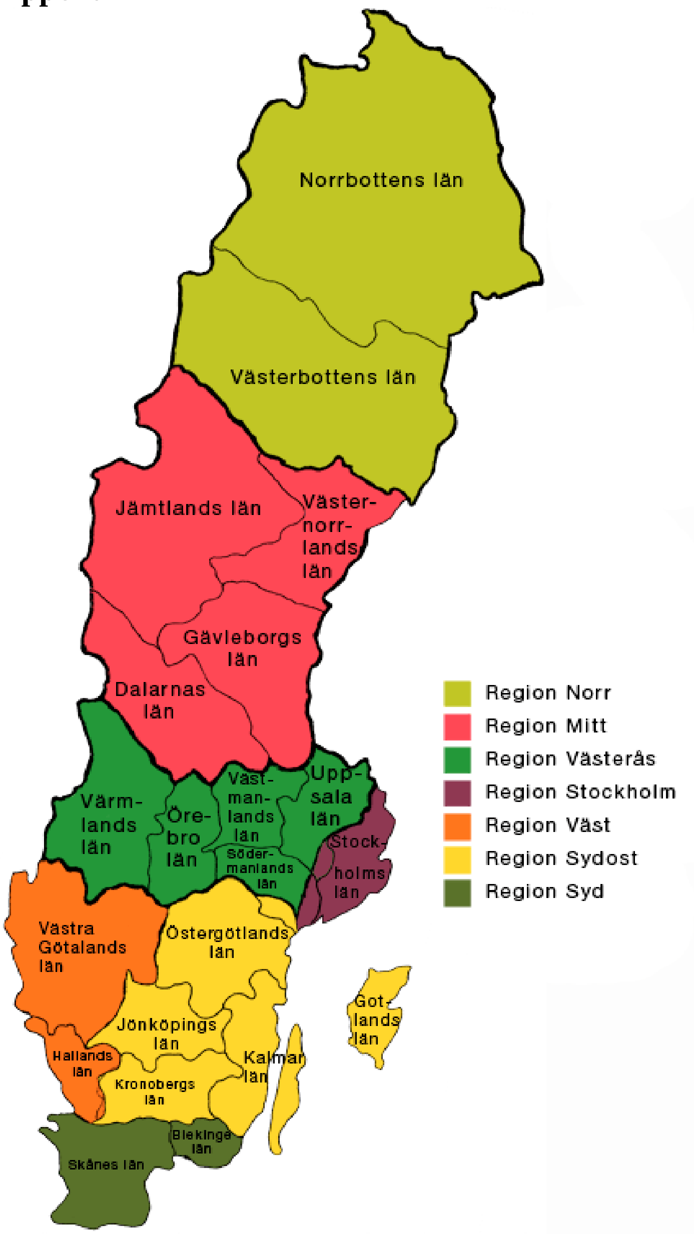


**Figure A1.** Geographical and NUTS 3 county division of Sweden.

**Appendix Table A1.** Descriptive statistics on MEA technical efficiency (TE) values across Clusters 1-3. Based on the Ward *hierarchical clustering* of regions (counties), over the three CAP periods, for variable costs (VC), fixed costs (FC), labour (L), assets (A), agricultural output (AO), diversified output (DO) and social output (SO),

| | **CAP 1: 1998-2002** | | | | | | | **CAP 2: 2003-2007** | | | | | | | **CAP 3: 2008-2013** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Inputs** | | | | **Outputs** | | | **Inputs** | | | | **Outputs** | | | **Inputs** | | | | **Outputs** | | |
| | **VC** | **FC** | **L** | **A** | **AO** | **DO** | **SO** | **VC** | **FC** | **L** | **A** | **AO** | **DO** | **SO** | **VC** | **FC** | **L** | **A** | **AO** | **DO** | **SO** |
| **CLUSTER 1** | | | | | | | | | | | | | | | | | | | | | |
| Obs (counties) | **5** | **5** | **5** | **5** | **5** | **5** | **5** | **7** | **7** | **7** | **7** | **7** | **7** | **7** | | | | | | | |
| Mean | .93 | .90 | .86 | .89 | .91 | .53 | .89 | .94 | .92 | .89 | .86 | .95 | .66 | .87 | | | | | | | |
| Min | .90 | .88 | .82 | .84 | .85 | .38 | .86 | .92 | .91 | .86 | .82 | .93 | .50 | .79 | | | | | | | |
| Max | .96 | .94 | .91 | .98 | .97 | .63 | .93 | .97 | .94 | .92 | .90 | .97 | .81 | .93 | | | | | | | |
| **CLUSTER 2** | | | | | | | | | | | | | | | | | | | | | |
| Obs (counties) | **8** | **8** | **8** | **8** | **8** | **8** | **8** | **4** | **4** | **4** | **4** | **4** | **4** | **4** | **8** | **8** | **8** | **8** | **8** | **8** | **8** |
| Mean | .96 | .94 | .88 | .88 | .96 | .74 | .84 | .96 | .94 | .90 | .85 | .96 | .86 | .78 | .94 | .94 | .93 | .84 | .95 | .80 | .84 |
| Min | .94 | .91 | .86 | .82 | .92 | .66 | .64 | .95 | .93 | .88 | .83 | .94 | .84 | .74 | .93 | .91 | .90 | .80 | .93 | .63 | .68 |
| Max | .97 | .97 | .90 | .96 | .98 | .85 | .97 | .96 | .95 | .92 | .88 | .97 | .88 | .83 | .96 | .96 | .96 | .87 | .97 | .85 | .88 |
| **CLUSTER 3** | | | | | | | | | | | | | | | | | | | | | |
| Obs (counties) | **8** | **8** | **8** | 8 | **8** | **8** | **8** | **10** | **10** | **10** | **10** | **10** | **10** | **10** | **13** | **13** | **13** | **13** | **13** | **13** | **13** |
| Mean | .99 | .97 | .96 | .98 | .99 | .93 | .98 | .98 | .97 | .97 | .96 | .98 | .93 | .95 | .97 | .98 | .97 | .93 | .98 | .93 | .96 |
| Min | .98 | .96 | .93 | .96 | .98 | .86 | .97 | .94 | .93 | .91 | .91 | .93 | .85 | .88 | .93 | .96 | .92 | .87 | .95 | .84 | .92 |
| Max | 1 | .99 | .98 | .99 | 1 | .99 | .99 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | .99 | .99 | .99 | .97 | .99 | .98 | .99 |

**Appendix Table A2.** Ward *hierarchical clustering* of regions over the three CAP periods. The variance between the regions decreased and the mean MEA technical efficiency (TE) increased from Cluster 1 to Cluster 3.

| | **Region** | **CAP 1 1998 - 2002** | **CAP 2 2003-2007** | **CAP 3 2008 - 2013** |
|---|---|---|---|---|
| Syd | Blekinge | 2 | 2 | 2 |
| | Skåne | 3 | 3 | 3 |
| Väst | Halland | 2 | 2 | 2 |
| | Väst. Götaland | 3 | 3 | 3 |
| Syd-ost | Gotland | 2 | 1 | 2 |
| | Jönköping | 2 | 2 | 3 |
| | Kalmar | 2 | 3 | 2 |
| | Kronoberg | 2 | 2 | 2 |
| | Östergotland | 3 | 3 | 2 |
| S | Stockholm | 3 | 3 | 3 |
| Västerås | Södermanland | 2 | 3 | 2 |
| | Uppsala | 3 | 3 | 3 |
| | Västmanland | 3 | 3 | 3 |
| | Värmland | 1 | 1 | 2 |
| | Örebro | 1 | 1 | 2 |
| Mitt | Dalarna | 3 | 1 | 2 |
| | Gävleborg | 1 | 1 | 3 |
| | Jämtland | 2 | 3 | 3 |
| | Västernorrland | 1 | 1 | 3 |
| Nor. | Norrbotten | 3 | 3 | 3 |
| | Västerbotten | 1 | 1 | 3 |

Note: Colours and the regions correspond to those in Figure A1 in the appendix. Cluster 1, Cluster 2 and Cluster 3 group counties with the lowest- (below the mean), around the mean and highest (above the mean) MEA TEs, respectively.