Analysis of the 2007/8 Defra Farm Business Survey Energy Module

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1. Summary

Key points

- This study has delivered an invaluable baseline estimate of energy use and greenhouse gas (GHG) emissions on commercial farms in England. Energy use and GHG emissions associated with particular commodities were quantified and results broadly agreed with those derived by Life Cycle Assessment, but with much scatter in the environmental performance of farms.

- Direct energy use on farms was generally less that indirect (embedded) energy use, except for horticulture, which is dominated by heating fuel use. In contrast, most GHG emissions are incurred on farms, rather than as embedded emissions.

- Scatter in both environmental and economic performance underlies the somewhat disappointing finding of no clear positive link between farm financial performance and energy use or GHG emissions. However, the mere existence of these ranges shows that there is scope for improvement in both financial and environmental performance and that there is no apparent barrier for both to be achievable in harmony.

- The recording of such farm-level energy data is essential for the future, as it should enable improvements to be made in efficiency of energy use. The improved UK agricultural GHG inventory will depend on high quality energy data on agricultural activities. This study will be invaluable in identifying the level of detail needed.

- Future data requirements include: contractor work rates and fuel use per unit area and per unit time, fertiliser and pesticide use by brand name, enhanced output data, especially animal live weights, and horticultural produce recorded by weight rather than by value.

Approach

- The study used a sample of 511 farms in the 2007/08 Farm Business Survey in England.

- Quantities of energy used on farm were recorded, both in direct form, e.g. diesel, electricity, and as embedded energy in materials such as fertilisers and feeds. These data and other factors were used to calculate GHG emissions from farms.

- The study used the Life Cycle approach – with the bought-in items, the energy use values and the GHG emissions including activities pre-farm gate; (e.g. extraction, refining and distribution) as well as emissions from on-farm use. Values for embedded energy and GHG emissions came mainly from previous research but some new inventory values were derived in the study, such as for contactor operations, wood grown on farms, and for some fertiliser types.

- GHG emissions mainly comprised: CO_2 from fuel, CH_4 from enteric emissions, CH_4 and N_2O from manure storage, N_2O from applications of fertiliser and manure to land, plus excretory returns from grazing livestock and leaching following grassland cultivation.

Findings: Energy and emissions per hectare

- There was, in general, a strong linear relationship across farm types between energy use per hectare and GHG emissions per hectare. This means it is possible to produce quick estimates of GHG emissions from energy data that are relatively easy to derive.

Farm type and size

- Energy use per hectare varied considerably across farm types and sizes. Highest users were specialist poultry farms: lowest were grazing farms in less favoured areas (LFA).
- GHG emissions per hectare followed broadly the same farm type trend as energy usage, but enteric CH_4 and field emissions of N_2O meant that grazing farms (LFA or lowland) tended to emit more GHG per hectare than general cropping and specialist cereal farms.
- For energy use and GHG emissions per hectare, farm size had much less impact than farm type.
- There was no overall significant difference between organic and non-organic farms on energy use per hectare or GHG emissions per hectare. The only exceptions were organic poultry and organic horticultural farms, where organic had significantly lower values in both cases.

Direct and indirect sources

- Apart from horticultural farms, energy use of most farm types was mainly indirect (i.e. embedded in inputs). This highlights the need to consider both types of energy use. GHG emissions were dominated by on-farm emissions, except on poultry farms.

Soil and biomass carbon: Effects of grassland cultivation and establishment, and woodland

- For most farms the effects of grassland cultivation, establishment and woodlands were relatively small, but the data only allowed a snapshot and may not be wholly representative over a longer time scale as the effects of land use change are long lasting.

- Total losses of soil C via grassland *cultivation* tended to outweigh gains from grassland *establishment*. Woodlands provided a net increase in soil C.

Economic and environmental performance

- An approach of using farm economic data to allocate energy use and GHG emissions to commodities was successful for most commodities. It gave results that were generally close to those obtained from LCA studies.

- There was a significant positive link between energy use per farm and income per farm, via higher total energy use on larger farms, which often have higher incomes. But there was no significant relationship on a per hectare basis between income, energy and GHG emissions.

- Beneath the whole farm level, for any commodity or commodity group, there was no reliable significant relationship between gross margin and energy use or emissions. This is undeniably both somewhat surprising and disappointing.

- There was a wide range of both economic and environmental performance in the farms studied. There may be many reasons for the variations, such as soil, rainfall, topography, degree of capitalisation, machinery age or use of contractors. Also, this analysis is a snapshot of one farming year. More detail is needed to understand the variation in economic and environmental performance across farms and across years.

- Within the commodities, milk was scrutinised in more detail. There was a weak relationship between energy use or GHG emissions per litre and net income per litre, and the slope was negative, as desired, albeit influenced by an outlier. However, the significant, although weak, negative slope for milk production and energy does accord with reports of increased profitability and environmental performance in dairying.

Introduction

A subset of 511 farms was the subject of an additional module on energy use and greenhouse gas (GHG) emissions in the 2007/8 Farm Business Survey. Additional questions were posed in order to determine the quantities of energy used on farms, both in direct form, such as diesel and electricity, together with embedded energy in materials such as fertilisers and feeds as well as young livestock. These values, together with other factors were used to calculate GHG emissions from farms. This report describes the analysis of the data by farm type and size as well as relating energy use and GHG emissions to the production of individual commodities.

Methods

The study applied Life Cycle Thinking in its approach, so that the energy use values include the overheads of extraction, refining and distribution as well as the "end of pipe emissions". This is consistent with Life Cycle Assessment (LCA) and recently released specification for carbon footprinting: PAS2050. It also includes the embedded energy (and GHG emissions) in bought-in items. This is an important feature of the analysis, particularly for livestock production. Most of the sources of values for embedded energy and GHG emissions came from the Cranfield Agricultural and Horticultural Life Cycle Inventory (CAHLCI), which includes major agricultural commodities, fertilisers and energy carriers (fuels), the latter being taken from the EU's Life Cycle Database (ELCD). Some new inventory values were derived in the study, such as for bought-in contactor operations, or for wood grown on farms, or for fertiliser types that were not wholly specific in the questions asked.

GHG emissions were calculated from fuels used together with point source and diffuse emissions of methane (CH_4) and nitrous oxide (N_2O). These included: enteric emissions of CH_4, CH_4 and N_2O from manure, N_2O from applications of fertiliser and manure to land (plus excretory returns from grazing livestock). Specific terms were also applied for the secondary N_2O from leaching following grassland cultivation. A limited analysis was also applied to the potential for losses and gains of soil C and uptake of biomass C, but these were on limited time duration. The IPCC Tier 1 emission factors were mostly applied in this analysis.

The sum of energy use and GHG emissions per farm was scaled by farm area for all representatives of robust farm types and sizes that were sampled. Some combinations were not represented and there was one "other": a mushroom farm. In addition, two allocation methods were applied in order to calculate the energy use and GHG emissions by commodity (or groups of commodities). This was based on the physical amounts produced wherever possible, although it was sometimes applied by financial output in horticulture, with the greater diversity of outputs in that sector. Regression analysis was also applied to relate energy use to commodity outputs.

Data envelopment analysis (DEA) was applied to the processed data in order to help identify the efficient frontier of production.

Economic and environmental performance were compared for some commodities, using gross margins and net incomes.

Results

Farm type and size

The energy use per hectare varied considerably across the farm types and sizes, ranging from 10 to 2,900 GJ/ha (Table 13). The differences in total energy use per hectare by farm type were generally statistically significant. The ratios of direct to indirect energy use tend to be systematically different, depending on farm type. The highest users of energy were specialist poultry farms and the lowest were grazing farms in less favoured areas (LFA),

Table 1 Ordering from highest to lowest of total energy use per hectare by farm types

	Farm type	Total energy use, GJ/ha
1	Specialist poultry	2900
2	Horticulture	1500
3	Specialist pigs	430
4	Dairy	36
5	Mixed	19
6	General cropping	16
7	Cereals	14
8	LFA grazing livestock	10
9	Lowland grazing livestock	10
10	Other (#)	1.7

(#) This is a mushroom farm and is not included further in the analysis emissions and energy use

There were broad similarities in the ordering of GHG emissions per hectare from farm types, but the contribution of factors like enteric CH_4 and field emissions of N_2O meant that general cropping and specialist cereal farms emitted less GHG per hectare than LFA or lowland grazing farms.

Table 2 Ordering from highest to lowest of GHG emissions and total energy use per hectare by farm types

	Type	Total GHG emissions, GWP, t CO_2e/ha
1	Specialist poultry	410
2	Horticulture	107
3	Specialist pigs	100
4	Dairy	8.0
5	Mixed	5.8
6	LFA grazing livestock	4.6
7	Lowland grazing livestock	4.1
8	Cereals	2.6
9	General cropping	2.4
10	Other [#]	0.4
[#] This is a mushroom farm and is not included further in the analysis emissions and energy use		

The significance of effects of farm size on energy use and GHG emissions were considerably less than for farm type. The main effects were that small poultry and horticultural farms use significantly less energy and emit less GHG per hectare than their medium and large counterparts. Part of this could be a tendency for smaller poultry units to be free-range (with inevitably lower stocking densities) and for smaller horticultural units to have less or no heated glass areas.

Direct and indirect sources

Horticultural farms were systematically different from other farm types in that 95% of energy use was on the farms, which was dominated by heated greenhouse systems (Table 3). Direct energy use ranged from 26% on pig farms to 51% on general cropping farms. This highlights the need to consider both types of energy use. GHG emissions for the other farm types were relatively larger (34% to 82%), mainly because of enteric CH_4 and field N_2O emissions, with grazing farms having the highest proportions of on farm emissions. Overall, most GHG emissions are incurred on farms, rather than as embedded emissions.

Table 3 Proportions of total energy and GHG emissions that are incurred directly on farms, rather than embedded in inputs (e.g. fertilisers, feeds, young stock).

	Count	Energy	GHG
Cereals	83	40%	66%
Dairy	77	36%	63%
General cropping	77	51%	66%
Horticulture	104	95%	93%
LFA grazing livestock	19	37%	81%
Lowland grazing livestock	41	48%	82%
Mixed	47	38%	66%
Specialist pigs	20	26%	54%
Specialist poultry	42	37%	34%

Organic and non-organic farms compared unit area basis

There was no overall significant difference between organic and non-organic farm energy use or GHG emissions per hectare. There were some sector-specific differences: both organic poultry and horticultural farms had significantly lower energy use and GHG emissions per hectare than their non-organic counterparts, for similar reasons to the general effects of size. In addition, organic poultry farms would operate with lower stocking densities and buildings tend to be more often naturally ventilated. This analysis is limited by the small number of organic farms in the sample and large inter-farm variability. It must be noted that these comparisons were per hectare and not per unit output.

Effects of grassland cultivation, grassland establishment and woodland

The losses of soil C from cultivations and gains of soil C from grassland establishment together with farm woodlands were estimated. The effects of grassland management were generally somewhat more negative than positive, while woodlands were always positive. There were some examples where either woodland or grassland (or both) contributed to C storage on the farm, but these are in the minority and tend to apply to smaller farms. For most farms sampled, the effects were relatively small, but the data only allowed a snapshot of land use changes. So, what is reported here is based on that, but may not be wholly representative of what happens on the farms over a longer time scale as the effects of land use change are long lasting. Apart from these instances of the change between arable and grassland, soil C was assumed to be constant on all farm types.

Regression

The value of applying regression analysis was limited. Few conclusive, significant relationships could be extracted and these only applied to direct and total energy use for field crops, even on cereal and general cropping farms. The estimate for total energy used for wheat at 2.7 GJ/t was close to 2.4 MJ/t in CAHLCI, while that for barley was about twice that in CAHLCI and the estimate for direct energy was non-significant. The explanation is: first, we have many possible outputs in many combinations and not enough farms in the sample to explain variation and second, the residual errors were not normally distributed so that fits were inevitably poor.

Allocation

The first method was based on the application of existing CAHLCI values for crops in order to partition whole farm energy use and GHG emissions between crops (and was applied to farms with crops only). The results gave generally good agreement between the crop values in CAHLCI and those resulting from the FBS data. Energy values were more closely aligned than GHG emissions. GHG emissions estimated from FBS data were about 75% of those in CAHLCI. The same approach was applied to milk production, but with less success. Some reasonable agreement was possible, but the sampled dairy farms included varying proportions of herd replacements and other cattle in various stages of beef production as well as a diversity of other enterprises. Agreement improved as the sample was screened to be more consistent.

Reasonable agreement was also found on poultry and pig farms. The method worked overall, although the uncertainties were substantial for many commodities, partly simply reflecting inter-farm variability.

The second method used economic allocation per enterprise to partition the energy use from purchases of fertilisers, fuels etc together with physical causality (e.g. enteric emissions could be ascribed directly to say beef or sheep). The method worked reasonably well with good overall agreement between energy use in CAHLCI and the FBS sample. The uncertainties were nonetheless relatively high with coefficients of variation (CoV: standard deviation divided by the mean) in the order of 40%, reflecting inter-farm variability. GHG emissions from crops were again about 75% of those in CAHLCI. The allocation of energy to animal production was generally less accurate than for crops, which should not be surprising because a larger number of inputs are required for animal than crop production. Milk and eggs were, however, estimated about as accurately as winter wheat. These commodities have relatively low breeding overheads and are fairly well optimised. Furthermore, the physical outputs that constitute the function units are well characterised, e.g. x hectolitres of milk or y dozen eggs. In contrast, weights of all stock for meat had to be estimated from general expectations (e.g. typical broiler of finished lamb weights) or from prices per kg. The liveweight-based commodities all required about an order of magnitude more energy than the crops. This is to be expected as animals consume crops, and concentrate them into livestock products that are functionally different, e.g. providing very high quality protein. There was reasonable agreement between results from CAHLCI and the FBS survey for energy use, although there seemed to be a systematic underestimate of pig energy. The FBS-derived estimates of energy use for animal commodities had a range of uncertainties from CoV 27% to 57%, with sheep animal being 92%. The FBS-derived estimates of GHG emissions were actually generally closer than energy and with smaller uncertainties (CoV 20% to 60%). There were no significant differences for producing these commodities on different farm types, but there was a hint that sheep produced on pig or poultry farms may incur an undue allocation, but this may just be an artefact of the method.

Economic and environmental performance

The first phase compared whole farm net income with energy use or GHG emissions (normalised per hectare), with farms divided into robust types. This showed a large range of incomes as well as energy use and GHG emissions. The energy use was stratified by farm type, but there was no obvious correlation. In the next phase, incomes (or margins) were related to energy use or GHG emissions by regression either at a farm level or by commodity.

There was no significant relationship between net farm income and energy use or GHG emissions on cereal farms. There was, however, a significant increase in whole farm energy use with net farm income, reflecting the higher total energy use on larger farms.

In horticulture, there was a very wide range of energy use per hectare owing to part of the sector using heated greenhouses. Whether these were included or not, there were no significant relationships between energy use or GHG emissions per hectare and net farm income. The range of incomes is also large owing to the wide range of food and ornamental outputs.

The remainder of the economic and environmental performance analysis focused on single commodities or commodity groups: winter wheat, winter barley, winter OSR, ware potatoes, sugar beet, milk, eggs, other cattle, sheep, wool, pigs and poultry. Liveweight gain was the metric for other cattle, sheep, pigs and poultry. After initial screening, outliers were eliminated systematically with the threshold for inclusion set at the gross margin of a commodity being at least 10% of the farm margin.

The relationships between gross margin and either energy use or GHG emissions per unit commodity can be summarised as follows. There were no reliable significant relationships between them for any commodity when considering all farm types and sizes. There were a few significant relationships in the animal sector, but these were reliant on outliers. This is undeniably both somewhat surprising and disappointing. What is also evident is that there is a wide range of both economic and environmental performance in the farms studied. For example, the ratios of the highest to lowest of both gross margin and energy use for winter OSR and winter barley were three and five respectively. This pattern was repeated across other crops, although with differing ranges. In livestock production, the range of gross margins can be higher than is seen in crop production, e.g. £0.01 to £0.42 per dozen eggs or about £100 to £13,000 per t liveweight gain for beef animals. The ranges of energy use and GHG emissions were similar to those for crops. There were some significant relationships, but these need qualifying. These occurred with pigs, poultry and wool. The pig ones relied on one outlier. The wool ones also seemed to be unduly influenced by a few outliers. Poultry production for both meat and eggs were split between two populations: fully housed and free range. The variation in energy use and GHG emissions was generally larger for free range than indoor, reflecting the high degree of optimisation in mainstream fully housed production.

Milk was scrutinised in more detail, being possible with more farm data available to analyse. As before, there was no relationship between gross margin and energy use or GHG emissions when considering the whole population. Farm size was investigated, but there were no trends within sizes, although the range of gross margins was larger for medium than small or large. There was a weak relationship between energy use or GHG emissions and net income and the slope was negative, as desired, but this was influenced by an outlier. There was a highly significant relationship between energy use per hectare and milk production per hectare. There were nine organically managed farms in the screened sample with gross margins from £12 to £21 per hectolitre. There were significant relationships for these farms with negatives slopes for both GHG emissions and energy use against gross margin, which is the desired effect: i.e. higher income and lower burdens per unit production. Energy use and GHG emissions (for organic milk) tended to be in the lower part of the ranges, but could not be said to be significantly different as a population from non-organic milk.

Organic winter wheat margins were systematically higher than for non-organic wheat, although there were only four organic farms out of 200. In contrast to organic milk, the slope between gross margin and energy use or GHG emissions was positive, but the sample is too small to support useful conclusions.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) successfully discriminated relatively efficient from inefficient Decision Making Units (DMUs) or farms. It has thus identified a set of relevant candidate benchmark farms and triggered a set of searching questions to account for the discrepancies between the inefficient farms and their peers. It has done its job in this respect. It maybe that the necessary simplifications of the number and measure of outputs, the approximations involved, or chance play a genuine role in making a DMU appear inefficient. It must also be remembered that farms are multi-functional in more ways than can be readily measured.

Various formulations of the DEA, criteria chosen and excluded outliers have been explored. Whilst these changes affect some details in the results there is broad pattern of the efficient peers being common across formulations, suggesting a degree of robustness. The DEA scores are broadly comparable if either GHG emissions or energy is used as the input vector, with many DMUs being efficient in both models if indirect inputs of energy off-farm are systematically and robustly accounted for.

Typically the DMUs are dominated by a small group of efficient peers some distance away, the histograms often have two peaks: one where the majority of the industry is and a smaller one of the smaller set of efficient peers that are on the *Pareto efficient frontier*. This may suggest that outliers play too big a role in the data, but that at least is a question that the DEA has revealed.

We have looked at farm size, region, type, and organic status as possible explanatory variables for the observed DEA scores. Some interesting effects due to farm type and organic status are suggested. However, these remain statistically elusive due to the restricted amount of data available relative to the heterogeneity of the industry. The use of statistics to investigate the role of explanatory variables that can explain DEA scores is still in its infancy due to the non-normal distribution of DEA scores. *Tobit* regression analysis and non-parametric ANOVA have been used/suggested as tools.

Energy and emissions per hectare

There were, in general, strong linear relationship across farm types between normalised energy use and GHG emissions. It was most obvious for horticultural and poultry units, in which there is a relatively high direct fuel use (Table 50). The fits were very good for high energy activities like specialist mono-gastric production and horticulture. They were inevitably poorer for other farming activities when enteric methane emissions and field emissions of N_2O play a relatively greater role. This, nonetheless, provides the ability to produce quick estimates from data that is relatively easy to derive.

Table 4 Summary of regression between energy use per hectare and GHG emissions per hectare across farm types. The regressions and slopes were all significant at p <0.001. These are ordered by decreasing quality of fit.

Farm type	Variance accounted for	Standard Error of regression	Slope, t CO_2e/GJ	Standard Error of slope
Specialist pigs	99%	10	0.181	0.0033
Specialist poultry	98%	101	0.141	0.0027
Horticulture	97%	59	0.0746	0.0014
Dairy	90%	1.27	0.219	0.0037
LFA grazing	69%	0.96	0.390	0.0266
Mixed	61%	1.79	0.236	0.0123
Lowland grazing	56%	1.35	0.355	0.0178
General cropping	53%	0.82	0.144	0.0059
Cereals	52%	0.72	0.178	0.0059

Concluding discussion

This analysis has delivered an invaluable baseline estimate of actual energy use and GHG emissions on contemporary commercial farms in England. Differences between some farm types are apparent, but not surprising. The effects of scale were limited to poultry and horticulture. Most farm energy use is embedded in indirect energy use, whereas most GHG emissions occur on farms themselves.

The use of two allocation methods delivered very useful results and allowed the energy use and GHG emissions associated with particular commodities to be quantified. These results were in broad agreement with those derived by LCA. It was also evident in these analyses that there was much scatter in the environmental performance of farms.

This scatter, together with that in economic performance, must underlie the somewhat disappointing relationships between farm financial performance and energy use or GHG emissions. The mere existence of these ranges shows that there is scope for improvement in both financial and environmental performance and that there is no apparent barrier for both to be achievable in harmony. The significant, although weak, negative slope for milk production and energy accords with reports from consultancies of increased profitability and environmental performance in dairying. DEA has shown considerable potential as a tool for analysing farm performance, although having a larger sample would have been helpful. It is a powerful tool for rapidly identifying outliers.

There may be many reasons for the variations, such as soil texture, rainfall, topography, farmer type, degree of capitalisation, livestock breeds, machinery age or use the of contractors. It must also be remembered that this analysis is a snapshot of one farming year. Between years, there may be yield and price variation as well as capital investments etc. More detail is needed to understand why the variation occurs and data from more years are needed to track changes.

In some cases, the allocation of energy use was slightly problematic in that high allocations of, say, electricity or a heating fuel were made on some farms in farm types where little electricity use might be expected for the farm operations themselves, e.g. LFA grazing. This suggests that energy used in the office could be distorting what is used for the actual farm activities (e.g. lighting lambing sheds). Nonetheless, this type of energy use is part of an overall farm activity, but not one that is usually included in LCA studies.

One area in which there was not enough data to make a substantial analysis was of organic production. This was because of the very limited data available, with small numbers of farms of different types and relatively high diversity of outputs. There is no fundamental reason why the analysis can not be applied to organic systems, it just needs more data.

The recording of energy related data on farms is essential for the future, as it should enable improvements to be made. The improved UK agricultural GHG inventory will depend on high quality activity data as well as improved and more specific emission factors. The experience gained in this study will be invaluable in identifying what level of detail of data is needed. Future data requirements include a better understanding of contractor work rates and fuel use per unit area and per unit time, fertiliser and pesticide use by brand name, enhancing the quality of the physical inputs and outputs of farms, especially animal liveweights and horticultural produce being recorded by weight rather than by value. Future recording to involve a systematic screening of recorded data to eliminate spurious values and highlight inconsistencies. Examples could be animal production without feed or excessively high fertiliser application rates. A larger sample of organic farms is also needed to allow a conclusive analysis to be made.

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Natural Resources Management Centre, Cranfield University, September 2010

Main Report

Introduction

The Farm Business Survey (FBS) normally collects data on the value of outputs and inputs, and the physical quantities of outputs but not much data on physical quantities of inputs. In the 2007/08 accounting year, extra data was collected relating to energy use, including physical quantities of inputs from a sample of 511 farms. The FBS was chosen to collect this information because the data are collected via interview by professional researchers who regularly visit the farms. It thereby enables a higher degree of accuracy and data robustness than a postal or telephone survey. This report describes an analysis of the data to understand better energy use on farms and the greenhouse gas (GHG) emissions associated with energy use as well as other biologically derived processes, such as enteric methane and field emissions of nitrous oxide. Much of the underlying basis of the analyses came from work conducted at Cranfield University (and previously at Silsoe Research Institute) on life cycle assessment (LCA) and systems modelling of agricultural commodity production (Audsley et al, 1997; Williams et al., 2006; Williams et al., 2009).

The study applied Life Cycle Thinking in its approach, so that the energy use values include the overheads of extraction, refining and distribution as well as the “end of pipe emissions”. This is consistent with Life Cycle Assessment (LCA) and recently released specification for carbon footprinting: PAS2050 (BSI, 2008). It also includes the embedded energy (and GHG emissions) in bought-in items. This is an important feature of the analysis, particularly for livestock production.

2. Methods

Direct and indirect energy sources

Farms use energy in direct forms such as diesel. Much energy can also be brought onto farms embedded in materials, feeds or stock, i.e. at some stage direct energy has been used to create, transport or nurture these items. Both forms are important. For example, Williams et al. (2006) analysed total energy used to produce a unit weight of non-organic bread by LCA and showed that the indirect energy is about 70% of the total. So, omitting indirect energy can substantially underestimate the true energy that is embedded in a farm commodity. Care is needed in how this is interpreted. For example, the energy used on a livestock farm includes much that is embedded in feeds, so that should be accounted for in estimating what it takes to produce the livestock. Similarly, the energy used to produce feeds must be traced back to fuels, fertilisers and machinery in order to establish what has been used to produce those feeds. But if a (simplified) region has two farms that produce (a) feed crops and (b) livestock, the energy calculated per farm by this method tells us what each farm uses to produce its outputs, but the sum of farm energy use in the region is not the sum of energy used on both farms as the embedded energy in the feeds is transferred to the livestock farms. The same argument applies to GHGs, so that the sum of GHG across all farm types if scaled up to the national level would NOT equate to a national inventory, since it would be double counting feed crops. Summing the GHG emissions per commodity and making due allowance for the final use of all crops (e.g. wheat for milling, fermentation or feed) would come much closer to forming a national GHG inventory.

Global warming potentials

Greenhouse gases are not equal in their effect on the atmosphere. The effects are interpreted by converting them to the equivalent effects in trapping solar energy of carbon dioxide (CO_2) of a fixed time period. The units of global warming potential (GWP) are in CO_2 equivalents, which are abbreviated to CO_2e. By common consent, this is normally 100 years (although values for 20 and 500 years are also calculated). The Intergovernmental Panel on Climate Change (IPCC) periodically updates the global warming potentials of gases and we use the most recent set (IPPC, 2007). For agriculture, the main gases are methane (CH_4) with a GWP of 25 and nitrous oxide (N_2O) with a GWP of 298. These are slightly different from those used in the current national inventory, which was constructed in response to the Kyoto protocol and uses the original IPCC values of 21 and 310 for CH_4 and N_2O respectively. The use of the more recent set of values is consistent with those used on PAS 2050 (BSI, 2008).

Scope of greenhouse gases quantified

In the current UK GHG inventory (Kyoto orientated and using the IPPC structure), the contribution of agriculture is limited to direct emissions from agricultural activities that are not related to energy use, e.g. N_2O from soils and CH_4 from manure. CO_2 is only included from the use of lime as a soil conditioner. The use of fuels for machinery, heating and ventilation and associated CO_2e emissions are included in the energy part of the overall national inventory. Estimates of the agricultural sector's contribution to energy related CO_2e emissions may be included in the inventory, but are not separately, explicitly recorded. The differences are summarised in Table 5.

Other gases do make a small contribution to GWP from agriculture, such as carbon monoxide (CO) from combustion and nitric oxide (NO) from manure. These have been reported under the overall umbrellas of CO_2, CH_4 and N_2O by transferring them to the nearest functional equivalent, e.g. CO comes from fossil fuel as does almost all CO_2, so its contribution was added to that of CO_2. These actually make very little difference to the overall outcome.

One area for which we currently have no data is leakage of air conditioning and refrigeration coolants. These have very high GWPs (often several thousand). They could make a contribution to emission from air conditioned field machinery and deliveries of anything that is cooled in transit. Retail type chilled counters are also prone to leakages and these could make a contribution from farm shops. Refrigeration units such as those used for cooling milk are hermetically sealed and not prone to leakage. Cooling units used for crops (e.g. potatoes) are also well sealed and often use low GWP coolants.

Table 5 Summary of main gases included in the UK agriculture GHG inventory and those considered in the present study

Gas	Source in current inventory	Other sources used in the present study	Comments
CO_2	Lime	Energy use	
		Energy generation overheads	
		Upstream inputs (e.g. pesticide, fertiliser, lime extraction and delivery, silage wrap)	
		Urea field emissions	
		Grassland change	These are accounted for in the UK LULUCF GHG inventory
		Woodland	
CH_4	Enteric from livestock	Energy generation fugitive emissions	
	Manure management	Where emitted in upstream input production and distribution	
N_2O	All N inputs to soils	Upstream inputs, especially nitrate fertiliser production	
	Manure management		
	Secondary conversion from ammonia, nitric oxide and leached nitrate		
Others		CO, and minor combustion gases	
LULUCF = Land use, land use change and forestry			

Conversion of raw data to consistent metrics

There were three main parts in this process, which we consider first from the perspective of energy use. The clearest aspect of energy use is fuels purchased and used on the farm. All main fuel types were converted to primary energy values (i.e. including upstream activities of extraction, refining and delivery) using conversion factors in the Cranfield Agricultural and Horticultural Life Cycle Inventory (CAHLCI) (Table 6). CAHLCI represents a set of outputs from Cranfield's agricultural and horticultural LCA work (Williams et al., 2006; Williams et al., 2009). Two types of renewable energy were included in the raw data: straw and wood. We used the CAHLCI values for wheat straw and developed a *de novo* estimate for wood using data from the literature (Appendix 1). These are all forms of direct energy.

Table 6 Factors used to convert physical units recorded by the FBS team into primary energy and GHG emissions (*).

FBS Fuel descriptions	FBS item code	Reference Unit	Primary Energy, MJ per unit	GHG emissions (GWP_{100}), kg CO_2e per unit
Red diesel	1	1 litre	43.1	3.07
Derv	2	1 litre	43.1	3.07
Petrol	3	1 litre	39.3	2.99
Engine lubricating oil	4	1 litre	48.1	3.45
Propane/LPG	5	1 kg	52.4	3.74
Kerosene	6	1 litre	41.2	3.03
RFO (residual oil, medium and heavy burning oils)	7	1 litre	48.1	3.45
Mains natural gas	8	1 m^3	39.9	2.40
Electricity	9	1 kWh	11.6	0.67
Wood (imported onto farm)	12	1 kg	0.323	0.023
Wood (grown on farm)	13	1 kg	0.262	0.0187
Coal	14	1 kg	23.0	2.37
Domestic heating oil (farm use)	15	1 litre	43.1	3.03

(*)All GHG emissions use the IPCC (2006) coefficients to convert species such as methane and nitrous oxide into global warming potentials (GWP) using the conventional 100 year time scale.
The source of the primary energy and GHG data for fuels (energy carriers) is the European Commission's "European Reference Life Cycle Database" (ELCD)

Agriculture is a high friction environment (e.g. soil wears tillage equipment and cereals wear the inside of harvesting machinery), and consequently machinery wears out relatively fast, compared with, say, a combustion process. In previous work, we established that the overheads of machinery and tractors represent about 30% of the direct energy use from diesel. This overhead was thus added to red diesel, which is mainly used for agricultural vehicles.

Materials (and animals) bought onto the farm contain embedded energy, i.e. the energy used to manufacture, or breed and feed, and deliver the item. On arable farms, these are mainly items like fertilisers (N especially), but more widely include pesticides, silage wrap, concentrated feeds, manures and younger livestock. Many of these are in CAHLCI, but *de novo* ones were also developed as needed. These were based on data from the literature, interpolation or extrapolation from CAHLCI or creating a new LCI from 1st principles. In some cases, proxies representing similar items could be used. Given the nature of the descriptions of items, some could be defined and quantified with much greater reliability than others. For example, ammonium nitrate and urea are well characterised items, while liquid manures are not. The embedded energy in manure is mainly a function of its nutrient composition. The management of manure can be very varied, e.g. different storage lengths or dilution with rain water or wash water. Quantities are also less easy to measure (or estimate by farmers) than synthetic N fertiliser.

For young livestock, estimates were made based on a set of assumptions. Again these vary considerably in reliability. Day-old chicks bought by broiler producers are well characterised, while a beef animal of 18-24 month is far more variable in its history and management options and hence embedded energy. Best estimates were made of embedded energies using derivations from the animal production module of the Cranfield LCA model (values are given in Appendix 2).

Contractor operations cover a wide range of activities. These were recorded by the hectare or hour. These vary in expected accuracy. Field operations per ha, such as ploughing, spraying and harvesting, are well characterised, while activities such as slurry and manure operations by the hour could include energy utilisation at widely differing rates. Best estimates were made using values from CAHLCI wherever possible, extrapolating from these with plausible work rates from standard farm management texts (e.g. Nix, ABC) or developing sets of scenarios from which means could be derived. In these contractor operations, separate terms for direct energy and machinery overheads were applied, as with farmer-purchased red diesel. We took the view that the normal arrangement would be for contractors to supply their own diesel. It is quite possible that some farmers supplied diesel to contractors.

The same basic approach was applied to GHG emissions. These occur as direct emissions, e.g. CH_4 from ruminant digestion or manure storage; N_2O from N applications in manure and synthetic nitrogen or CO_2 from combustion. There are also secondary effects, e.g. N_2O from leached nitrate and ammonia. All items bought in contain embedded GHG emissions, which may have been derived from combustion, direct N_2O from fertiliser manufacture or any process that is implied in animal feeds or animals themselves. Two areas of GHG emissions from soils were excluded: C losses from peat soils and N_2O from organic soils (not to be confused with organically managed soils). This was because the exact locations of farms were not known and hence the soils being managed were not known.

CAHLCI and the Cranfield LCA model were used as the first data sources whenever possible, for consistency with the energy data. In some cases, where disaggregation of the model was not readily possible or for technical reasons, general emission factors were taken from the IPCC (2007) guidelines on national reporting of GHG inventories (usually only Tier 1 was possible). These included daily emissions of enteric methane from cattle or manure management.

Effects of woodland and cultivating or establishing grassland

Values for C uptake by trees were taken from the Country Land and Business Association's CALM calculator (http://www.calm.cla.org.uk). It provides a range of values for conifers and broadleaf woodland in woodland ranges of tree ages (Table 7). The age and area of farm plantations were recorded in the energy module and the closest values for C uptake were used. It should be noted that these are broad average numbers and not the ones that would be used in commercial plantations in which much more detail may be known about the operation.

Table 7 Biomass uptake rates in woodland from the CALM tool converted to measures of GWP

	Biomass uptake rate, t CO_2e $ha^{-1}year^{-1}$	
Age, years	**Conifer**	**Broadleaf**
5	1.4	`0.7
15	21	15
25	14	11

Areas of grassland that were established or cultivated in the recording year were included in this survey module. The potential effects on emissions from these were estimated: no changes were estimated in any other areas of grass on the farms. Changes in soil and biomass C from cultivating grassland (generally a loss of C and hence source of GHG emissions) and establishing grassland (gain of soil C) were calculated from data in the UK LULUCF GHG inventory (Thomson et al. (2008). This source provides estimates of the changes in equilibrium values of soil C (to a depth of 1 m) when changing use, e.g. arable to grassland. These are weighted averages that include the distribution of soil types and so would not necessarily apply to the individual soils in the surveyed farms, but are indicative. There are some typical challenges when dealing with changes in soil C and land use change (LUC). These occur because of the long-term, non-linear (1st order kinetics) changes that occur between soil C equilibrium states. These can be summarised as:

1. How long has the soil been under a particular land use (unless the soil C density is actually known)?
2. What is the rate constant that should be applied?
3. Over what time scale should changes be calculated and averaged or integrated?

These have been approached in various ways for different applications. For example, in PAS2050 (BSI 2008) the full change in soil C equilibrium is included and the change is linearised over 20 years after the LUC occurs, although reaching 99% of the change could take 50 to 300 years (Thomson et al., 2008). The national inventory uses the 1st order equations along with best estimates of land use history. We opted to use the 1st order equations and take the average rate of change over the first 20 years after LUC. In the absence of better data, we assumed that both grassland and arable land were previously in equilibrium, although this would not always be the case in rotational systems. Some over-estimation would thus occur in some cases. The net effect of these calculations is the sum of the total biomass change (i.e. all biomass changes were assumed to occur in 1 year) and the average of 20 years of changes in soil C (Table 8).

Table 8 Summary of emissions from LUC between arable and grassland (derived from Thomson *et al*. (2008))

	From grass to arable	**From arable to grass**
Difference in soil C equilibria (kg C m^{-1})	-23	23
Rate constant, k	-0.046	-0.023
average change 20 years (t CO_2e ha^{-1} $year^{-1}$)	25.3	-15.5
Change in biomass C as emission rate, t CO_2e ha^{-1}	-1.8	1.8
Net emission rates (soil & biomass), t CO_2e ha^{-1}	23.5	-13.7

There may have been other changes in land use, such as cultivation of land that had been in set aside or setting aside some corners of fields for non-agricultural purposes, but these could not be captured.

Screening data

All data are prone to containing errors. Some are simply random variation and should be accounted for by calculating statistical uncertainties. Sometimes, however, there are errors that appear to have resulted from erroneous data entry, or perhaps a misunderstanding about units or some other error. A case in point is lime applications. Purchases were meant to be recorded in tonnes, but this led to apparently impossible application rates being used. This assertion is based on the British Survey of Fertiliser Practice, which gives lime application rates for many years. Lime is not usually applied every year on a farm, so that the amount applied in any one year could easily be say five times more than the average over the long term. This may also be countered by lime not necessarily being applied over the whole farm in any one year. Even allowing for that, apparent average application rates over the whole farm of 1000 t per ha are implausible and the only rational explanation is that the values were recorded in kg, like other fertilisers. A careful analysis of the data was made and a cut applied at 10 t/ha (averaged over the whole farm adjusted agricultural area), with all purchases above being assumed to be in kg and scaled accordingly (Appendix 3).

A second area is manure. This was highlighted when a pig farm apparently produced energy as well as pigs. This resulted from a gross over-estimate of the nutrient content of slurry and hence the credit to the farm of nutrients that were exported. The volume of slurry that was reported seemed to very high compared with the expected volume of undiluted excreta produced by the pigs on that farm. Given the uncertainty of this example (not isolated) and the variable nutrient losses from manures and composts, it was felt that all these values should be excluded because of adding to much noise to the dataset. It is probable that some types of manure are much more consistent than others, e.g. broiler litter, but it would be unbalanced to include some imports or exports.

A third area is contractor energy. 72% of farms used contractors for some activities. As noted above, the potential errors in some areas are large, especially ones per unit time. In general, the more contractor energy was used, the greater the noise. So, the cut-off of 20% energy from contracting was applied to reduce the errors in the data. This excluded 98 farms from most subsequent analyses.

Post-harvest energy can be used for grain drying or grain cooling and long-term cooling of unstable crops like potatoes or apples. It may also be used for rapid cooling of some horticultural crops like tomatoes or strawberries. Such values are not erroneous *per se*, but the occurrence on any farm may result from chance, e.g. a dry cereal harvest, or management choice, e.g. always selling main crop potatoes to another business for storage. This means that nominally similar farms could use more or less energy for post harvest activities for very different reasons. So, separate sets of data were prepared for analysis with post-harvest energy being included or excluded so that farms could be compared on a consistent basis as well as "as is". The spread of data was such that most farms including post-harvest energy were on a continuum, with about six outliers in which the post-harvest energy ranged from 1.4 to 4.7 times the rest of the energy used (the highest value was on a small farm producing only apples). On some farms there may be other energy-using enterprises, like juicing. Also, one area that was excluded was the purchase of packaging materials by horticultural farms and egg producers.

Specific additional pre-processing

Sugar beet pulp may be bought by farmers across England, but is currently only produced in the East with a few well defined factories. The delivery distances of beet pulp delivered (as purchased straights) to farms was estimated from the farm location (within a local government area – LGA). The geographic mean of the factors was taken as the origin, with "crow flying" distances to the centre of each LGA calculated from digital maps. A tortuosity coefficient of 1.25 was applied to these distances to compensate for actual road patterns.

There were some unusual farms in the dataset, e.g. a very small one upon which only 3rd party horses were kept and one mushroom farm. A few were also apparently outliers, although this often became obvious only post hoc and analyses were then repeated. The horse farm was removed from all analyses.

Farm area

This might seem too simple a concept, but different areas are recorded and have validity in different contexts and care was needed in making the selection when scaling farm activities in order to normalise them. Three main choices concern the Agricultural Area (AgArea), Total Adjusted Agricultural Area (TotalAdj), which included shared rough grazing, and the area of heated and unheated glass (relevant for specialist horticultural farms). For most analysis (e.g. energy per unit area) the Total Adjusted Agricultural Area was used, but in some cases this was not recorded and so the Agricultural Area was used, which often was close to or the same as the area of heated glass.

Statistical analyses

Farms were grouped by size and type (robust farm types) and the means of energy use and GHG emissions were calculated along with variance and standard deviation. Types and sizes were then compared using analysis of variance, both one and two way. Log transforms of values were used to ensure that the data were sufficiently normal to make the use of ANOVA valid.

Farm energy use was examined using multiple linear regressions applied to commodities.

Data envelopment analysis (DEA) was used to compare farms with their peers.

Other statistical analyses were applied as needed.

Allocation and DEA methods

These are described in their own sections, but it should be noted that two allocation methods were applied. The first used LCA data as a basis and expanded from the simplest situation, while the second used economic allocation.

Relating economic and environmental performance

The main approach was to relate production of commodities to the enterprise gross margin and net farm income.

3. Results

The types and sizes of farms that were selected by the FBS team (Table 9) show a reasonable representation of farm types. There were some omissions from the range of possibilities, with no large LFA or lowland livestock farms but these are probably very unusual by their nature anyway. There were also few very small farms in the sample.

Table 9 Numbers of farm types and sizes in the sample

	Large	Medium	Small	Very small (part-time)	Grand Total
Specialist Cereals	45	28	10		83
Specialist Dairy	48	26	3		77
General cropping	57	17	3		77
Specialist Horticulture	64	27	11	2	104
LFA grazing livestock		6	13		19
Lowland grazing livestock		7	29	5	41
Mixed	18	16	13		47
Other			1		1
Specialist Pigs	9	4	7		20
Specialist Poultry	16	16	10		42
Grand Total	**257**	**147**	**100**	**7**	**511**

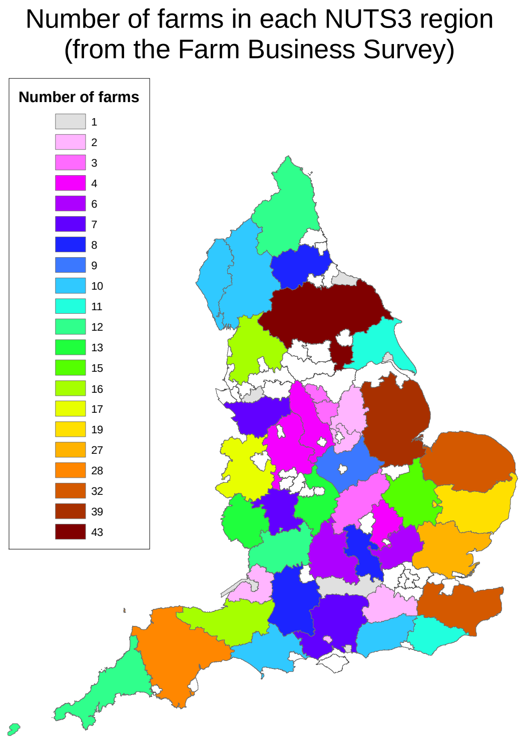
There were 30 organic farms in the sample (Table 10). These were systematically different in range from the overall sample, with few large farms, only one specialist cereal farm and no specialist pig farms. This should not be a great surprise given the different outlook and history of organic farming, although one could have imagined more mixed farms being represented.

Table 10 Numbers of organic farm types and sizes in the sample

	Large	Medium	Small	Grand Total
Specialist Cereals			1	1
Specialist Dairy	3	4	2	9
General cropping	1	2	1	4
Specialist Horticulture		1	1	2
LFA grazing livestock		1	1	2
Lowland grazing livestock		1	4	5
Mixed			3	3
Other				0
Specialist Pigs				0
Specialist Poultry		3	1	4
Grand Total	**4**	**12**	**14**	**30**

The farms were well reasonably well distributed over the country (Figure 1).

Figure 1 Approximate numbers and locations of farms in the survey sample.



Statistical analysis by farm type and size.

The results that follow were obtained by summing the energy use and GHG emissions per farm and then normalising by dividing by the adjusted agricultural area to obtain values per ha. The overall values for energy use include all the sizes within farm types (Table 11). The use of direct energy in sectors like horticulture and poultry is about two orders of magnitude larger than most field-based farm types. Thus reflects the extensive use of heating fuels in these sectors as well as electricity for ventilation, feeders and manure management in poultry farms. Indirect energy use on poultry farms is again about two orders of magnitude larger than most field-based farm types. This reflects mainly feed purchases as well as young birds. The lowest value for energy use is on LFA grazing farms, remembering that this is per ha, not per unit output.

The energy use of farms in the sample shows considerable variation as indicated by the coefficient of variation (CoV, i.e. standard deviation divided by the mean). Even within farm types, however, there can be substantial variety in the profile of enterprises and variation within enterprises. For example, specialist poultry production includes both fully housed and free range birds that produce not only eggs and finished birds for meat, but also day old chicks, pullets and

turkeys. Horticultural farms include ones with only heated glasshouses as well as unheated field crops, which may be edible or ornamental. Animal enterprises exist on cereal and general cropping farms, but the relatively narrow range of activities of cereal farms means that the CoV for this farm type is lower than for the others.

The indirect energy use is clearly a considerable term for all farm types and the averages are often larger than the direct values. The reasons vary between farms, but on cereal farms, fertilisers form the main contribution, while feeds can be the main terms on animal farms, especially pig and poultry. It is noteworthy that the indirect energy use on horticultural farms is about 15 times lower than direct, reflecting heating energy use in glasshouses.

The significance of differences between farm size and types (per unit area) was examined using one-way analysis of variance (ANOVA). The one "other" farm type was not included in this analysis. Total (i.e. direct+ indirect) energy use was examined in this analysis, hence including all embedded and bought-in energy or emissions.

Farm type and total energy use per ha

Most farm types were significantly ($p<0.05$) different from each other in energy use per ha (Table 12). Mixed farms were least likely to be different from others, probably owing to the broad spectrum of possible activities on any individual farm and therefore LFA grazing farms were not different from other field based types except for cereals. The highest three energy users per ha were thus specialist poultry, horticulture and pigs with the grazing livestock types being lowest (Table 13). This agrees with typical expectations, although some might be surprised that the total energy per ha of an LFA grazing farm is not significantly different from cereals or general cropping farms.

Table 11 Total direct and indirect energy use per unit area on robust farm types with scaling by adjusted agricultural area (or agricultural area, if no value recorded). All farm sizes are included in each type

		Direct Energy, GJ/ha			Indirect Energy (*), GJ/ha		
	Count	**Average**	**Std Dev**	**CoV, %**	**Average**	**Std Dev**	**CoV, %**
Cereals	83	5.6	2.2	39%	8.4	3.7	44%
Dairy	77	13	6.4	49%	23	18	79%
General cropping	77	8.0	4.1	51%	7.8	5.3	68%
Horticulture	104	1,500	3,800	260%	87	490	560%
LFA grazing livestock	19	3.7	2.1	58%	6.3	4.5	70%
Lowland grazing livestock	41	4.7	3.8	80%	5.0	4.0	80%
Mixed	47	7.3	4.7	65%	12	11.5	93%
Other (#)	1	0.090			1.6		
Specialist pigs	20	110	180	170%	320	401	130%
Specialist poultry	42	1,070	2,200	210%	1,800	3,040	170%
(*) includes energy used by contractors. (#) This is a mushroom farm							

Table 12 Significant differences (P<0.05) between total energy use per ha of farm types using log transforms. Significance is shown by s appearing in intersecting grids.

Dairy	*								
Cereals	S	*							
Gen. Crop.	S		*						
Hort.	S	S	S	*					
Mixed				S	*				
Pigs	S	S	S		S	*			
Poultry	S	S	S	S	S	S	*		
LFA Graz.	S			S		S	S	*	
Lowland Graz.	S	S	S	S	S	S	S		*
	Dairy	Cereals	Gen. Crop.	Hort.	Mixed	Pigs	Poultry	LFA Graz.	Lowland Graz.

Table 13 Ordering from highest to lowest of total energy use per ha by farm types

	Farm type	Total energy use, GJ/ha
1	Specialist poultry	2900
2	Horticulture	1500
3	Specialist pigs	430
4	Dairy	36
5	Mixed	19
6	General cropping	16
7	Cereals	14
8	LFA grazing livestock	10
9	Lowland grazing livestock	9.7
10	Other (#)	1.7

The analysis of GHG emissions has some similarities to energy use, but with some distinct differences too (Table 14). Poultry and horticulture were the highest emitters per ha for both direct and indirect emissions, and were again about two orders of magnitude larger than the lower emissions from field cropping.

Most farm types emit significantly ($p<0.05$) different GHGs per ha (Table 15) with the ordering given in Table 16. The descending order of poultry, horticulture, pigs and dairy still applies, but the general cropping farms emit significantly ($p<0.05$) less GHGs per ha than LFA grazing farms.

The general trends are in line with the energy use results and both clearly support the idea that arable production (per unit area) had smaller GHG emissions than non-ruminant livestock production and dairying. Specialist pigs and poultry units typically see their downstream food production burdens concentrated into the small area that is often little more than the land their houses stand on, unlike ruminant farms that are associated with a relatively large area of grazing land. Lowland grazing, LFA grazing and general cropping were not significantly different from each other.

Table 14 Total direct and indirect GHG emissions per unit area on robust farm types with scaling by adjusted agricultural area (or agricultural area, if no value recorded). All farm sizes are included in each type

		Direct GHG emissions, GWP, t CO_2e/ha (*)			Indirect GHG emissions, GWP, t CO_2e/ha (#)		
	Count	**Average**	**Std Dev**	**CoV, %**	**Average**	**Std Dev**	**CoV**
Cereals	83	1.7	0.92	53%	0.87	0.59	68%
Dairy	77	5.0	2.0	41%	3.0	3.9	130%
General cropping	77	1.6	1.0	60%	0.82	0.74	90%
Horticulture	104	100	290	280%	7.1	40	560%
LFA grazing livestock	19	3.7	1.4	39%	0.86	0.63	73%
Lowland grazing livestock	41	3.4	1.7	49%	0.74	0.86	120%
Mixed	47	3.8	2.2	57%	2.0	2.7	140%
Other	1	0.12			0.23		
Specialist pigs	20	54	69	130%	46	63	140%
Specialist poultry	42	140	250	180%	270	470	170%
All farms	511	36	155	430%	27	160	580%
(*) includes all fuels, enteric emissions from animals, field emissions of N_2O.							
(#) includes embedded GHG in bought in materials and animals, machinery overheads and secondary emissions of N_2O.							

Table 15 Significant differences (P<0.05) between total GHG emissions per ha of farm types using log transforms

Dairy	*								
Cereals	S	*							
Gen. Crop.	S		*						
Hort.	S	S	S	*					
Mixed		S	S	S	*				
Pigs	S	S	S	S	S	*			
Poultry	S	S	S	S	S		*		
LFA Graz.			S	S		S	S	*	
Lowland Graz.	S			S		S	S		*
	Dairy	Cereals	Gen, Crop,	Hort.	Mixed	Pigs	Poultry	LFA Graz.	Lowland Graz.

Table 16 Ordering from highest to lowest of GHG emissions and total energy use per ha by farm types

	Type	Total GHG emissions, GWP, t CO_2e/ha
1	Specialist poultry	410
2	Horticulture	107
3	Specialist pigs	100
4	Dairy	8.0
5	Mixed	5.8
6	LFA grazing livestock	4.6
7	Lowland grazing livestock	4.1
8	Cereals	2.6
9	General cropping	2.4
10	Other	0.4

The proportions of energy used and GHG emissions for each farm type that are direct are shown in Table 17 and indicate that for most farm types the direct energy used is in the region of 40%. Horticulture is much higher (because of heating fuels) and pigs rather lower. Direct GHG emissions are more varied by type, but are generally higher than energy use. Field N_2O and enteric CH_4 are the main causes.

Table 17 Total energy and GWP per ha and proportional contributions from direct and indirect sources

Farm type	Total Energy, GJ/ha	Total GHG t CO_2e/ha	Proportions of direct/total energy	Proportions of direct/total GHG
Cereals	14	2.6	40%	66%
Dairy	36	8.0	36%	62%
General cropping	16	2.4	51%	66%
Horticulture	1500	110	94%	93%
LFA grazing livestock	10	4.5	37%	81%
Lowland grazing livestock	10	4.2	49%	82%
Mixed	20	5.8	37%	66%
Other	1.7	0.35	5%	34%
Specialist pigs	430	99	25%	54%
Specialist poultry	2800	410	38%	33%
All farms	580	63	68%	57%

Effect of farm size on energy use and GHG emissions

The significance of differences between farm size and types (per unit area) was examined using one-way analysis of variance (ANOVA). There was a significant effect of size, when considering all farm types, which was that small farms used less energy per ha than medium or large farms. This is energy per ha and not per unit output. There was not a significant effect of size (for all farm types) of GHG emissions per ha.

The effects of farm size and type interactions were examined using two-way ANOVA (Table 18). For most farm types, there were no significant effects of size on energy use: the exceptions were horticulture and poultry. For both specialist poultry and horticulture, small farms used significantly ($p<0.05$) less energy per ha and produced lower GHG emissions per ha than their medium and large counterparts (Table 19). Part of this could be a tendency for smaller poultry units to be free-range and for smaller horticultural units to have less or no heated glass areas. Because of the minority of significant differences that were found, the overall effects of size-type interactions were not significant (Table 18). Given these findings, the farm types were largely treated as one set in subsequent analyses.

Table 18 Results of two-way ANOVA of farm type and size for energy use per ha.

Source of variance	d.f.	s.s.	m.s.	v.r.	F pr.
Type ignoring Size	8	145	18.1	56.94	< 0.001
Type eliminating Size	8	139	17.4	54.47	< 0.001
Size ignoring Type	2	13.6	6.82	21.37	< 0.001
Size eliminating Type	2	7.3	3.67	11.49	< 0.001
Type.Size	14	5.45	0.390	1.22	0.257
Residual	375	119	0.319		
Total	399	277	0.697		

Table 19 Results of two-way ANOVA of farm type and size for GHG emissions per ha.

Source of variance	d.f.	s.s.	m.s.	v.r.	F pr.
Type ignoring Size	8	94.37	11.80	39.87	< 0.001
Type eliminating Size	8	98.29	12.29	41.54	< 0.001
Size ignoring Type	2	1.	0.914	3.09	0.047
Size eliminating Type	2	5.76	2.88	9.74	< 0.001
Type.Size	14	7.05	0.504	1.70	0.053
Residual	375	111	0.296		
Total	399	218	0.5467		

Organic and non-organic farms compared unit area basis

Comparisons of energy use and GHG emissions by farm type between organic and non-organic farms (per ha) were also made using two way ANOVA. There was not an overall significant difference between organic and non-organic farm energy use or GHG emissions per ha (Table 20 and Table 21). There were some specific differences at the level of $p<0.05$. Both organic poultry and horticultural farms had significantly lower energy use and GHG emissions per ha than their non-organic counterparts. Much of the difference between horticultural farms could be explained by the relative absence of heated glass on the organic farms. On poultry farms, all organic farms would operate with lower stocking densities and buildings tend to be more often naturally ventilated. This analysis is of course limited by the small number of organic farms in the sample and large inter-farm variability, so that more differences could become apparent if more samples were available. It must be noted that these comparisons were per ha and not per unit output.

Table 20 Results of two way ANOVA of farm type and organic vs. non-organic systems on energy use per ha.

Source of variance	d.f.	s.s.	m.s.	v.r.	F pr.
Type ignoring Organic	8	145.5	18.18	54.59	< 0.001
Type eliminating Organic	8	143.9	17.99	54.02	< 0.001
Organic ignoring Type	1	4.02	4.02	12.08	< 0.001
Organic eliminating Type	1	2.51	2.51	7.53	0.006
Type.Organic	6	2.12	0.354	1.06	0.384
Residual	384	128	0.333		
Total	399	278	0.697		

Table 21 Results of two way ANOVA of farm type and organic vs. non-organic systems on GHG emissions per ha.

Source of variance	d.f.	s.s.	m.s.	v.r.	F pr.
Type ignoring Organic	8	94.37	11.8	38.02	< 0.001
Type eliminating Organic	8	94.93	11.9	38.25	< 0.001
Organic ignoring Type	1	0.851	0.851	2.74	0.099
Organic eliminating Type	1	1.413	1.41	4.55	0.033
Type.Organic	6	3.20	0.533	1.72	0.115
Residual	384	119	0.310		
Total	399	218	0.547		

The general lack of significant effects of sizes and types on energy use and GHG emissions is perhaps not too surprising given the large uncertainties in the basic data (Table 11 and Table 14).

Regression analysis

Classic multiple linear regression was applied to the survey data with the aim of quantifying energy use on the whole farm in relation to the range of outputs produced across all farm types. Although log transformation was applied to the data used in ANOVA, it was not helpful in reducing errors in the regression analysis and our statistical consultant advised against its use. Untransformed data were thus used in the results that are now reported. The range of outputs was simplified by grouping them into the following categories (Table 22).

Although our aim was to use physical outputs wherever possible, these were not recorded for many horticultural outputs. So, revenue was commonly chosen for most horticultural commodities. With animal production, some net outputs are clearly identifiable, e.g. milk or eggs, but others are more diffuse, e.g. beef or sheep in which sales and purchases of stock of varying weights, ages and values occur. In some instances, farms actually lose net livestock (by number or weight) over a year.

Table 22 Output units used in multiple linear regression across farms

Field Crops	Units of output	Horticultural Crops	Units of output	Animal Outputs	Units of output
Barley	Weight	Ornamentals	Value	Eggs produced	Dozen
Bio-energy	Weight	Other	Value	Whole Milk	Volume
Legumes	Weight	Salads-Herbs	Value	Wool	Weight
Oilseeds	Weight	Soft Fruit	Value	Dairy Cattle Total Average	Head
Other Arable	Weight	Top Fruit	Value	Other Cattle Total Average	Head
Other Cereals	Weight	Vegetables	Value	Sheep Total Average	Head
Potatoes	Weight			Pigs Total Average	Head
Sugar Beet	Weight			Poultry Total Average	Head
Wheat	Weight				

The value of applying regression analysis was limited. Few conclusive, significant relationships could be extracted and these only applied to direct and total energy use for field crops (Table 23 and Table 24) on cereal and general cropping farms. The estimate for total energy used for wheat at 2.7 GJ/t was close to 2.4 MJ/t in CAHLCI, while that for barley was about twice that in CAHLCI and the estimate for direct energy was non-significant. The estimates for total energy used for potatoes, oilseed and sugar beet were reasonable, but not exceptionally good.

The explanation of this is twofold. First, we have many possible outputs in many combinations and not enough farms in the sample to explain variation. Second, the residual errors were not normally distributed (as with ANOVA) so that fits were inevitably poor. Our statistical advisor suggested that taking logs would not be suitable for this application. Further effort in this area was concentrated on the allocation methods.

Table 23 Fitted values of total energy use to crops using regression analysis

Parameter	Estimate, GJ/t	s.e.	p
Barley	4.6	0.81	<.001
Legumes	1.1	1.36	0.401
Oilseeds	3.8	0.80	<.001
Potatoes	0.88	0.13	<.001
Sugar Beet	0.25	0.07	<.001
Wheat	2.7	0.14	<.001

Table 24 Fitted values of direct energy use to crops using regression analysis

Parameter	Estimate, GJ/t	s.e.	p
Barley	1.7	0.54	0.002
Legumes	-0.12	0.91	0.900
Oilseeds	0.40	0.54	0.457
Potatoes	0.73	0.08	<.001
Sugar Beet	0.20	0.05	<.001
Wheat	1.2	0.10	<.001

Post -harvest energy

On the 79 farms where post-harvest energy use was recorded, 6.4% of the direct energy used by those farms was for post-harvest activity. This is about 3% of direct energy use on all farms.

Post-harvest energy use for grains

These were calculated from all farms where only grains were harvested and energy use for post-harvest activities were recorded. All grains were summed without any weighting on the basis that there was no evidence to identify what grains may have been dried or not. This gave the result of a mean energy use for grain of 142 MJ/t (Table 25), albeit with a large range.

Table 25 Estimates of energy use per t grain harvested, where energy use has been recorded

mean	142
min	2
max	409
s.d.	106
CoV	75%
n	45
Lower CI	-66
Upper CI	350

Applying this mean value with farms where grains and potatoes are both cropped, the mean value + upper CI was used to identify outliers, i.e. assuming energy was being used for potato storage. Removing these led to a modified estimate (Table 26), which differed little.

Table 26 Revised estimates of post-harvest energy use per t grain harvested, where energy use has been recorded

mean	134
min	2
max	409
s.d	102
CV	76%
n	67

Post-harvest energy use for potatoes

The energy use for potatoes was further examined by subtracting the mean grain energy use from the total on-farm use to estimate what was used for potatoes where both grains and potatoes were grown. The results suggested two small populations of energy use, one high and one low. For the higher range, the mean energy use was 860 MJ/t and 50 MJ/t for the lower range (Table 27). The scatter in the grain-only data is such that it must be recognised that values in the low range for potatoes could imply no energy use by potatoes. The energy use for potatoes falls into a mixture of categories, with some using ventilation only and others using refrigeration so that two ranges are quite plausible. Storage times also vary considerably.

Table 27 Estimates of post-harvest energy use in MJ per t potatoes harvested, where energy use has been recorded

	More likely high energy use	More likely low energy use
mean	862	49
min	194	5
max	1,206	97
s.d	435	40
CoV	50%	82%
n	5	5

The results compare well with the national average values used in CAHLCI in which the post-harvest energy use for wheat, OSR, field beans and main crop potatoes are 138, 162, 166 and 619 MJ/t respectively.

The data for post-harvest energy by other crops was sparse. Furthermore, the quantification of some crops was only possible by revenue value rather than by weight. From the limited data, we can say relatively little (Table 28). The range for top fruit appeared to embrace two orders of magnitude.

Table 28 Estimates of post harvest energy use in horticulture per £ revenue (RV), only on farms where such energy use has been recorded

	Salads &/or Herbs RV	Top Fruit RV
mean	2.3	26
min	1.6	0.3
max	2.9	96
s.d.	0.9	46
CoV	39%	176%
n	2	4

Effects of grassland cultivation and establishment and woodland

The losses of soil C from cultivations and gains of soil C from grassland establishment together with farm woodlands were estimated. The results (Figure 3 and Table 29) show that the effects of grassland management are generally somewhat more negative than positive, while woodlands are always positive. There are clearly some examples whether either woodland or grassland has created a C sink on the farm, but these are in the minority and tend to apply to smaller farms. For most farms sampled, the effects are relatively small.

Please note that the data only allow a snapshot of land use changes. So, what is reported here is based on that, but may not be wholly representative of what happens on the farms on a longer time scale and the effects of land use change are long lasting.

Figure 2 Effects on overall farm C footprint of including changes in grassland area and of forestry normalised to a ha of agricultural area

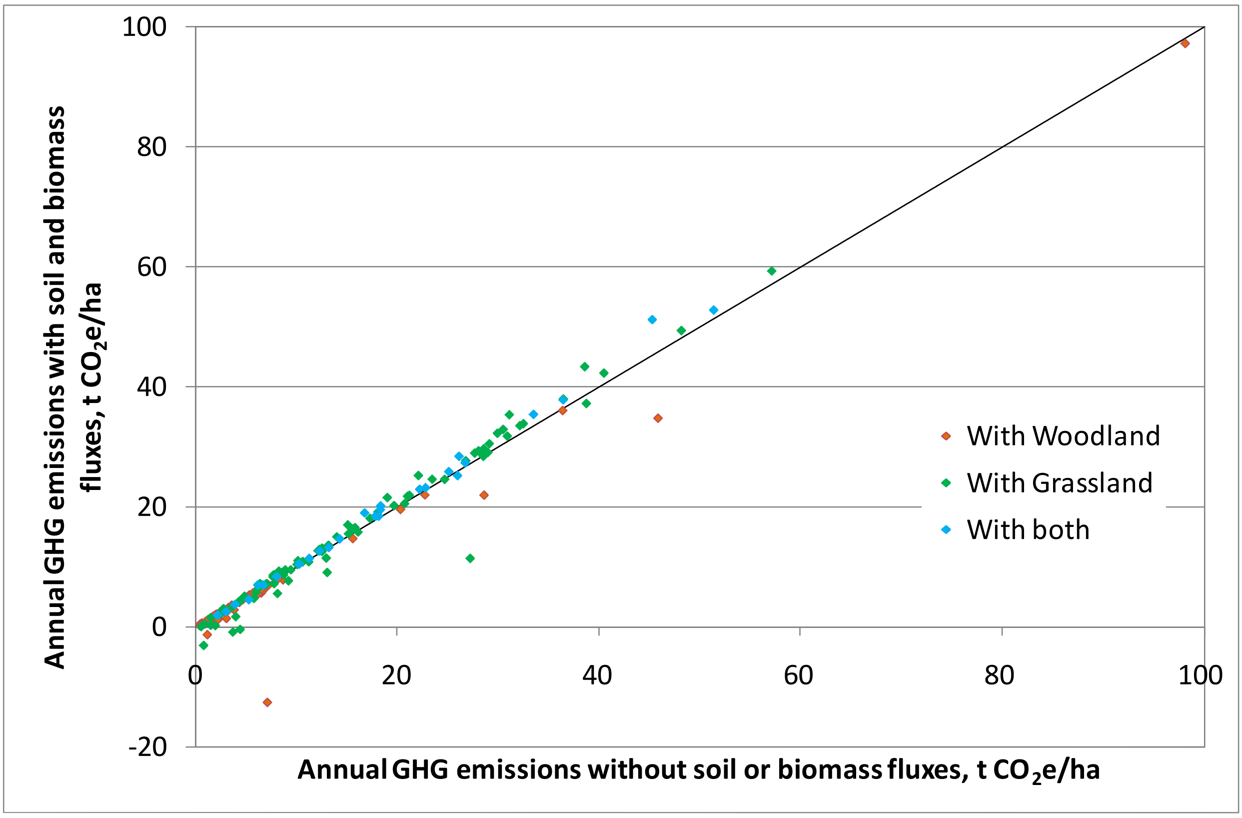


Table 29 Relative and absolute effects of biomass and soil C on whole farm GHG emissions. Note that positive values represent increases in emissions

	Effect as % difference			**Effect as t CO_2e/ha**		
	With Woodland	**With Grassland**	**With both**	**With Woodland**	**With Grassland**	**With both**
mean	-18%	-14%	3%	-0.8	0.1	1.0
max	0%	17%	16%	0.0	5.8	7.0
min	-275%	-555%	-18%	-20	-18	-0.9
CoV	-219%	-479%	286%	-3.1	19	1.6
n	78	86	28	78	86	28

4. Allocation of energy and GHG to farm outputs using LCA values as a basis

Almost all farms produce more than one output and a useful insight into farm operations can be obtained by allocating farm energy use and GHG emissions to individual commodities (or commodity groups) rather than just to the whole farm itself. The part of the analysis started with cereal farms (being the most straightforward) and progressed through to farms with more complex outputs. It became clear early on that arable farms are much more easy and reliable to analyse than livestock or mixed farms.

Methods

This was initially applied to non-organic specialist cereal farms. The starting point was to take the amounts of each commodity produced by each farm and multiply these by the energy and emission factors from CAHLCI for these commodities to obtain farm-specific total energy use and GHG emissions. This total was compared with the farm total that was calculated from the FBS data that were recorded by operation and input (e.g. fertiliser, pesticide, fuel etc). Uniform errors were assumed to apply from each commodity and farm-specific correction factors were calculated to obtain a perfect match between LCA-based the FBS-based totals for each individual farm. For each commodity, the averages of the farm-specific LCA energy and emission correction factors were calculated to obtain an improved FBS-derived value to account for the allocation of the energy and GWP per commodity.

This method was initially applied to sub-populations of the farms, restricting the farms to those with just one type of output, so that one output is accountable for the entire farms emission and energy use. It was then applied to sub-populations of farms that have multiple outputs, using the previously FBS-derived factors to account for the energy use and emission for a commodity, so that the remaining energy use and emissions are accounted for by the new, and yet unassigned, commodity. Additional commodities were then introduced and the process was repeated until all were accounted for. This took up to five iterations with the sub-populations of the farm type increasing at every stage.

CAHLCI does not include all crops recorded by the FBS so that some values for energy and GHG emissions were estimated by proxy from existing data. In order to reduce error or bias, only cereal farms without grain drying were included.

The analysis is summarised here, the complete set is shown in Appendix 4.

Table 30 Data used in the commodity allocation analysis

Commodity	Quantity
Crops	Weights produced, t
Dairy	Milk volume (m^3)
Pigs	Weight on sale
Poultry (enterprise code = 74 to 79 & 87)	Egg number (dozen)
Poultry (enterprise code = 81 & 83)	Weight on sale (derived from revenue from sale use average of £/kg to convert to weight if weight not recorded)

N.B. The contribution of organic residues from the energy and GWP farm totals was excluded. Also excluded were the two arable farms the FBS rate recorded was far too high to be believable: farms #229 and #253.

The energy and emission factors per commodity from CAHLCI are in, Table 31, and the energy and emission factors that were obtained after each analysis are summarised at the end of this section.

Table 31 The energy and emission factors per t commodity from previous LCA work in CAHLCI. Note that some are proxies, based on the nearest crop equivalent.

Crop	Primary Energy used, GJ/t	GHG emissions as GWP, t CO_2e/t
Beans for stockfeed	2.4	0.50
Durum wheat	2.4	0.49
Green peas - processing	2.2	0.24
Linseed	5.1	1.0
Mixed barley	2.3	0.42
Mixed wheat	2.3	0.46
Other oilseed rape - double low	5.1	1.0
Peas dry for human	2.4	0.50
Peas for stockfeed	2.4	0.50
Potatoes first early	1.4	0.19
Processing potatoes	0.78	0.095
Seed potatoes	0.79	0.095
Spring barley	2.2	0.4
Spring oats	2.2	0.4
Spring oilseed rape	5.1	1.0
Spring oilseed rape - double low	5.1	1.0
Spring wheat	2.4	0.49
Sugar beet	0.37	0.042
Ware potatoes	0.78	0.095
Winter barley	2.3	0.43
Winter oats	2.3	0.43
Winter oilseed rape - double low	5.1	1.0
Winter oilseed rape - not double low	5.1	1.0
Winter wheat	2.3	0.46

Results of the allocation exercise

Cereal and general cropping farms

Farms were initially selected without any animals and with only combinable crops. This gave a sub-population of 26 farms. More crops were introduced into the analysis, so that the final number of farms after five stages was 63 (Table 32).

Table 32 Crops grown on specialist cereal farms and numbers included in the commodity allocation analysis

Sub-population size	**26**	**28**	**33**	**61**	**63**
Crop	**Stage 1**	**Stage 2**	**Stage3**	**Stage4**	**Stage5**
Beans for stockfeed	✓	✓	✓	✓	✓
Durum wheat	✓	✓	✓	✓	✓
Peas dry for human	✓	✓	✓	✓	✓
Peas for stockfeed	✓	✓	✓	✓	✓
Spring barley	✓	✓	✓	✓	✓
Spring oilseed rape - double low	✓	✓	✓	✓	✓
Spring wheat	✓	✓	✓	✓	✓
Winter barley	✓	✓	✓	✓	✓
Winter oats	✓	✓	✓	✓	✓
Winter oilseed rape - double low	✓	✓	✓	✓	✓
Winter wheat	✓	✓	✓	✓	✓
Green peas - processing		✓	✓	✓	✓
Mixed barley		✓	✓	✓	✓
Mixed wheat		✓	✓	✓	✓
Other oilseed rape - double low		✓	✓	✓	✓
Spring oats		✓	✓	✓	✓
Spring oilseed rape		✓	✓	✓	✓
Winter oilseed rape - not double low		✓	✓	✓	✓
Potatoes first early			✓	✓	✓
Processing potatoes			✓	✓	✓
Seed potatoes			✓	✓	✓
Ware potatoes			✓	✓	✓
Sugar beet				✓	✓
Linseed					✓

A good correspondence between the energy and GWP calculated directly from the LCA values in CAHLCI and those derived from the FBS data was obtained from Stage 1 (Figure 3 and Figure 4), with a better fit for energy than GWP. A similar pattern was seen after progressing through to Stage 5, when all crops were included (Figure 5 and Figure 6). The scatter for energy use was reasonably balanced around the ideal line, while there was a general underestimate of GHG emissions by the FBS derived values of about 8%.

Figure 3 Total energy use on cereals farms growing only combinable crops calculated from CAHLCI and FBS-derived values (Stage 1 of allocation analysis). [Note log y axis.]

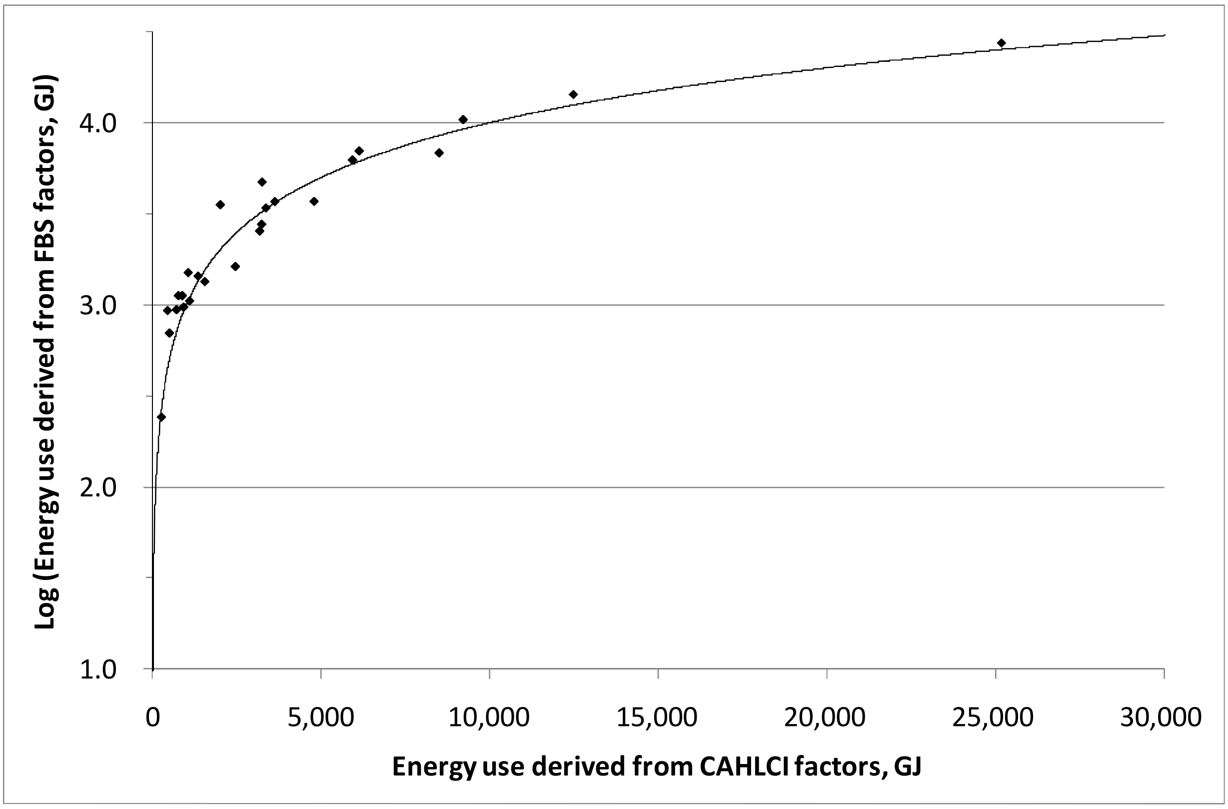


Figure 4 Total GHG emissions on cereals farms growing only combinable crops calculated from CAHLCI and FBS-derived values (Stage 1 of allocation analysis) [Note log y axis.]

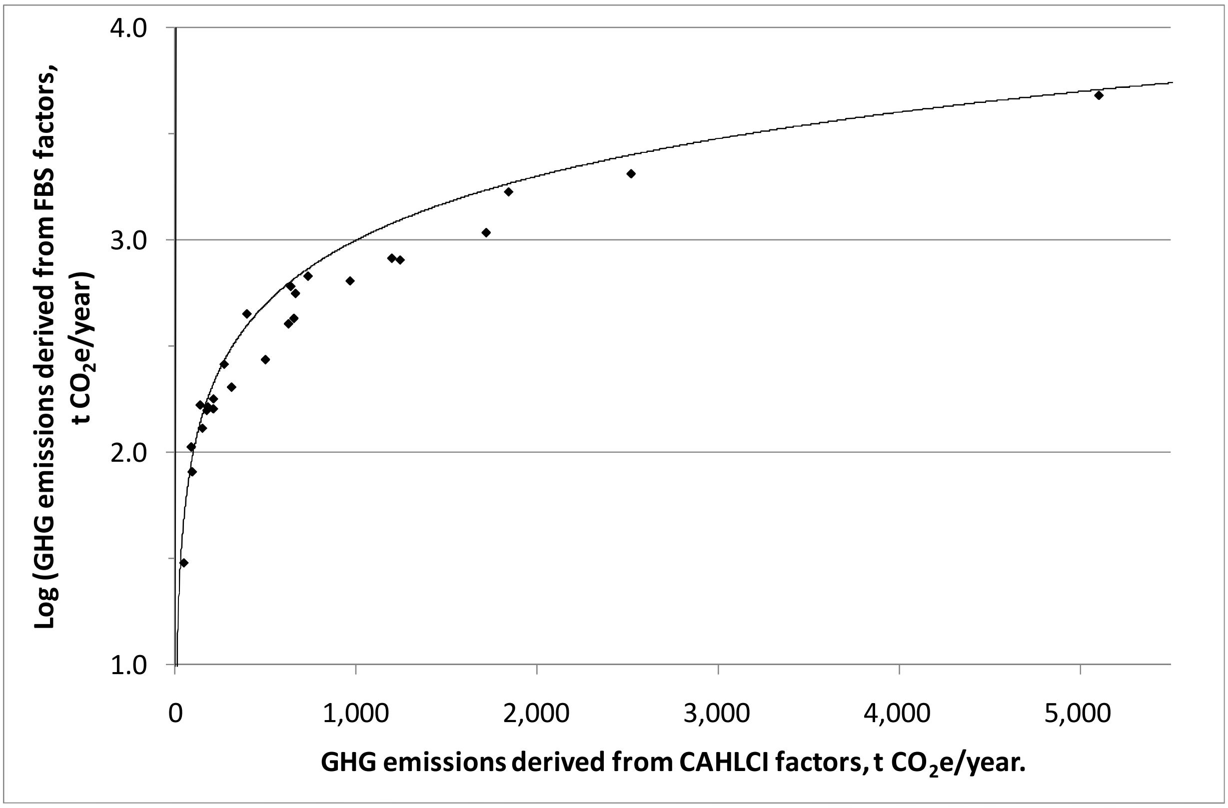


Figure 5 Total energy use on cereals farms growing all recorded crops calculated from CAHLCI and FBS-derived values (Stage 5 of allocation analysis)

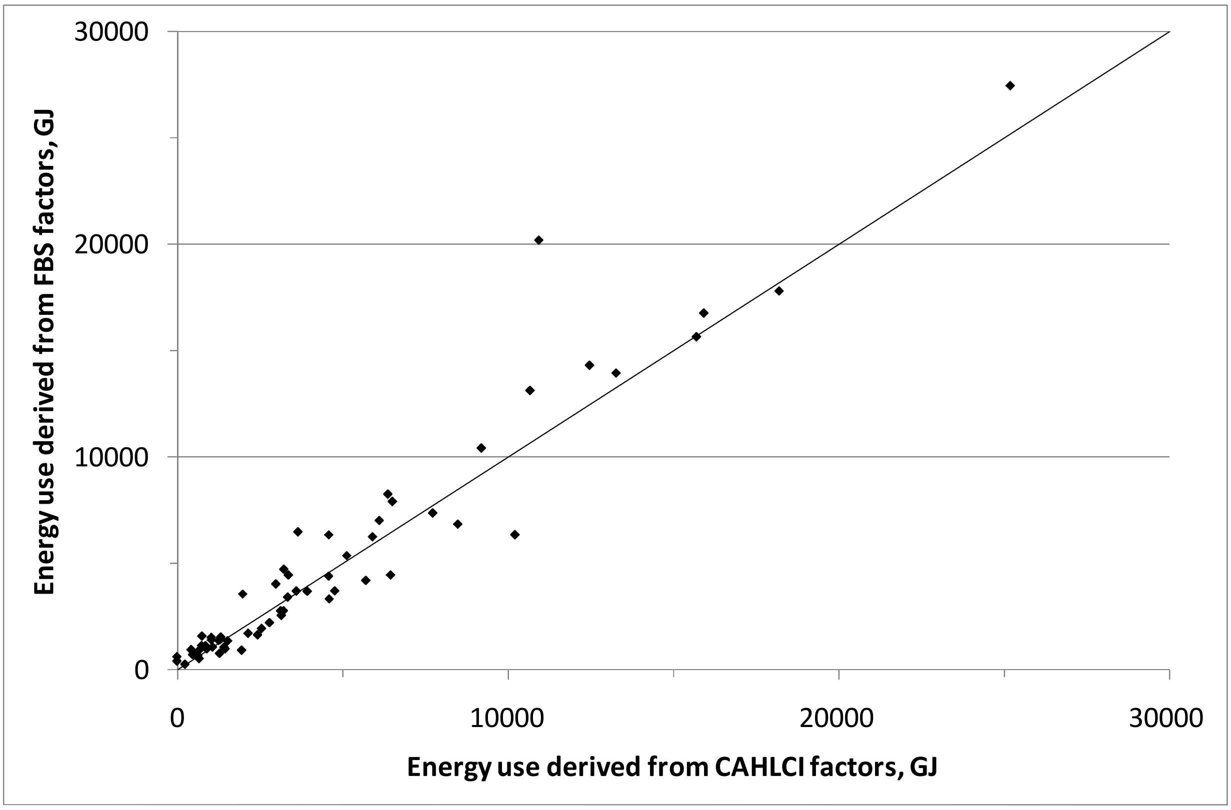
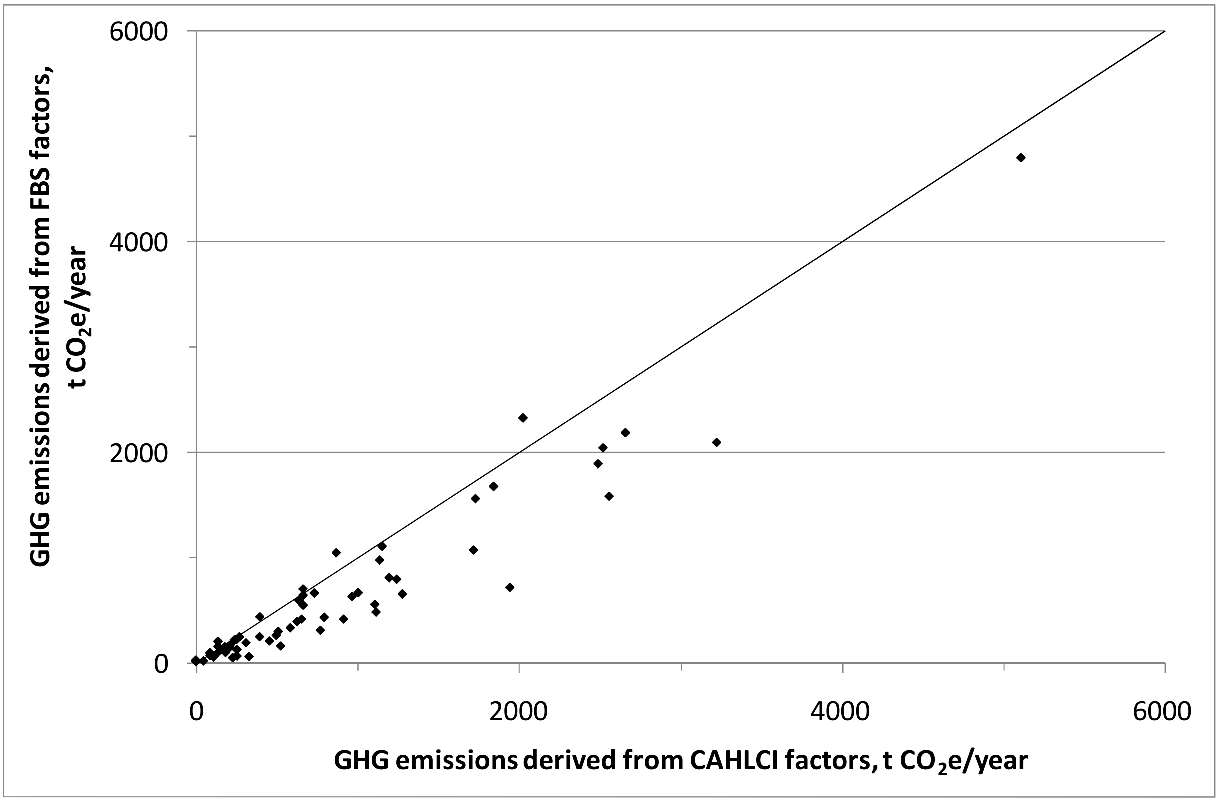


Figure 6 Total GHG emissions on cereals farms growing all recorded crops calculated from CAHLCI and FBS-derived values (Stage 5 of allocation analysis)



The energy and emission factors per commodity from the LCA and after applying the analysis (Table 33) showed that reasonably close agreements were obtained between the mean values, although the error implied by the standard deviations reflect the degree of scatter.

Table 33 Values for crop energy and GHG emissions used from the LCA analyses in CAHLCI and the final mean values (and standard deviation) derived from the FBS data. Values are rounded to 2 significant figures.

	Primary Energy used, GJ/t			**GHG, t CO_2e/t**		
Crop (t)	**CAHLCI value**	**After analysis of FBS data**	**Standard deviation**	**LCA Factor**	**After analysis of FBS data**	**Standard deviation**
Beans for stockfeed	2.4	2.5	0.8	0.50	0.37	0.13
Durum wheat	2.4	2.5	0.8	0.49	0.36	0.13
Green peas - processing	2.2	2.3	0.73	0.24	0.18	0.061
Linseed	5.1	5.5	1.7	1.0	0.77	0.27
Mixed barley	2.3	2.4	0.77	0.42	0.31	0.11
Mixed wheat	2.3	2.4	0.77	0.46	0.34	0.12
Other oilseed rape - double low	5.1	5.5	1.7	1.0	0.77	0.27
Peas dry for human	2.4	2.5	0.8	0.5	0.37	0.13
Peas for stockfeed	2.4	2.5	0.8	0.5	0.37	0.13
Potatoes first early	1.4	1.5	0.47	0.19	0.15	0.05
Processing potatoes	0.78	0.83	0.26	0.095	0.071	0.025
Seed potatoes	0.79	0.84	0.27	0.095	0.071	0.024
Spring barley	2.2	2.3	0.73	0.40	0.30	0.10
Spring oats	2.2	2.3	0.73	0.40	0.30	0.10
Spring oilseed rape	5.1	5.5	1.7	1.00	0.77	0.27
Spring oilseed rape - double low	5.1	5.5	1.7	1.00	0.77	0.27
Spring wheat	2.4	2.5	0.8	0.49	0.36	0.13
Sugar beet	0.37	0.39	0.12	0.042	0.031	0.011
Ware potatoes	0.78	0.83	0.26	0.095	0.071	0.025
Winter barley	2.3	2.5	0.78	0.43	0.32	0.11
Winter oats	2.3	2.5	0.78	0.43	0.32	0.11
Winter oilseed rape - double low	5.1	5.5	1.7	1.0	0.77	0.27
Winter oilseed rape - not double low	5.1	5.5	1.7	1.0	0.77	0.27
Winter wheat	2.3	2.4	0.77	0.46	0.34	0.12

Allocation analysis with milk

Although a dairy farm is conceptually straightforward, the variations are considerable. Specialist dairy farms may include other arable or animal enterprises. A major common, and subtlety complex one, concerns other cattle. In the Cranfield LCA, the commodity of milk is modelled in the context of exact numbers of herd replacements being maintained to keep herds (at three production levels) at a constant size. On actual farms, the numbers of herd replacements may differ for a variety of reasons (e.g. increasing herd size or selling breeding heifers or running a flying herd) and some offspring may be kept for beef production. While a detailed (and lengthy) interview with each farmer would clarify the function of different animals, this was not possible. So, a critical feature of the analysis was the estimation of the legitimate breeding overheads that were needed.

Five analyses were applied to an initial population of 68 non organic dairy farms and can be summarised as:

- Set 1. 42 farms without arable outputs, but including some other animals. No cut-off ratio for other cattle.
- Set 2. 43 farms with no other animals, with arable crops if the factor has been calculated. No cut-off ratio for other cattle.
- Set 3. 27 farms with no other animals, no arable crops, no dairy cow : other cattle ratio limit
- Set 4. 17 farms, with no other animals, with arable crops if the factor has been calculated. Cut-off limit applied of 3 dairy cows to 2 other cattle (sub-set of Set 2).
- Set 5. 11 farms with no other animals, no arable crops and a cut-off limit applied of 3 dairy cows to 2 other cattle (sub-set of Set 3).

Given that set 1 included other animals, it was not surprising that the apparent energy use per unit milk were generally higher from the FBS-derived data than from the LCA-based data (Figure 7), although in contrast the GHG emissions were generally lower (Figure 8). Both sets of data included one obvious outlier, in which the average milk yield was apparent 1.4 hectolitres per cow per year, compared with the average of 66 per cow per year. This farm was excluded from further numerical analysis. There were other farms with relatively high energy use per unit milk, but without clear reasons. The FBS-based energy estimates are higher but include more outputs so that if they were accounted for by the LCA then it would give a better match between the two. There was much more scatter in the plots than for arable crops. This is to be expected, given that many more variables, assumptions and management options apply to dairying than arable production.

There was, rather surprisingly, less scatter in the data on GHG emissions than energy use. It seems likely that the high contribution of enteric methane and field N_2O emissions dominate compared with the relatively smaller variation from energy-related emissions. The underestimate of GHG emissions was about 15%. It should be noted that the LCA-derived values used a more sophisticated method for calculating enteric emissions than was possible with the FBS data and this may explain part of the difference.

Figure 7 Total energy use on dairy farms without arable outputs, but with other animals calculated from CAHLCI and FBS-derived values (Set 1)

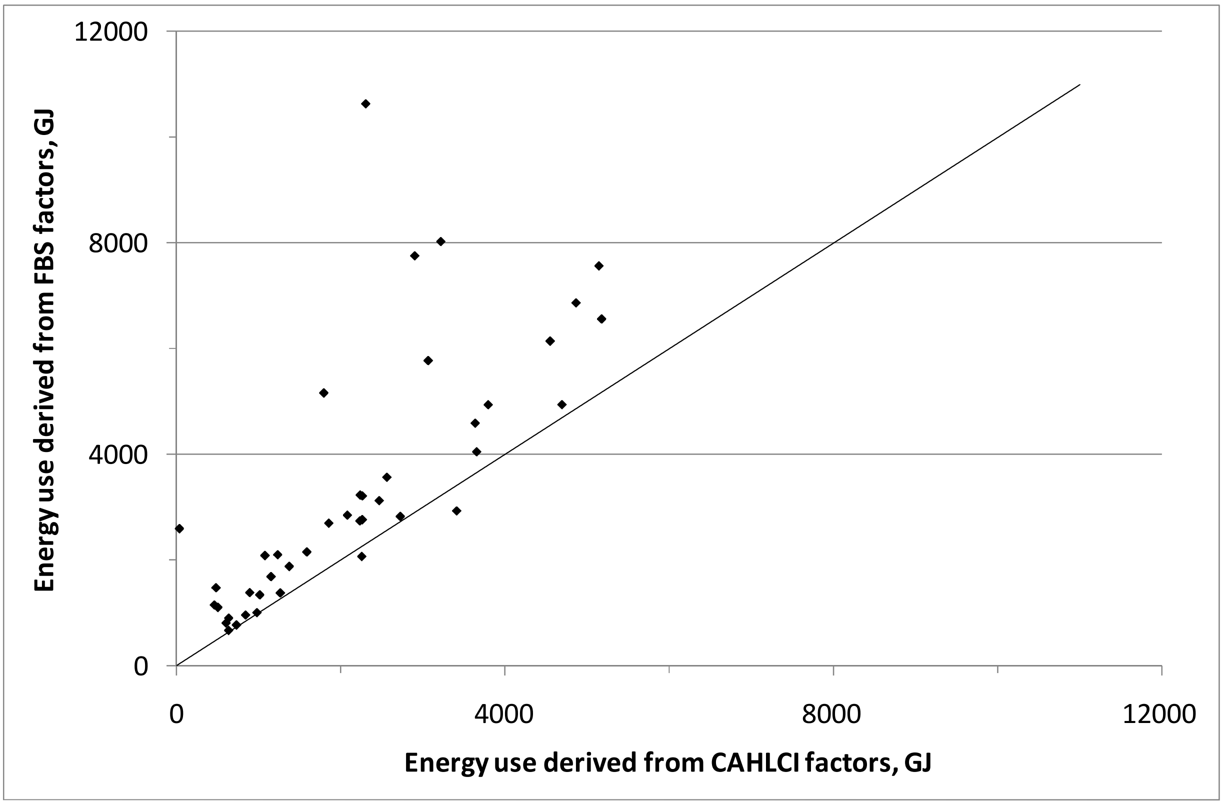
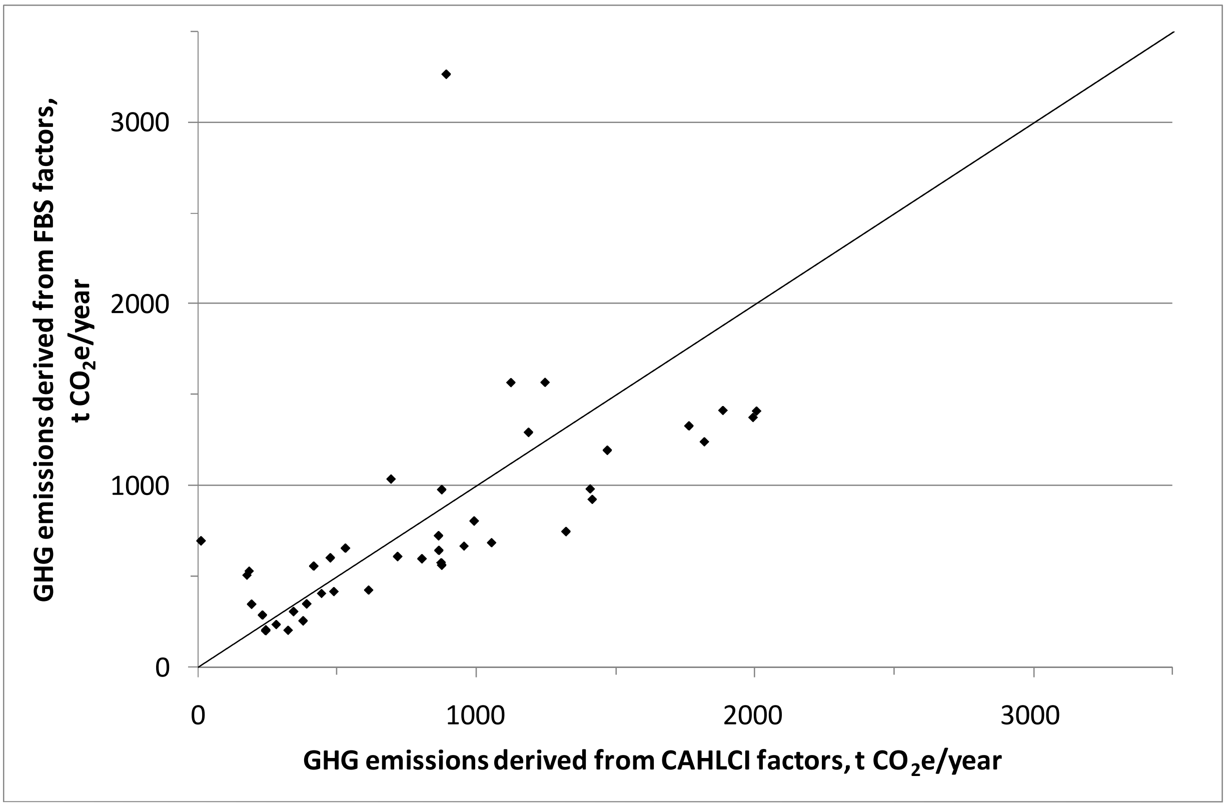


Figure 8 Total GHG emissions on dairy farms without arable outputs, but with other animals calculated from CAHLCI and FBS-derived values (Set 1)



In the second set, other species of animals were excluded, but crops that had been analysed previously were included. Again, there was more scatter in the energy data (not illustrated) and an apparent overestimate of energy per unit milk along with an apparent underestimate, by about 15%, of GHG emissions (Table 34).

Table 34 Comparison of energy use and GHG emissions per unit milk produced between the LCA-derived values in CAHLCI and the FDS-derived values

	Milk Energy use, MJ/hectolitre			**Milk GHG Emissions, kg CO_2e/hectolitre**		
	CAHLCI	**FBS-derived factor**	**standard deviation**	**CAHLCI**	**FBS-derived factor**	**standard deviation**
Set 1	270	430	200	110	110	69
Set 2	270	430	190	110	100	55
Set 3	270	420	220	110	100	64
Set 4	270	340	89	110	76	18
Set 5	270	310	51	110	69	5

In the third set, there were no arable outputs or other species of animals. This gave similar answers to those from Set 2 (Table 34). In the last two sets, the potential for other cattle to confound the results for milk was investigated, in that some might be kept for beef production instead of being herd replacements. Farms with ratios of "other cattle" to dairy cattle that exceeded the cut-off ratio were excluded from the analysis. The effect was to give lower results for both energy use and GHG emissions compared with the comparative subpopulations that included more other cattle (Table 34), which is to be expected. The errors were also reduced and less scatter is visible (Figure 9 and Figure 10 illustrate Set 5). We started from the assumption that the LCA values are about right for UK milk (and indeed our values accord closely with others obtained in the UK and overseas). The key is in the allocation of resources and breeding overheads to the milk producing dairy cow: hence the cut-off ratio that was applied. Of course, within the populations of dairy farms that were analysed, there was variation in the level of performance, but some of the values obtained from Sets 1, 2 and 3 seem implausibly high (when compared with expected values from agricultural handbooks (e.g. ABC, Nix) and strongly indicate resource use by other enterprises, e.g. beef or rearing dairy replacement heifers for sale. This clearly indicates the need for careful assessment, on any farm, of the resources going into each bovine enterprise.

Figure 9 Total energy use on dairy farms without arable outputs, but with other animals calculated from CAHLCI and FBS-derived values (Set 5)

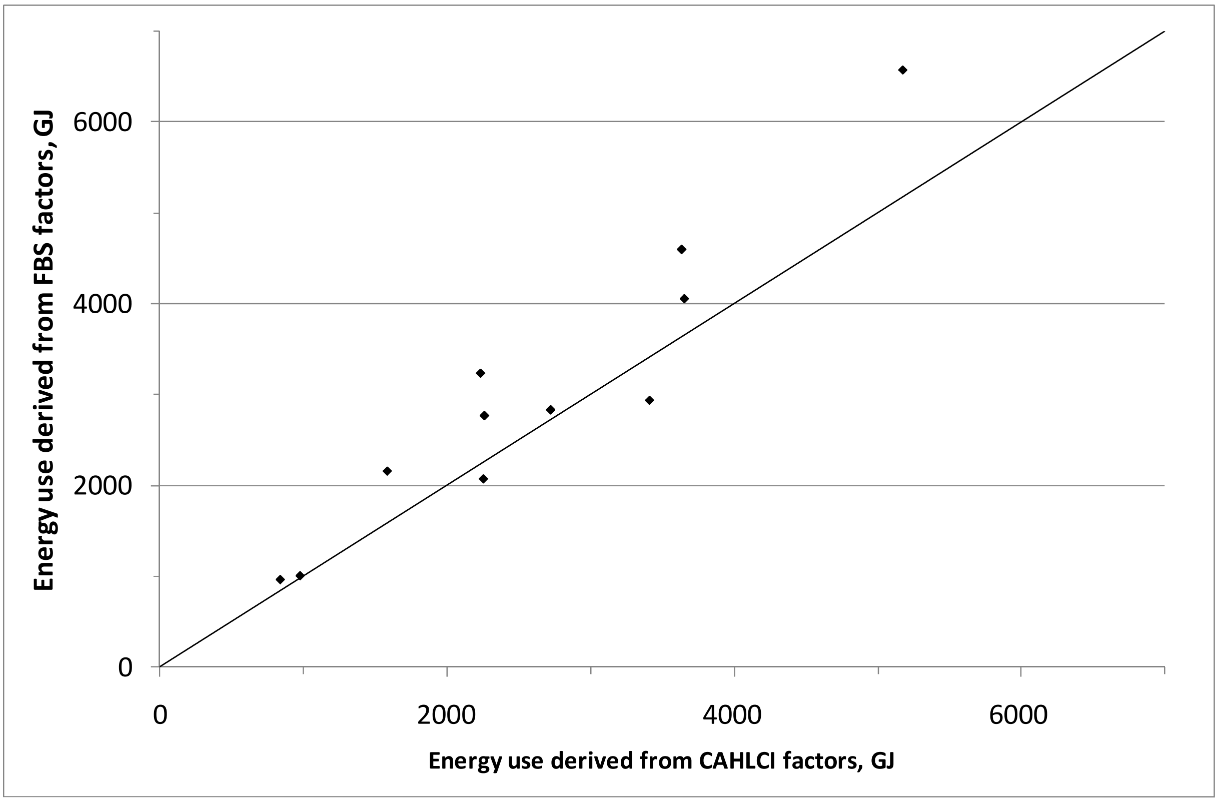
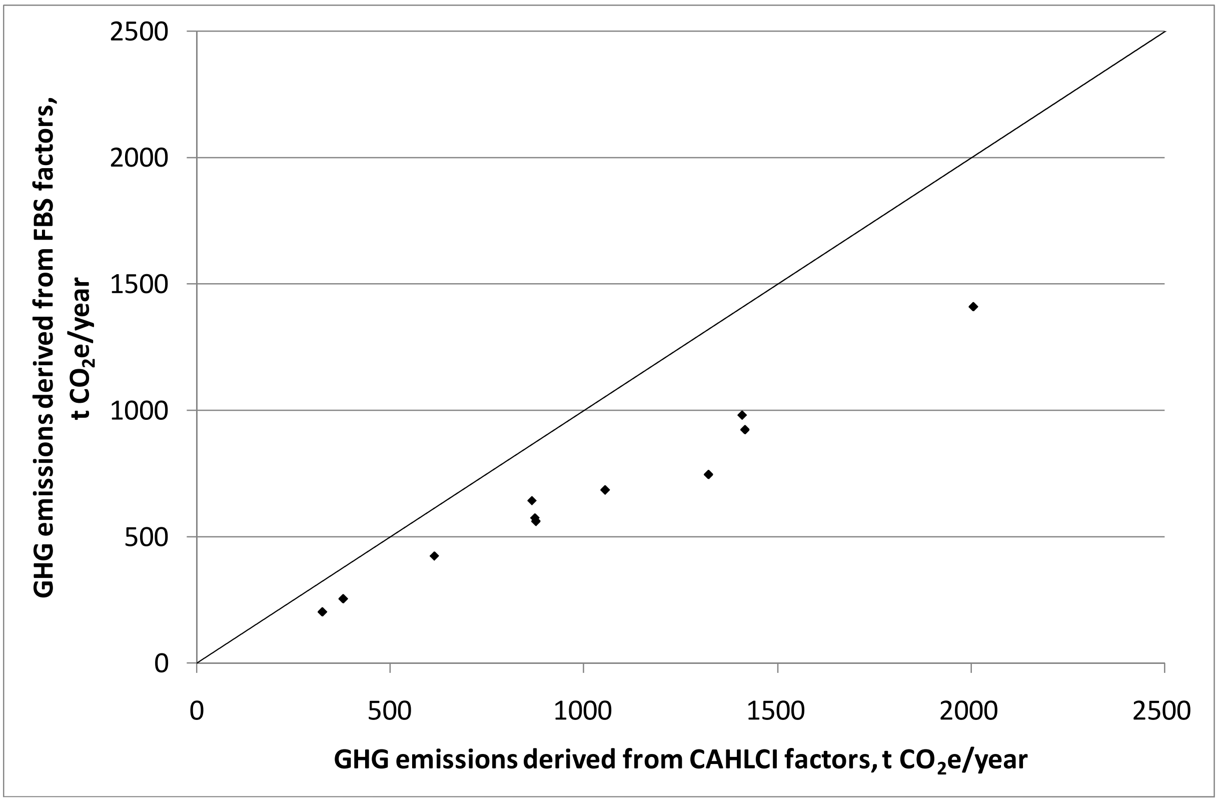


Figure 10 Total GHG emissions on dairy farms without arable outputs, but with other animals calculated from CAHLCI and FBS-derived values (Set 5)



The sensitivity to the ratio of other cattle to dairy cows was examined. It was found that there was a significant correlation between the ratio and energy use and GHG emissions (with the slope and constant also being significant (Figure 11 and Figure 12)).

Figure 11 Effect of ratio of other cattle / dairy cows on energy use for milk production

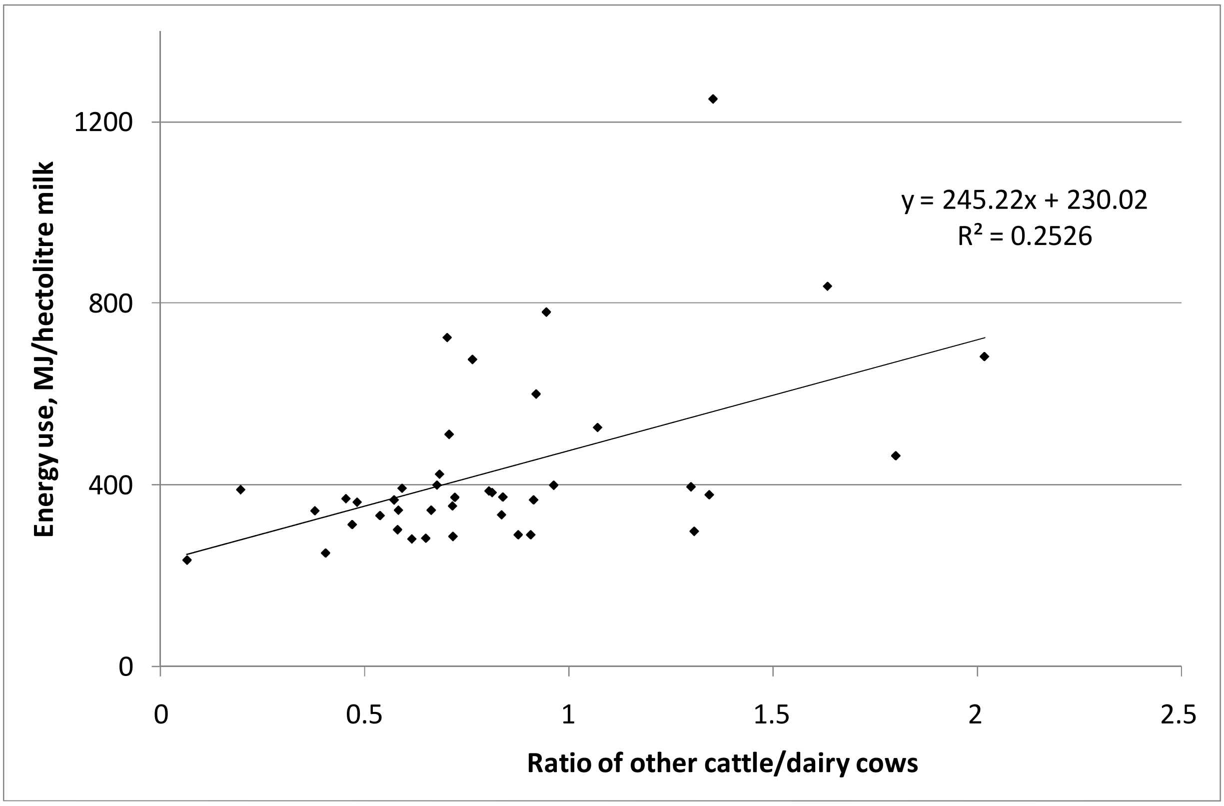
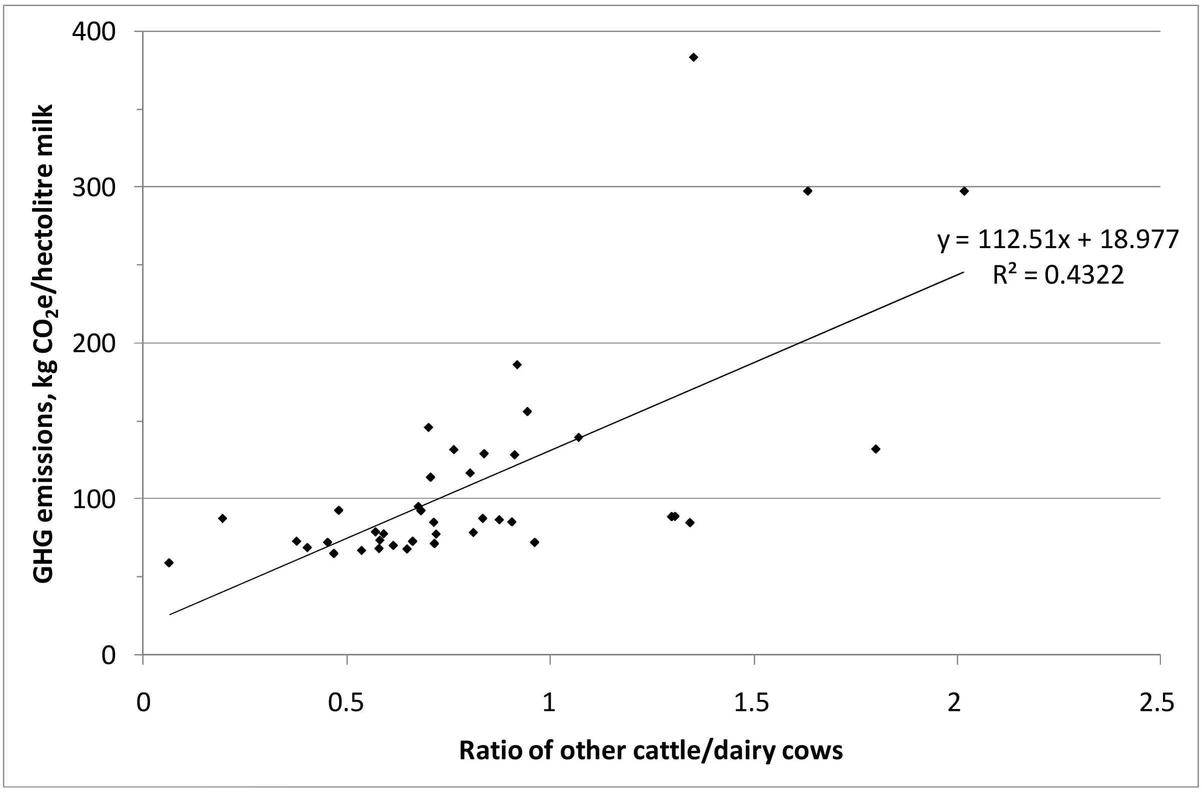


Figure 12 Effect of ratio of other cattle / dairy cows on GHG emissions from milk production



Allocation analysis with poultry

Analysis was applied to the FBS farms that were classified as Specialised Poultry, but focussed on eggs for human consumption and broiler chickens, i.e. excluding any farms with an Enterprise Code #74 (breeding), #80 (buying hatching eggs) or #84 (Ducks geese). This left 31 farms, of which some contained other commodities. One farm had other cattle, barley and wheat. Two farms had other cattle and sheep. One farm had pigs, one had oilseed and wheat, one had other cattle and another had bioenergy crops. All farms were included in the analysis, with values for other outputs that had been previously calculated being applied when possible. The reference values in CAHLCI that were derived by LCA are in Table 35

Table 35 Energy and emission factors from LCA for poultry

Commodity	Primary Energy used, GJ/t	GWP, t CO_2e/t
Eggs - mixed battery/deep litter/barn/free range	12.7	2.4
Eggs - farmyard/non commercial	11.8	2.5
Eggs – battery	13.5	2.4
Eggs - (free range)	12.0	2.5
Live weight - broilers	11.3	1.8
Live weight - turkeys	16.2	2.9

The results showed generally close agreement between energy use and GHG emissions across all farm types, even with those that had other enterprises (Figure 13 and Figure 14). In contrast to milk, the average FBS-derived estimates for energy use and GHG emissions both tended to be higher than those in CAHLCI. On systematic difference is the omission of manure exports from poultry farms in the FBS data (Table 36 and Table 37). This may have contributed to the differences. There was little effect on other commodities.

Figure 13 Total energy use on poultry farms calculated from CAHLCI and FBS-derived values

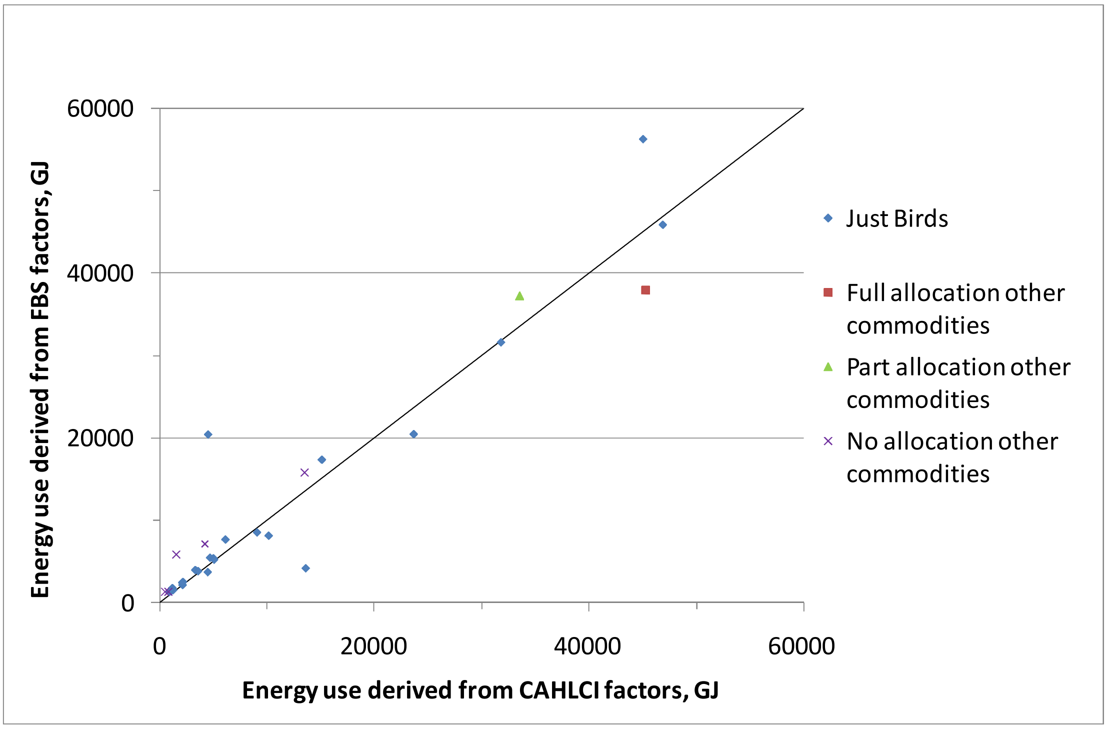


Figure 14 Total GHG emissions on poultry farms calculated from CAHLCI and FBS-derived values

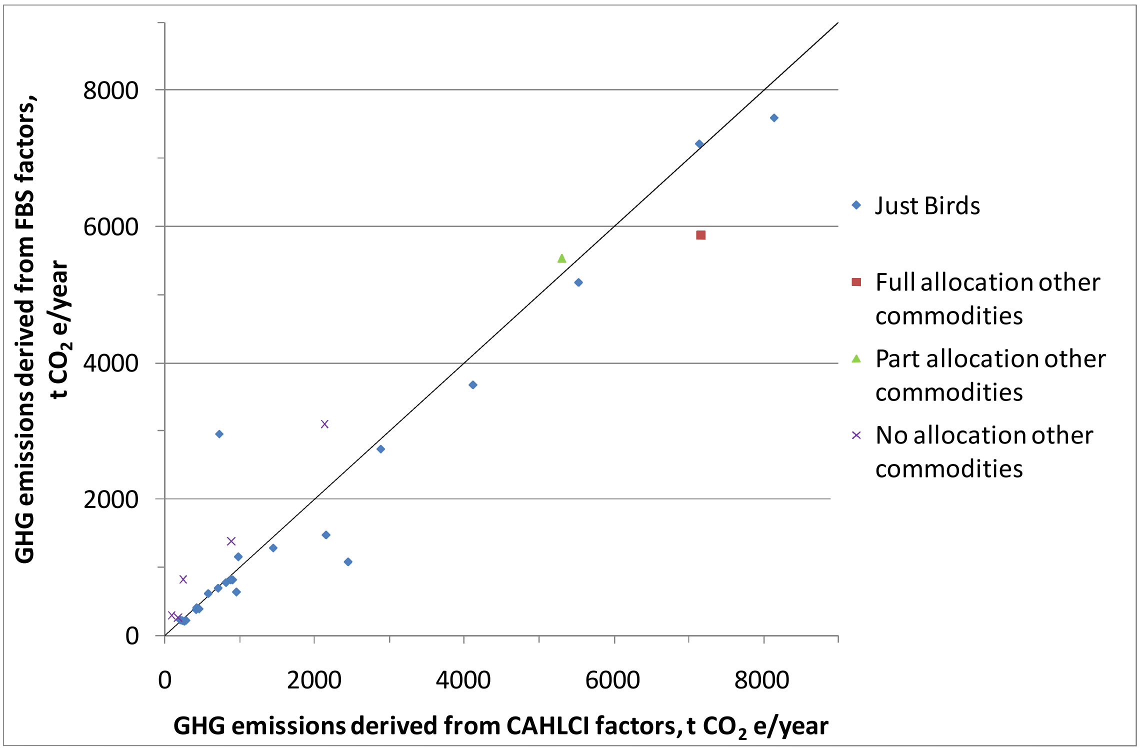


Table 36 Energy and GHG emissions factors for poultry commodities from farms with only birds or eggs as outputs

	Primary Energy used, GJ/t			GHG emissions, CO_2e/t		
	LCA value	FBS-derived value	Standard deviation	LCA Factor	FBS-derived value	Standard deviation
Eggs - mixed battery/deep litter/barn/free range	12.7	17.4	10.7	2.42	2.97	1.96
Eggs - farmyard/non commercial	11.9	16.2	10.0	2.49	3.05	2.02
Eggs – battery	13.5	18.5	11.4	2.35	2.89	1.91
Eggs - (free range)	12.0	16.4	10.0	2.53	3.10	2.05
Live weight - broilers	11.2	15.4	9.4	1.78	2.19	1.45
Live weight - turkeys	16.2	22.1	13.6	2.90	3.56	2.36

Table 37 Energy and GHG emissions factors for poultry commodities from farms with birds, eggs and other commodities as outputs

	Primary Energy used, GJ/t			GHG emissions, CO_2e/t		
	LCA value	FBS-derived value	Standard deviation	LCA Factor	FBS-derived value	Standard deviation
Eggs - mixed battery/deep litter/barn/free range	12.7	17.4	10.7	2.42	2.97	1.96

Eggs - farmyard/non commercial	11.9	16.2	10.0	2.49	3.05	2.02
Eggs – battery	13.5	18.5	11.4	2.35	2.88	1.91
Eggs - (free range)	12.0	16.3	10.0	2.53	3.10	2.05
Live weight - broilers	11.2	15.4	9.4	1.78	2.19	1.45
Live weight - turkeys	16.2	22.1	13.6	2.90	3.56	2.36

Allocation analysis with pigs

The pig sector is more complex than the poultry sector, in that most farms in the FBS were either broiler or egg producers. Pig farms can include several outputs, e.g. weaners, stores or finished pigs and thus may include breeding units or not. We concentrated on farms that included finishing, some of which had breeding too. Analysis was applied to 11 FBS farms that were classified as being specialised pigs which included these categories of enterprise: outdoor fat pigs (1 farm), indoor fat pigs (9 farms) and mixed breeding/buying weaners selling fat pigs/other (1 farm). One of these also had sheep, another farm also had other cattle and wheat while three farms had arable (winter wheat and barley; winter wheat; winter wheat, barley and sugar beet). The analysis was applied twice, firstly by ignoring any of the other commodities, secondly using the factor for those commodities that have been previously calculated.

Figure 15 Total energy use on pig farms calculated from CAHLCI and FBS-derived values

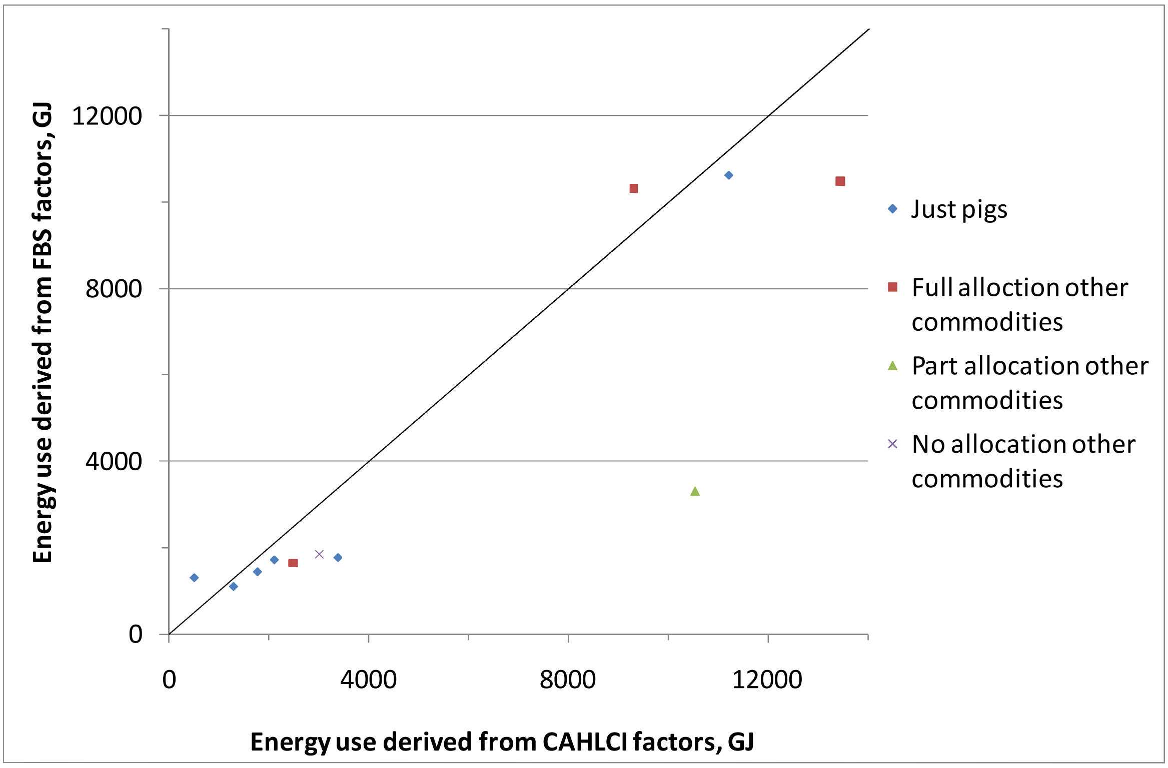
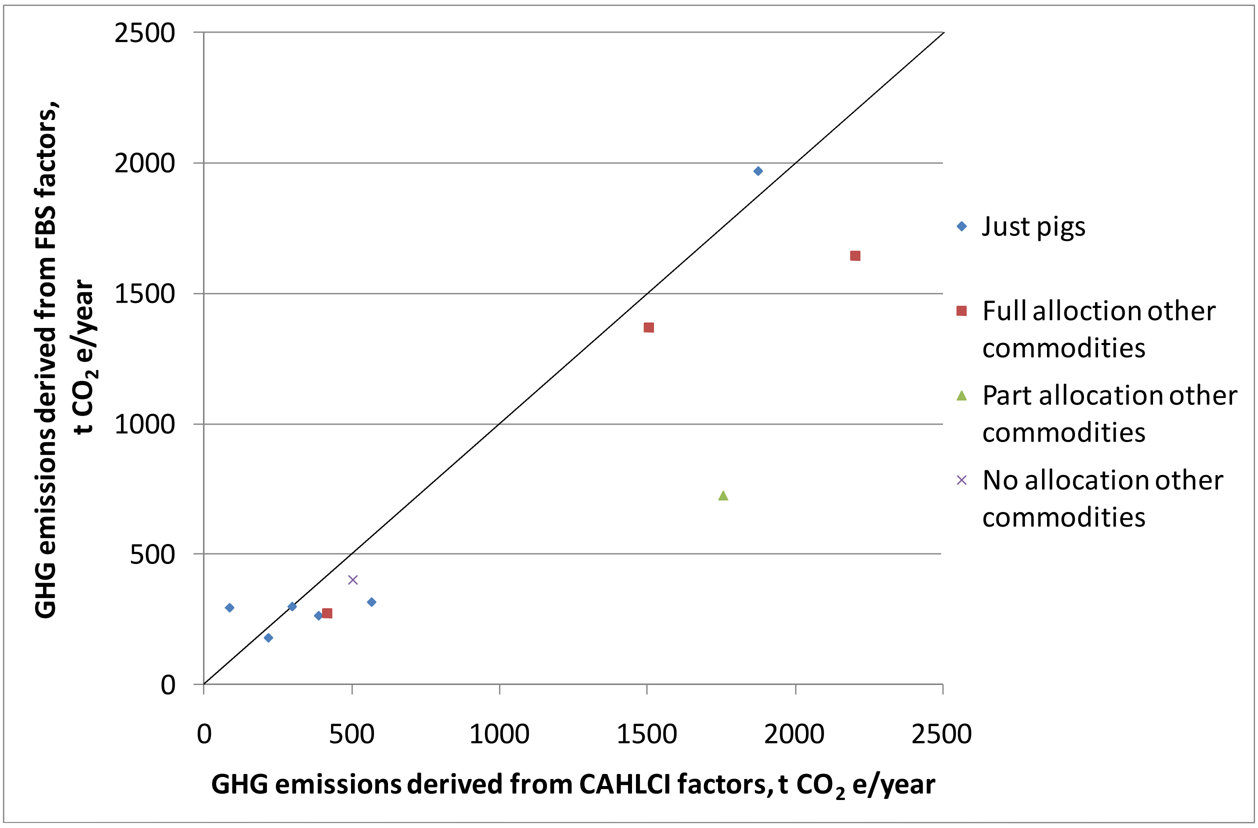


Figure 16 Total GHG emissions on pig farms calculated from CAHLCI and FBS-derived values



The values derived from the FBS data were close to the original LCA-based ones, although there was considerable uncertainty in the averaged estimates. (Table 38 and Table 39). There was more difficulty trying to compare pigs than the other commodities owing to the range of breeding overheads that were included in the FBS data in contrast to the LCA values.

Table 38 Energy and GHG emissions factors for finished pigs from farms with only pig outputs

	Primary Energy used, GJ/t			GHG emissions, CO_2e/t		
	LCA value	FBS-derived value	Standard deviation	LCA Factor	FBS-derived value	Standard deviation
Indoor breeding selling: Fat pigs	19	17	11	3.1	3.2	2.5
Mixed breeding/buying weaners selling fat pigs/other	19	17	11	3.1	3.2	2.5
Outdoor breeding selling: Fat pigs	15	14	9.0	2.8	2.9	2.3

Table 39 Energy and GHG emissions factors for finished pigs from farms with mixed outputs and allocations to other commodities provided where possible

	Primary Energy used, GJ/t			GHG emissions, CO_2e/t		
	LCA value	FBS-derived value	Standard deviation	LCA Factor	FBS-derived value	Standard deviation
Indoor breeding selling: Fat pigs	19	17	11	3.1	3.1	2.6
Mixed breeding/buying weaners selling fat pigs/other	19	17	11	3.1	3.1	2.6
Outdoor breeding selling: Fat pigs	15	14	8.9	2.8	2.8	2.3

Allocation from LCA résumé

A method was developed and applied for allocating burdens between commodities and deriving new average values for commodities from the FBS. The method was more reliable for arable than animal commodities, because of the wider range of options and assumptions in animal production. The method was not applied to beef and sheep systems owing to the great diversity of farm sub-types, including diverse and unknown weights and ages of stock that are bought and sold. The results provide averages of energy use and GHG emissions for some commodities, which provide some baseline values. The scatter in the results also indicates the scope for improvement.

One area of uncertainty associated with this analysis is the energy expended in overheads, such as running an office or maintaining vehicles and general use of electricity on the farm for purposes like lighting or indeed other enterprises, like a farm shop. The method applied assumed that energy use was used for specific commodities, but some aspects of overheads or other energy using non-farming enterprises should not be allocated uniformly across all outputs. It implies a source of error in the analysis. It may be possible to minimise it with more information.

Allocation of burdens using economic allocation

Crops with physical measures of outputs

The main agricultural crops, like wheat, barley, oilseed rape, potatoes and sugar beet, all have recorded outputs by weight so comparisons can be made with the values in CAHLCI. Also, the economic allocation method allowed more farms to be included in the analysis, so differences between farm types could be investigated. Winter wheat was the most commonly grown crop, with 193 farms followed by oilseed rape at 107 and winter barley at 91. Durum wheat, rye and seed potatoes were only grown on one farm each.

Production of winter wheat on all farm types took an average of 2.6 GJ/t and emitted 0.33 t CO_2e. This compared well with 2.3 GJ/t and 0.46 t CO_2e in CAHLCI. Both estimates from the FBS data had a CoV of about 35%, so they are not significantly different from those in CAHLCI. Results for winter OSR and winter barley were also close to those in CAHLCI (Table 40). Indeed most crops grown in any quantity produced similar results and the comparisons were well within the error range of the FBS-based estimates.

Table 40 Primary energy used to grow main crops on all farm types calculated by economic allocation from the FBS data plus LCA values from CAHLCI for the nearest equivalent crop

Crop	Average, GJ/t	Std. Dev, GJ/t	CoV	Count	CAHLCI, GJ/t
Beans for Stockfeed	2.5	0.98	39%	42	2.4
Durum wheat	3.2			1	2.4
Linseed	4.1	1.57	38%	3	5.1
Mixed Barley	3.1	1.49	48%	9	2.3
Mixed Cereals	1.9			1	2.3
Mixed wheat	2.1	0.18	8%	2	2.3
Other protein crops	6.0	1.40	23%	3	
Peas for combining	2.3	0.50	22%	17	2.4
Potatoes first early	1.4	0.79	55%	2	1.4
Processing potatoes	0.8	0.19	23%	2	0.78
Rye	2.8			1	2.4
Seed potatoes	0.7			1	0.79
Set a side	0.0			0	
Spring Barley	3.1	1.04	34%	67	2.2
Spring Oats	3.2	0.92	29%	6	2.2
Spring Oilseed rape	4.8	2.85	59%	7	5.1
Spring Wheat	2.5	1.00	40%	4	2.4
Sugar beet	0.3	0.13	54%	49	0.37
Triticale	4.6	1.52	33%	8	
Ware potatoes	1.1	0.40	37%	42	0.78
Winter Barley	2.9	0.98	34%	91	2.3
Winter Oats	2.7	1.07	39%	30	2.3
Winter Oilseed rape	4.8	1.46	30%	107	5.1
Winter Wheat	2.6	0.90	35%	193	2.3

The generally good agreement between the FBS derived values and those in CAHLCI is very encouraging and suggests that the approach is well justified. It is also clear that there is much scatter in the farm data, suggesting that there is again considerable scope for making improvements.

The GHG emissions from crops calculated from the FBS data were broadly similar to those in CAHLCI and generally within the error band of the FBS values. The FBS values all behaved in the way expected, with much lower values per t for root crops like potatoes and sugar beet than for cereals. The FBS values were, on average, about 80% of those in CAHLCI. It is not clear what has caused this and to what (if any) extent it is an artefact of either the allocation method or the need to apply simplifying assumptions for the FBS analysis.

Table 41 GHG emissions from growing main crops on all farm types calculated by economic allocation from the FBS data, plus LCA values from CAHLCI for the nearest equivalent crop

Crop	Average, t CO_2e/t	Std. Dev, t CO_2e/t	CoV	Count	CAHLCI, t CO_2e/t
Beans for Stockfeed	0.27	0.10	37%	42	0.5
Durum wheat	0.61			1	0.49
Linseed	0.43	0.09	21%	3	1.0
Mixed Barley	0.35	0.13	36%	9	0.42
Mixed Cereals	0.16			1	0.445
Mixed wheat	0.25	0.03	12%	2	0.46
Other protein crops	0.77	0.25	33%	3	
Peas for combining	0.23	0.07	32%	17	0.5
Potatoes first early	0.20	0.19	96%	2	0.19
Processing potatoes	0.085	0.051	60%	2	0.095
Rye	0.32			1	
Seed potatoes	0.11			1	0.095
Set a side				0	
Spring Barley	0.34	0.12	35%	67	0.4
Spring Oats	0.36	0.11	32%	6	0.4
Spring Oilseed rape	0.64	0.41	64%	7	1.0
Spring Wheat	0.29	0.15	53%	4	0.49
Sugar beet	0.031	0.018	57%	49	0.042
Triticale	0.46	0.14	31%	8	
Ware potatoes	0.13	0.06	45%	42	0.095
Winter Barley	0.35	0.11	32%	91	0.43
Winter Oats	0.35	0.15	44%	30	0.43
Winter Oilseed rape	0.72	0.29	40%	107	1.0
Winter Wheat	0.33	0.12	36%	193	0.46

Effects of farm type on main crops

In practice, more crops are grown on specialist cereal or general cropping farms than other farm types. No single crop type is grown on all farm types, but winter wheat, OSR and winter barley are the most widespread. Given the uncertainties of the estimates, no conclusions about the farm types are possible. There is a hint that crops grown on dairy farms take more energy than other farm types (and this trend was echoed across all other crops), but whether this is a real effect or an artefact of the allocation method can not be determined without more detailed analysis (Table 42). It is often assumed that mixed systems give benefits, but these findings neither confirm nor deny this.

The effects of farm type on GHG emissions (Table 43) were a little more varied over farm types, but with high uncertainties, again no conclusions can be drawn between farm types.

Table 42 Average primary energy used to grow common crops across different farm types (GJ/t)

	Winter Wheat		Winter Barley		Winter Oilseed rape		Average of 3 crops
	Mean	Count	Mean	Count	Mean	Count	
All Farms	2.6	193	2.9	193	4.8	107	3.4
Cereals	2.4	69	2.5	69	4.8	53	3.2
Dairy	3.5	17	4.0	17	6.1	2	4.6
General Cropping	2.4	61	2.6	61	4.7	33	3.2
Horticultural	2.4	4		4	3.4	1	2.9
LFA Grazing			5.5	1			5.5
Lowland Grazing	3.7	2	3.7	2			3.7
Mixed	2.8	32	3.1	32	5.0	16	3.6
Specialist Pigs	3.4	6	3.0	6	5.0	1	3.8
Specialist Poultry	2.9	2	3.8	2	4.9	1	3.9

Table 43 Average GHG emissions from common crops across different farm types (t CO_2e/t)

	Winter Wheat		Winter Barley		Winter Oilseed rape		Average of 3 crops
	Mean	Count	Mean	Count	Mean	Count	
All Farms	0.33	193	0.35	91	0.72	107	0.47
Cereals	0.34	69	0.33	37	0.77	53	0.48
Dairy	0.40	17	0.49	8	0.81	2	0.57
General Cropping	0.29	61	0.28	16	0.64	33	0.40
Horticultural	0.22	4			0.43	1	0.22
LFA Grazing			0.50	1			0.17
Lowland Grazing	0.33	2	0.36	6			0.23
Mixed	0.35	32	0.37	19	0.75	16	0.49
Specialist Pigs	0.44	6	0.36	3	0.85	1	0.55
Specialist Poultry	0.31	2	0.36	1	0.46	1	0.38

Crops with financial measures of outputs

The diverse outputs of many crops from vegetables to fruit and flowers were only consistently recorded by financial value, so there is no independent comparison. These crops are mainly grown on general cropping and horticultural farms (Table 44). The more classically horticultural-type crops use relatively small amounts of energy per £, mostly under 6 MJ/£, but the one value for hops was over 100 MJ/£ and the two other more arable crops of herbage seeds and "other arable crops" used about 8,000 MJ/£. The pattern for GHG emissions was broadly similar (Table 45).

Again, there was much scatter and a generally smaller sample than for field crops. The diversity of crops is such that no real recommendation can be made without considering each farm in more detail.

Table 44 Financial allocation of energy use to minority crops using revenue value as measure of output, MJ/£

		Fresh vegetables	Top and soft fruit	Strawberries	Flowers and ornamentals	Nursey stock	Vineyard selling wine grapes	Medicinal plants, aromatics and spices	Hops	Herbage seed	Other arable crops
All Farms	Average	14	3.2	3.4	5.6	4.7	1.4	17	122	7,839	8,111
	Std Dev	15	1.5	1.8	3.6	3.0	0.9	4.9			
	CoV	110%	46%	53%	64%	63%	66%	29%			
	Count	59	24	4	39	10	2	4	1	1	1
Cereals	Average		2.2					19			
	Std Dev		0.8					1.6			
	CoV		38%					8%			
	Count		2					2			
General Cropping	Average	13	2.5		6.4		0.7	19	122	7,839	8,111
	Std Dev	12	0.5		3.7						
	CoV	94%	19%		58%						
	Count	23	2		6		1	1	1	1	1
Horticultural	Average	14	3	3	5	5	2	10			
	Std Dev	17	2	2	4	3					
	CoV	120%	46%	53%	66%	63%					
	Count	36	19	4	33	10	1	1			
Lowland Grazing	Value		2.4								
	Count		1								

Table 45 Financial allocation of GHG emissions from minority crops using revenue value as measure of output, kg CO2e/£

		Fresh vegetables	Top and soft fruit	Strawberries	Flowers and ornamentals	Nursey stock	Vineyard selling wine grapes	Medicinal plants, aromatics and spices	Hops	Herbage seed	Other arable crops
All Farms	Average	1.15	0.26	0.21	0.40	0.35	0.10	2.17	8.94	634	503
	Std Dev	1.22	0.12	0.14	0.27	0.20	0.05	1.02			
	CoV	1.06	0.47	0.69	0.66	0.57	0.47	0.47			
	Count	59	24	5	39	10	2	4	1	1	1
Cereals	Average		0.39					2.76			
	Std Dev		0.30					0.11			
	CoV		0.77					0.04			
	Count		2					2			
General Cropping	Average	1.39	0.20		0.51		0.07	2.51	8.94	634	503
	Std Dev	1.30	0.05		0.34						
	CoV	0.93	0.23		0.66						
	Count	23	2		6		1	1	1	1	1
Horticultural	Average	1.00	0.25	0.21	0.38	0.35	0.13	0.65			
	Std Dev	1.17	0.11	0.14	0.25	0.20					
	CoV	1.17	0.42	0.69	0.66	0.57					
	Count	36	19	5	33	10	1	1			
Lowland Grazing	Value		0.21								
	Count		1								

Allocation and animal production

The allocation of energy to animal production was generally less accurate than for crops, which should not be surprising, because a larger number of inputs are required for animal than crop production. Milk and eggs were, however, about as accurately estimated as winter wheat or OSR (Table 46). These commodities have relatively low breeding overheads and are fairly well characterised. The liveweight-based commodities all took about an order of magnitude more energy than the crops. This is to be expected as animals consume crops, and concentrate them into livestock products that are functionally different, e.g. proving very high quality protein.

The commodity called "poultry not eggs" includes only poultry enterprises that sell finished broilers (enterprise code 81). The commodity called "Pigs" includes those farms mainly selling finished (fat) pigs (enterprise code 66, 69 & 72).

The error (statistical uncertainty expressed as CoV) for pig is smaller than for poultry and the difference in energy per t liveweight is less than might be expected. The energy used per t liveweight gain is still higher for other cattle and sheep, than for pigs or poultry, but the error is high too.

Table 46 Primary energy used to produce livestock and livestock products on all farms, allocated financially. The functional units for animals are liveweight gain across all types of that species.

	Eggs	Milk	Poultry not eggs	Pigs	Other cattle	Sheep animal (live-weight)	Sheep wool
	GJ/12k eggs *	GJ/hl	GJ/t	GJ/t	GJ/t	GJ/t	GJ/t
Average	9.2	0.34	12.9	10.0	27.4	20.3	2.6
Std Dev	2.5	0.11	6.4	4.7	15.5	18.6	1.8
CoV	28%	33%	50%	47%	57%	92%	69%
Count	20	81	10	17	160	117	100
FBS/CAHLCI	98%	124%	76%	43%	85%	91%	

* 12 k eggs weigh 0.72 t

Comparisons were possible between the FBS-derived animal commodity values and those from CAHLCI. This was enabled by converting the deadweight based CAHLCI values back to liveweight (using one average value of killing out percentage per commodity). It is also a simplification in that the outputs from CAHLCI represent the exact balance of breeding and finishing needed to produce a t of deadweight while we do not know to what extent the sample in the FBS reflects the overall structure of the sectors. Nonetheless, the results are generally encouraging, with good agreement for eggs, other cattle and sheep liveweight (Table 46). The FBS values appear to underestimate energy for pig weight substantially and to a lesser extent for poultry not eggs, and over-estimate the energy needed for milk. The underestimation for pig weight is partly explained because pig enterprises may include varying proportions of breeding, growing and finishing systems, while the CAHLCI results are balanced between breeding and finishing. The results in Table 46 include all farm types and some commodities are concentrated on specialist units, especially dairy, pigs and poultry. We do not know whether this underestimate is a function of the allocation method or systematic differences. One factor to be remembered is that the Cranfield LCA focuses on only the energy used specifically for an enterprise and does not include any overheads like farm offices. These terms have been included in the FBS data and have thus been allocated to the various enterprises in the farm. It is not clear to what extent this influences the outcomes. Some energy is clearly allocated from sources that would not be used in contemporary agricultural field activities, e.g. coal, which must surely be used for heating an office on an LFA farm with only sheep and beef.

As with crops, animal production is not strictly limited to farm types, although it has more influence than with crop production. Milk production is concentrated on dairy farms and pigs on pig farms. Consequently the errors tend to be smaller on those farms and the agreement with the LCA values in CAHLCI tend to be closer (Table 47).

The same comparison between the FBS values and those from the Cranfield LCA model were made (Table 48). There was generally good agreement for eggs, milk, poultry, pigs and other cattle, although the values from the FBS data under-estimated sheep (liveweight) emissions compared with the LCA values. The errors in the data were generally slightly lower than for the energy

There were apparent differences in GHG emissions between farm types (as with energy use), although the error levels mean that there was no significant effect (Table 49). One feature that appears in both energy use and GHG emissions is that sheep seem to receive a noticeably higher allocation when produced on pig or poultry farms. This may be an artefact of a relatively low intensity production system being alongside higher intensity systems and the associated economic allocation.

Table 47 Primary energy used to produce livestock and livestock products on different farm types, allocated financially. The functional units for animals are liveweight gain across all types of that species.

Farm type		Eggs GJ/12k eggs *	Milk GJ/hl	Poultry not eggs GJ/t	Pigs GJ/t	Other cattle GJ/t	Sheep animal GJ/t	Sheep wool GJ/t
Cereals	Average	5.4				23.7	16.9	2.6
	Std Dev					14.8	5.5	1.2
	CoV					62%	33%	48%
	Count	1				29	16	13
	FBS/CAHLCI	58%				73%	76%	
Dairy	Average		0.34		6.3	36.6	20.7	2.0
	Std Dev		0.11			22.0	10.3	1.4
	CoV		32%			60%	50%	71%
	Count		74		1	21	23	18
	FBS/CAHLCI		125%		27%	114%	93%	
General cropping	Average	8.2	0.44		10.4	24.2	20.2	4.0
	Std Dev				5.6	11.9	11.4	2.9
	CoV				54%	49%	56%	71%
	Count	1	1		5	18	7	7
	FBS/CAHLCI	88%	163%		45%	75%	91%	
Horticultural	Average					25.0	10.8	0.8
	Std Dev					10.1		
	CoV					40%		
	Count					2	1	1
	FBS/CAHLCI					78%	48%	
LFA grazing	Average					31.2	16.1	2.1
	Std Dev					16.2	5.8	1.1
	CoV					52%	36%	54%
	Count					17	16	16
	FBS/CAHLCI					97%	72%	
Lowland grazing	Average					27.2	19.0	3.0
	Std Dev					14.8	6.7	2.0
	CoV					54%	35%	66%
	Count					36	28	26
	FBS/CAHLCI					84%	85%	
Mixed	Average	9.3	0.30	11.3	3.9	25.1	16.5	2.3
	Std Dev		0.12		3.5	11.2	6.2	1.6
	CoV		39%		90%	45%	37%	71%
	Count	1	6	1	2	31	19	18
	FBS/CAHLCI	100%	110%	66%	17%	78%	74%	
Specialist pigs	Average				11.5	25.9	41.1	5.8
	Std Dev				3.6	10.2	31.3	
	CoV				32%	39%	76%	
	Count				9	2	3	1
	FBS/CAHLCI				49%	81%	184%	
Specialist poultry	Average	9.5		13.0		26.7	62.6	

Std Dev	2.6	6.7	22.2	87.5
CoV	27%	52%	83%	140%
Count	17	9	4	4
FBS/CAHLCI	101%	77%	83%	281%

Table 48 GHG emissions from production of livestock and livestock products on all farms, allocated financially. The functional units for animals are liveweight gain across all types of that species.

	Eggs	Milk *	Poultry not eggs	Pigs	Other cattle	Sheep animal	Sheep wool
	t CO_2e/ 12 k eggs	kg CO_2e/ hl	t CO_2e/t	t CO_2e/t	t CO_2e/t	t CO_2e/t	t CO_2e/t
Average	1.40	88	1.98	2.99	14.50	9.03	1.17
Std Dev	0.29	17	0.90	0.68	6.76	4.48	0.70
CoV	21%	20%	45%	23%	47%	50%	60%
Count	20	81	10	17	201	117	100
FBS/CAHLCI	80%	84%	72%	74%	99%	61%	

* Note that milk is in kg CO_2e, other commodities are in t CO_2e

Table 49 GHG emissions from production of livestock and livestock products on different farm types, allocated financially. The functional units for animals are liveweight gain across all types of that species.

		Eggs	Milk *	Poultry not eggs	Pigs	Other cattle	Sheep animal	Sheep wool
Farm type		$t\ CO_2e/$ 12 k eggs	kg CO_2e/ hl	$t\ CO_2e/t$	$t\ CO_2e/t$	$t\ CO_2e/t$	$t\ CO_2e/t$	$t\ CO_2e/t$
Cereals	Average	0.80				11.72	8.56	1.35
	Std Dev					5.10	2.41	0.67
	CoV					44%	28%	50%
	Count	1				29	16	13
	FBS/CAHLCI	46%				80%	58%	
Dairy	Average		89		2.63	17.85	9.38	0.89
	Std Dev		18			9.22	4.86	0.63
	CoV		20%			52%	52%	71%
	Count		74		1	59	23	18
	FBS/CAHLCI		85%		65%	122%	63%	
General cropping	Average	1.52	93		3.26	11.45	8.26	1.74
	Std Dev				0.80	4.15	2.38	1.12
	CoV				24%	36%	29%	64%
	Count	1	1		5	18	7	7
	FBS/CAHLCI	88%	89%		81%	78%	56%	
Horticultural	Average					12.22	7.53	0.57
	Std Dev					3.73		
	CoV					30%		
	Count					2	1	1
	FBS/CAHLCI					84%	51%	
LFA grazing	Average					15.36	8.41	1.11
	Std Dev					5.20	1.72	0.52
	CoV					34%	20%	47%
	Count					17	16	16
	FBS/CAHLCI					105%	57%	
Lowland grazing	Average					14.41	8.49	1.26
	Std Dev					4.53	1.82	0.64
	CoV					31%	21%	50%
	Count					36	28	26
	FBS/CAHLCI					99%	57%	
Mixed	Average	1.30	81	2.48	2.03	12.90	7.97	1.09
	Std Dev		14		0.29	4.37	2.45	0.75
	CoV		17%		14%	34%	31%	69%
	Count	1	6	1	2	34	19	18
	FBS/CAHLCI	75%	78%	90%	51%	88%	54%	
Specialist pigs	Average				3.10	13.98	19.19	0.98
	Std Dev				0.54	5.51	15.81	
	CoV				17%	39%	82%	
	Count				9	2	3	1
	FBS/CAHLCI				77%	96%	129%	
Specialist poultry	Average	1.43		1.93		11.14	14.21	
	Std Dev	0.27		0.94		7.15	12.65	
	CoV	19%		49%		64%	89%	
	Count	17		9		4	4	
	FBS/CAHLCI	82%		70%		76%	95%	

Note that milk is in kg CO_2e, while other commodities are in t CO_2e

5. Economic efficiency

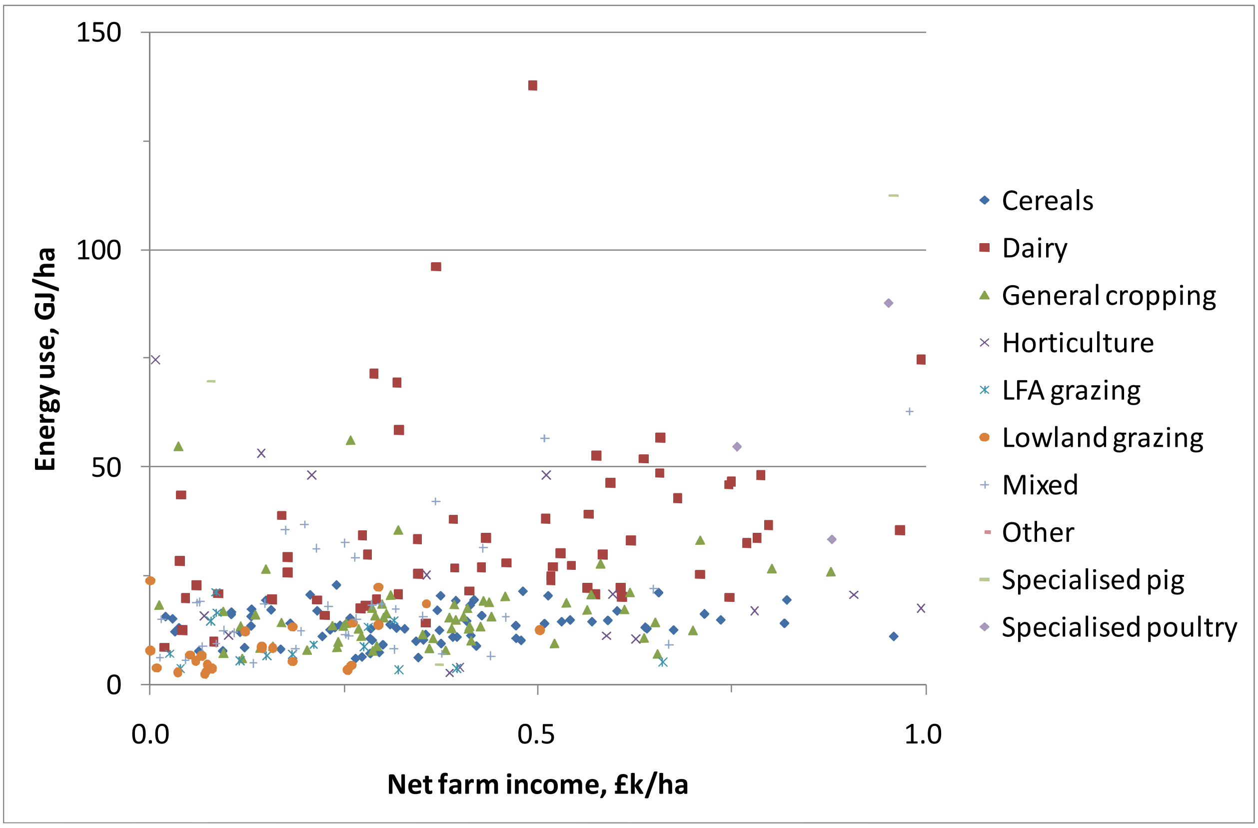
This is partly addressed in the section on data envelopment analysis, but it is the main focus on this section. The question under consideration is: is there a relationship between the amount of energy used, or amount of emissions produced, with the financial gain of the farm? The net farm income was used as the indicator of farms' financial gain (item code 79, table M2). This value is calculated as "Gross Margin – Total Fixed Costs" and so also incorporates indirect costs. It was then normalised as net income per ha for farms with mixed outputs and to physical outputs where possible. The net incomes were then compared with the energy used or GHG emissions normalised by the same scalars. This approach was only used for farm types and some general observations. Gross margins were used for individual commodities.

Regression equations and coefficients are shown on plots even when there is not a significant relationship. This is merely for completeness and does not imply that the use of such equations has any validity.

Results

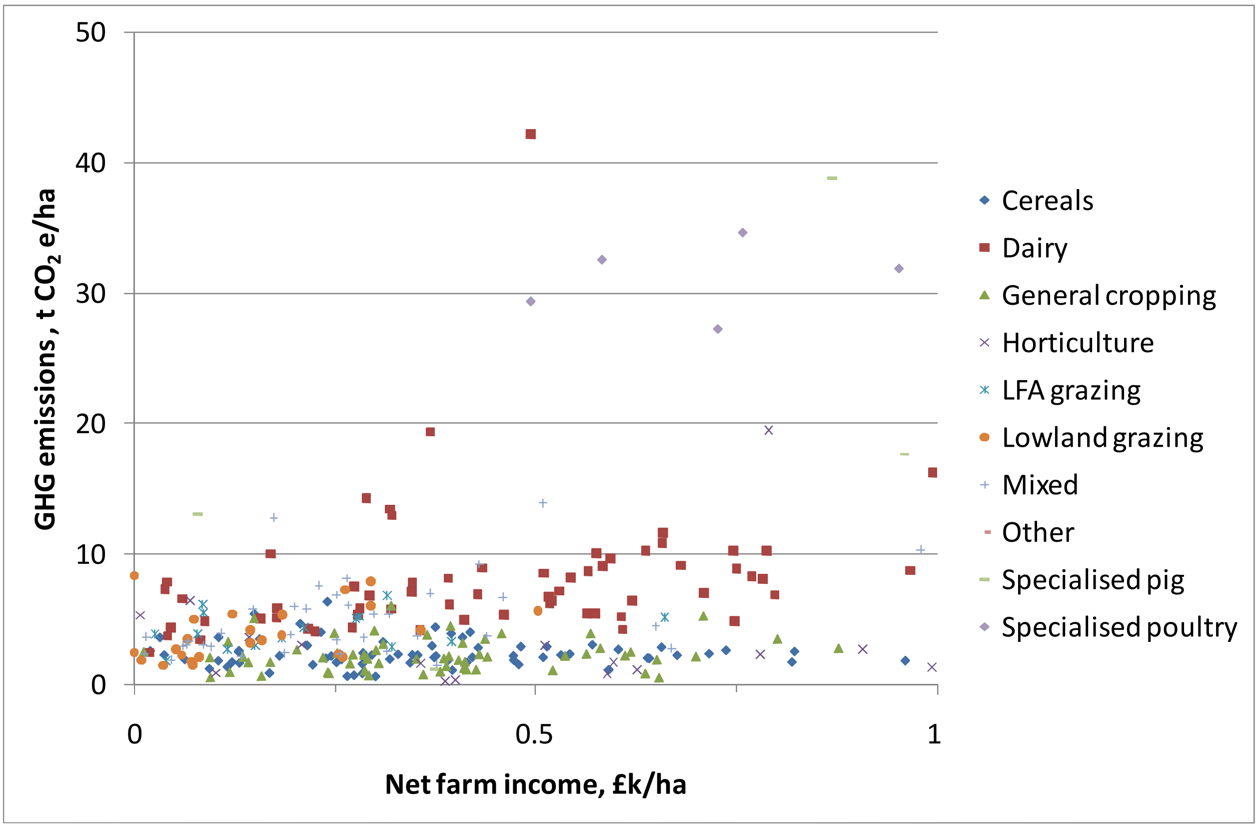
Grouping all farm types together did not show any obvious relationships, mainly because a few farm types have both much higher energy use and income per ha than other farm types. Figure 17 shows the stratification of the industry with the grazing farm types using the least energy, but also getting the least net income (noting that the data range is restricted). This progressed through the cropped farms in the middle, with animal farms using more energy per ha, but attaining the greater net income per ha. Within any range where there is an overlap in the farm types, the values range substantially.

Figure 17 All farm types energy use versus net income per ha for a restricted value range



A generally similar pattern was seen for GHG and net income per ha (Figure 18). Looking at the same focused ranges for the emissions the same stratified pattern for the farm types in the lower ranges of the values was seen, but for this case the cropping farms have the lower emissions range, then grazing, with animals being the worst polluters per ha.

Figure 18 All farm types emissions versus net income per ha for a restricted value range

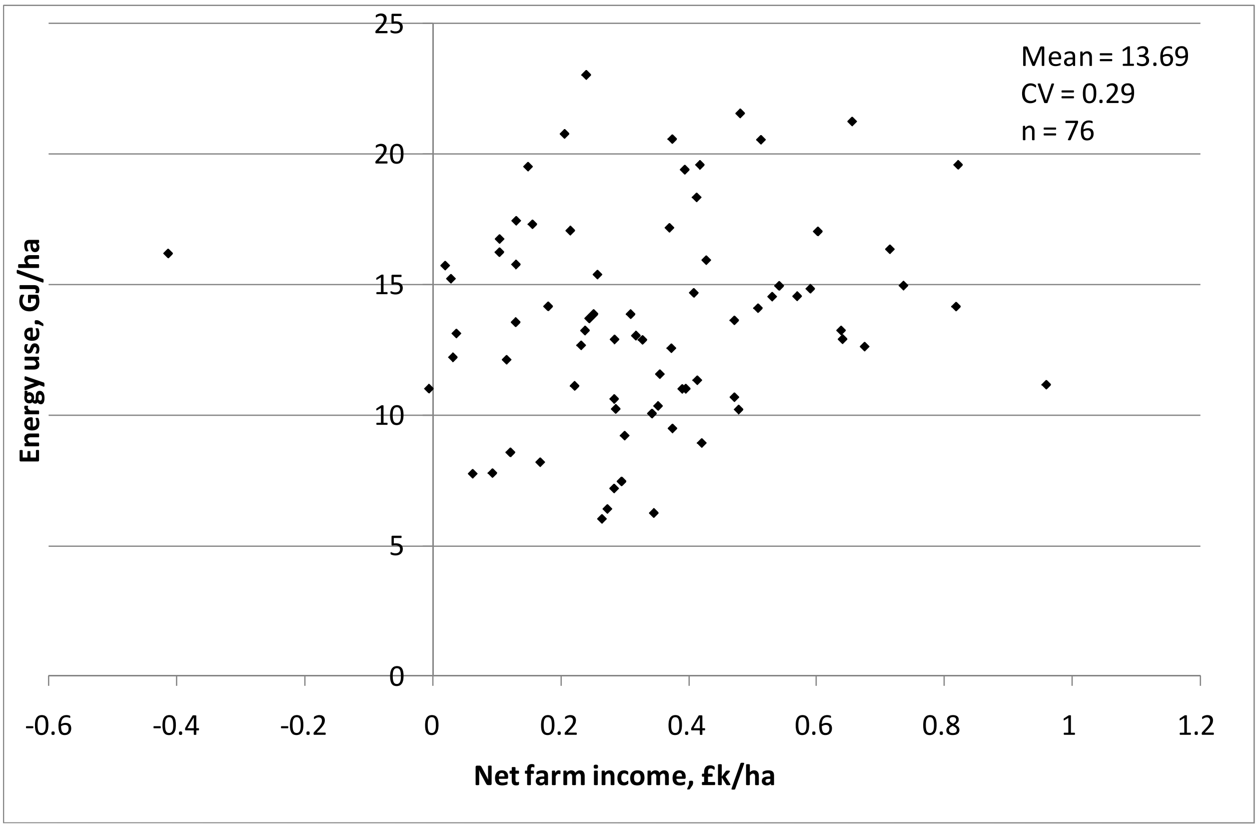


Given this wide range of values per farm type, each farm type was subsequently assessed separately using regression. The quality of the relationships obtained was assessed by the regression coefficient (as r^2), the statistical significance of the regression itself as well as the slope and intercept. Given that rather weak correlations with large scatter can still be significant at $p<.05$, it is considered that the threshold of significance should be $p<.001$.

Cereal farms

There was not a significant relationship between energy use or GHG emissions and net income per ha (Figure 19). The mean energy use and GHG emissions per ha were 13.7 (29%) GJ/ha and 2.6 t (55%) CO_2e/ha (with coefficients of variation in parenthesis).

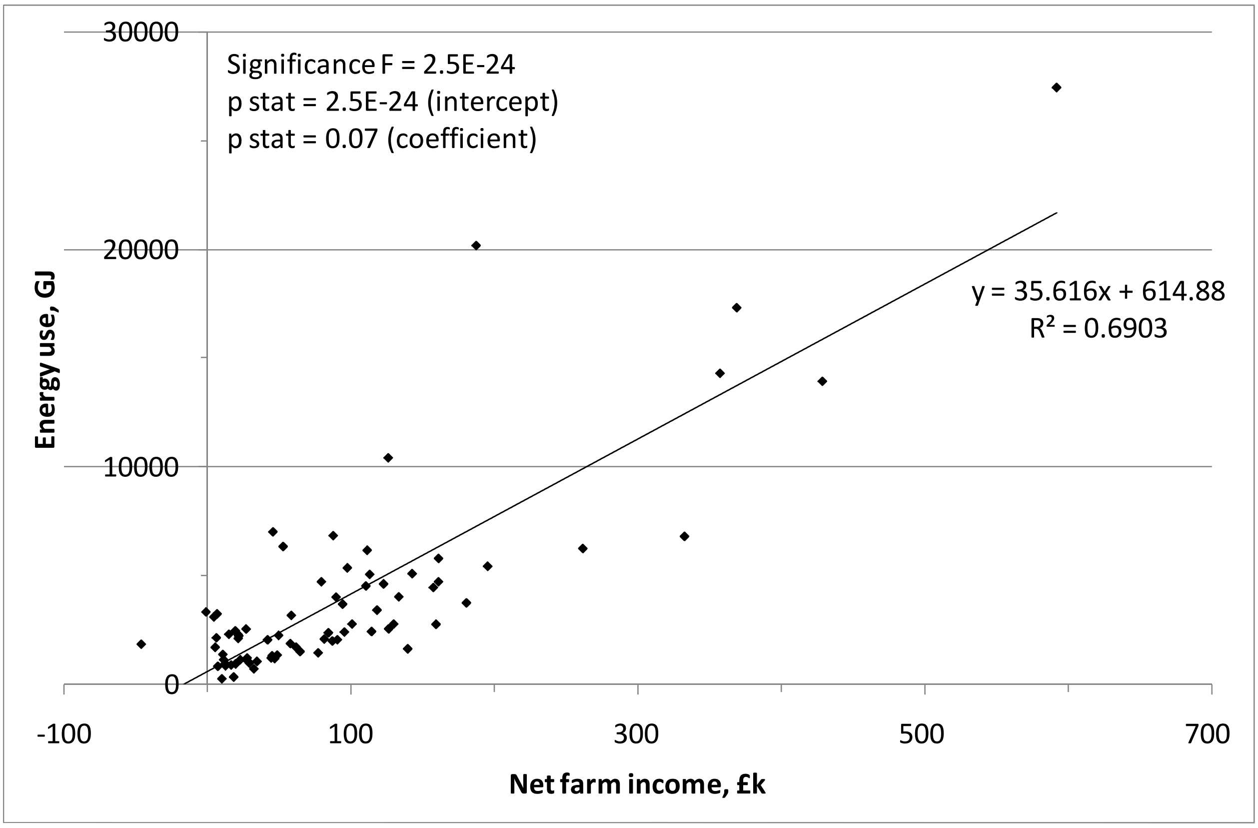
Figure 19 Cereals farms energy use versus net income per ha



There was, however, a significant correlation between total energy used and total net farm income (Figure 20) with the following summary of the regression analysis.

Regression analysis summary			
Observations	76		
R^2	0.755		
Adjusted R^2	0.752		
Significance of regression (p value)	<.001		
	Coefficient	S.E.	p-value
Intercept	584.090	320.656	<.05
Slope	34.462	2.279	<.001

Figure 20 Total energy use versus total net income on cereals farms

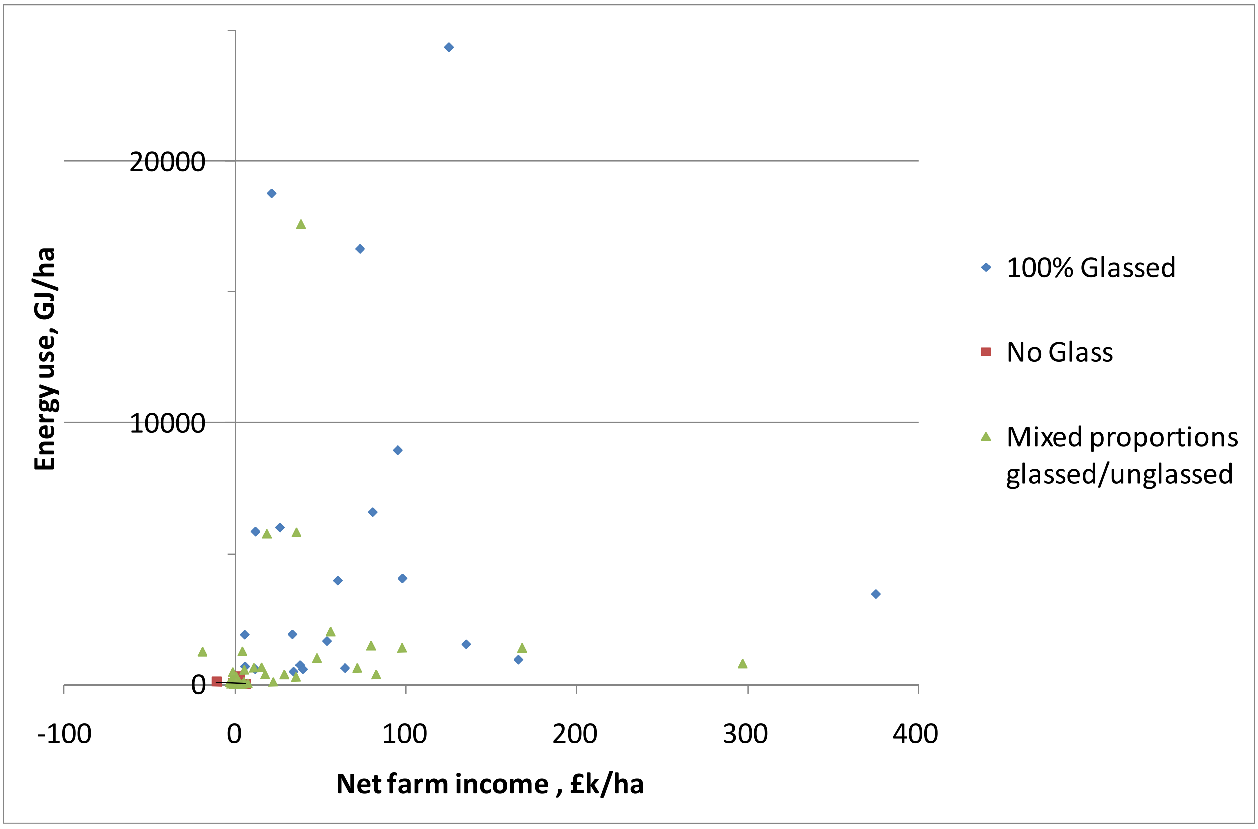


Horticulture

Horticulture presents interesting challenges because of the great diversity of outputs, e.g. tomatoes and bedding plants as well as the varied physical growing environments: heated glass, unheated glass (or polytunnels) or fields (with or without fleece or black plastic mulch). Horticultural farms were analysed first considering them all together, then as populations of all glass, no glass and mixed; all heated, partly heated, unheated and without glass.

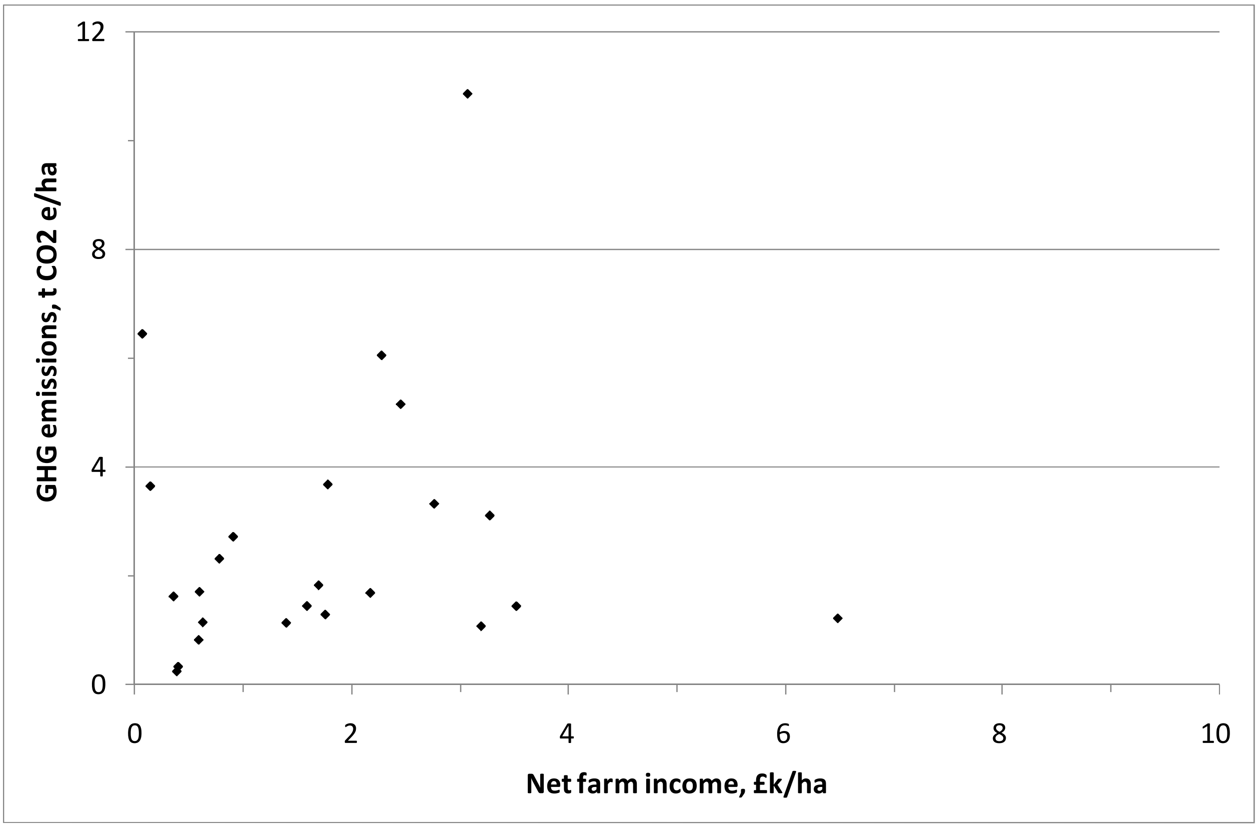
Again, with all farms considered together, there was no significant relationship between energy use or GHG emissions per ha and net income per ha. Figure 21 shows the range of horticultural farms as sub populations grouped as: 100% under glass, 0% under glass and mixed proportions. The results are swamped by the high earnings of the glassed areas since they are relatively small farms producing intensively grown produce. It was not possible to relate energy use to physical outputs owing to their great diversity and limited data, e.g. only a few tomato growers included weights of tomatoes produced. Cash revenue is not a very good guide to weight owing to the range in value of products like loose classic *vs*. cherry on the vine tomatoes.

Figure 21 Horticultural farms. Energy use versus net income per ha



There were significant correlations between net farm income per ha and both energy use and GHG emissions per ha for farms with no crops grown under glass. In both cases, the slopes were positive, but both depended on one outlying data point, which created a somewhat artificial situation. Removing this outlier meant that there was no significant relationship. There were, similarly, no significant correlations between net farm income per ha and energy use or GHG emissions per ha for farms with 100% heated glass, 100% unheated glass or mixtures of heated and unheated glass.

Figure 22 Relationship between GHG emissions and net income per unit area for horticultural farms with no glass, without one outlying point



Commodities and gross margin

This analysis was applied to five main crops and eight animal outputs. The crops were winter wheat, winter barley, winter OSR, ware potatoes and sugar beet. The animal commodities were milk, eggs, other cattle, sheep (liveweight gain), sheep (wool), pigs and poultry. After initial screening, it was decided to set a threshold to eliminate outliers systematically. From the previous work on allocation, it was clear that commodities making a small contribution to farm revenue could easily have unreasonably high burdens allocated to them. So, the threshold was set at the gross margin of a commodity being at least 10% of the farm margin.

The relationships between gross margin and either energy use or GHG emissions per unit commodity can be summarised as follows. There were few reliable significant relationships between them for any commodity when considering all farm types and sizes, although there were some promising relationships (Figure 23 and Figure 62).

Figure 23 Energy use & gross margin per unit commodity for other cattle

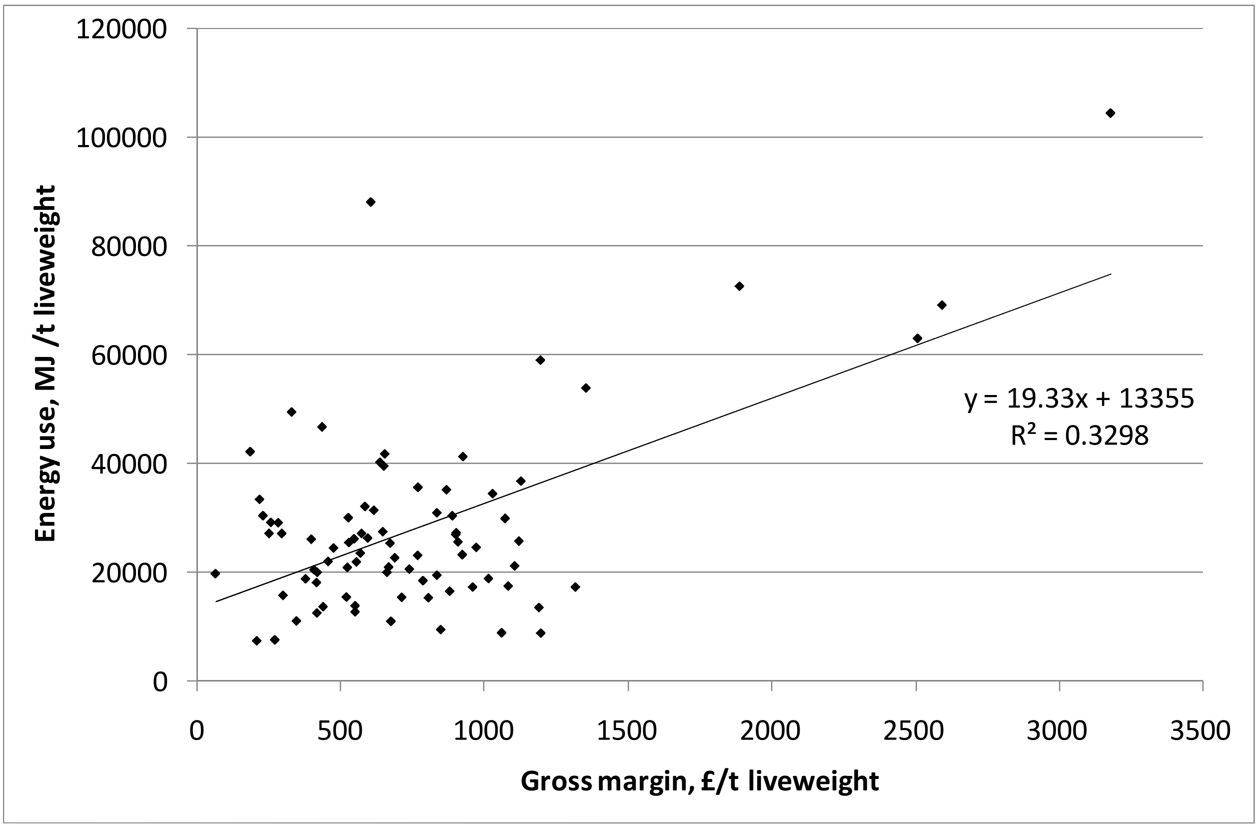


Figure 24 GHG emissions & gross margin per unit commodity for other cattle

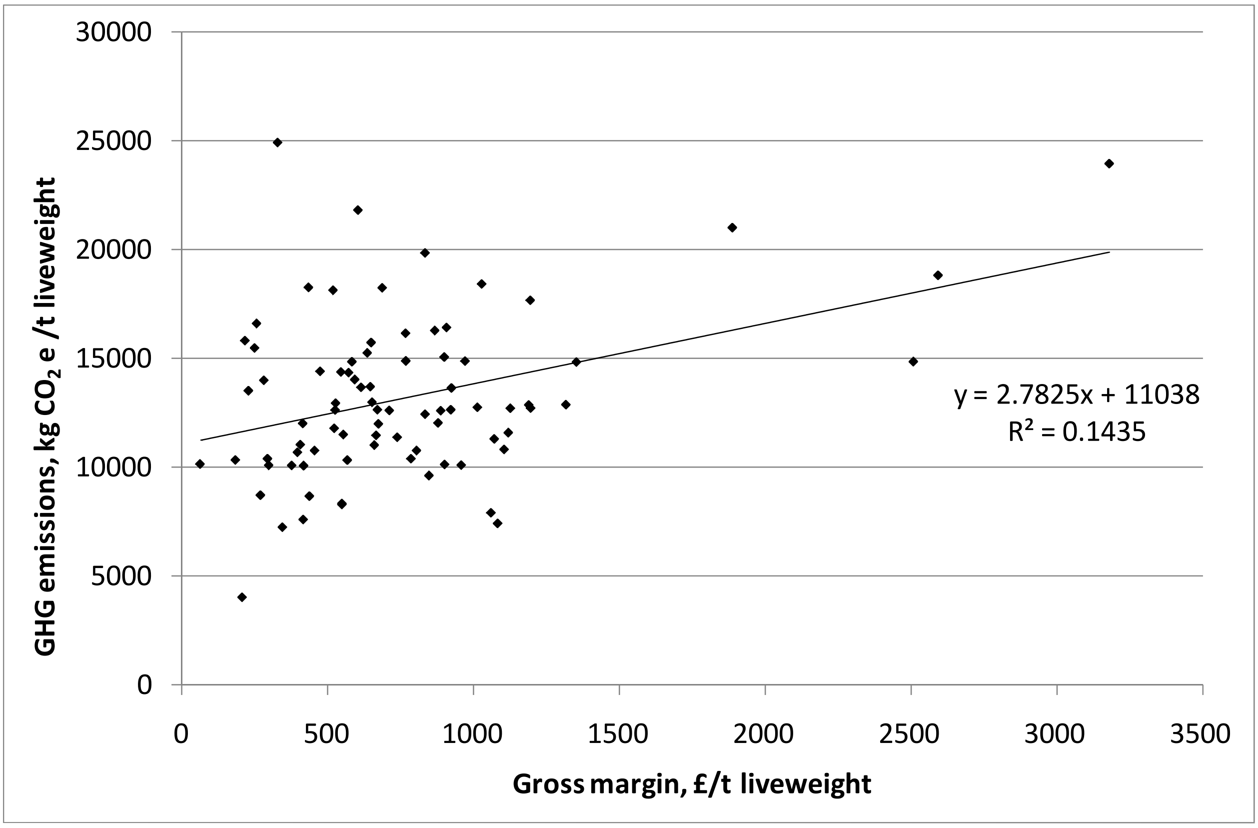


Figure 25 Energy use & gross margin per unit commodity for sheep (liveweight gain)

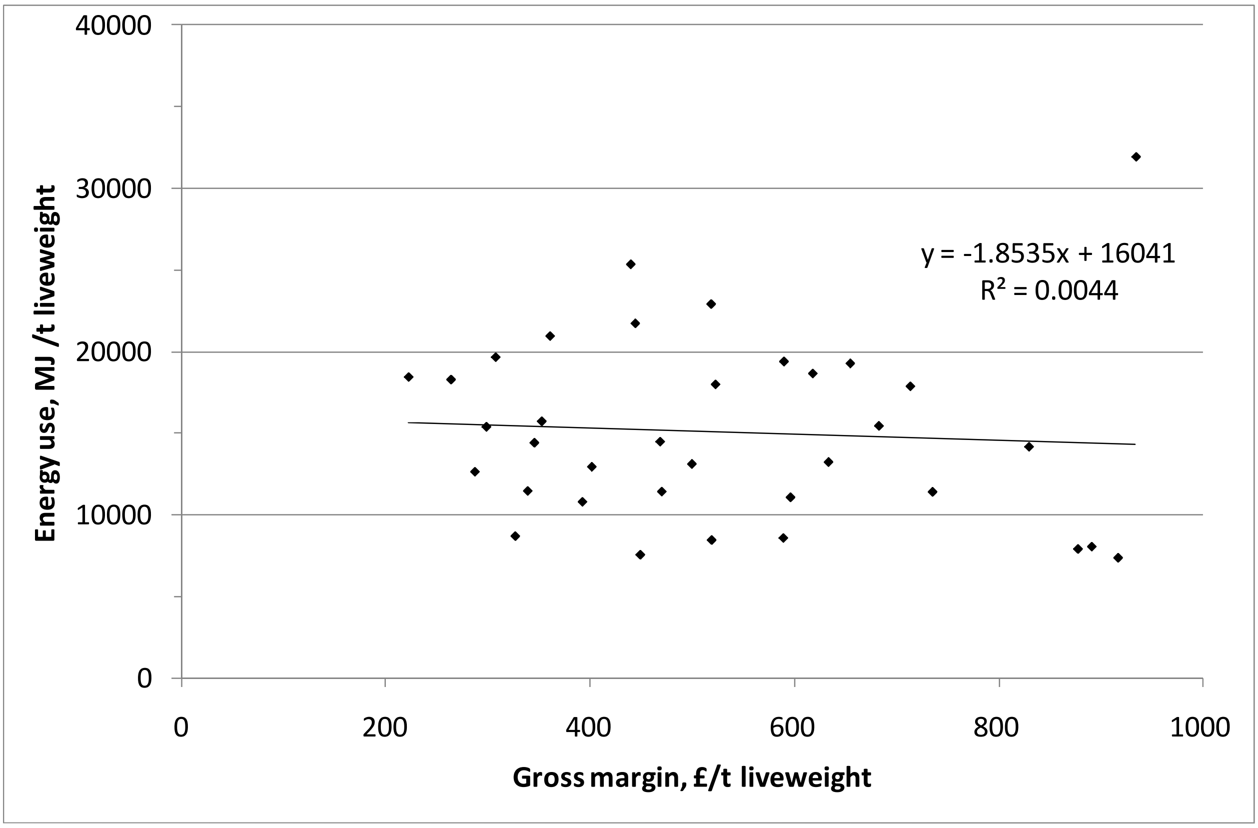


Figure 26 GHG emissions & gross margin per unit commodity for sheep (liveweight gain)

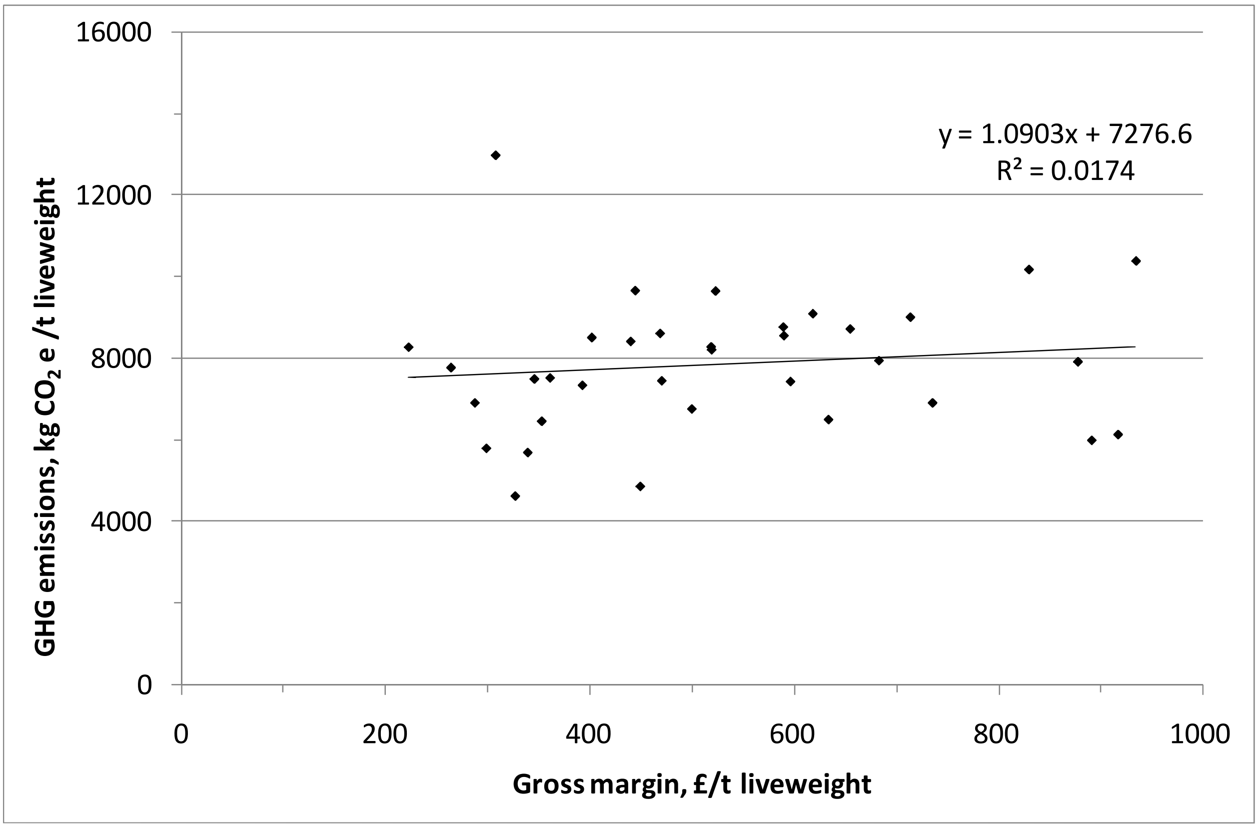


Figure 27 Energy use & gross margin per unit commodity for sheep (wool)

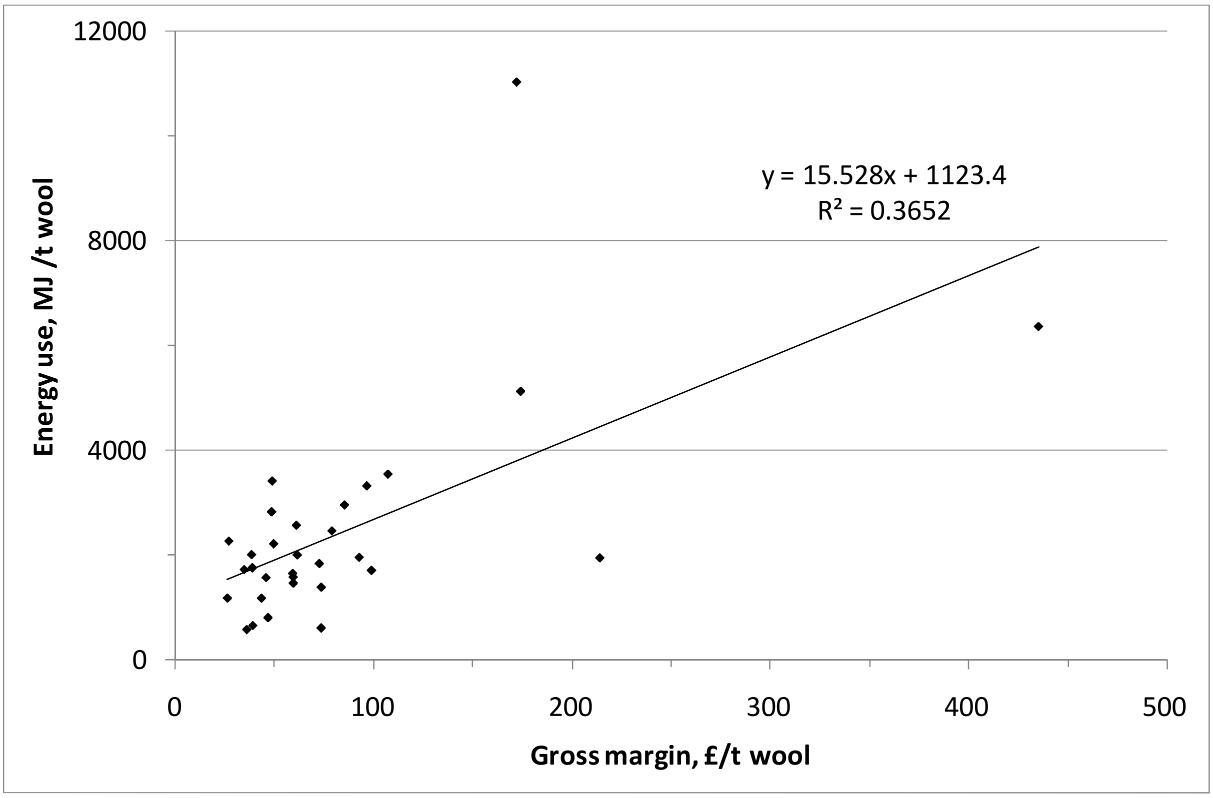


Figure 28 GHG emissions & gross margin per unit commodity for sheep (wool)

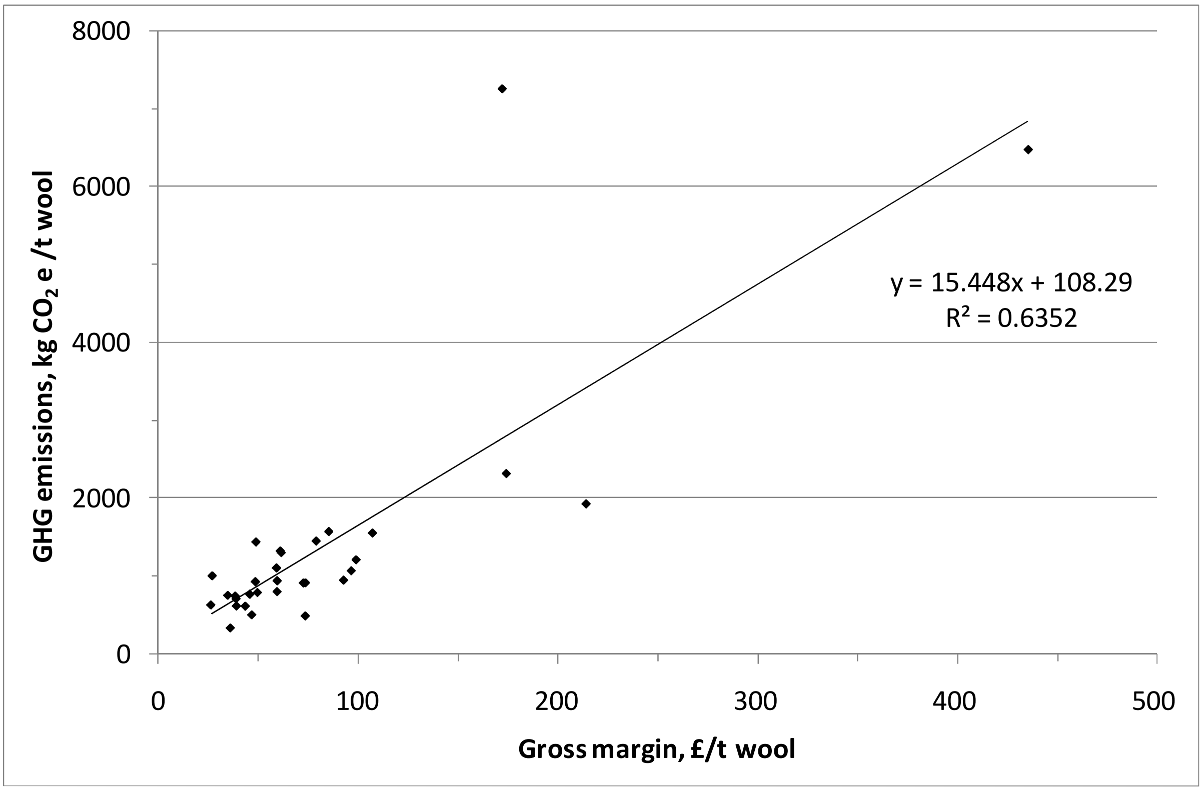


Figure 29 Energy use & gross margin per unit commodity for pigs

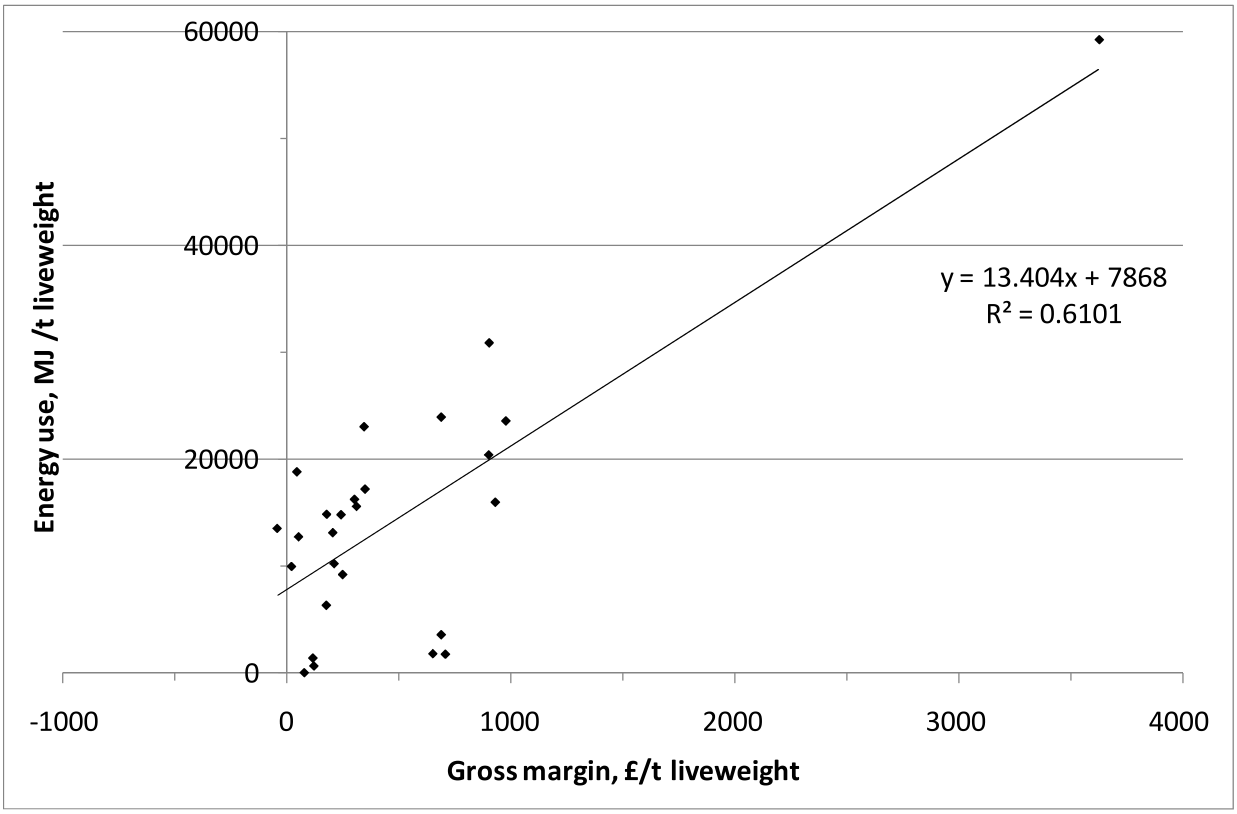


Figure 30 GHG emissions & gross margin per unit commodity for pigs

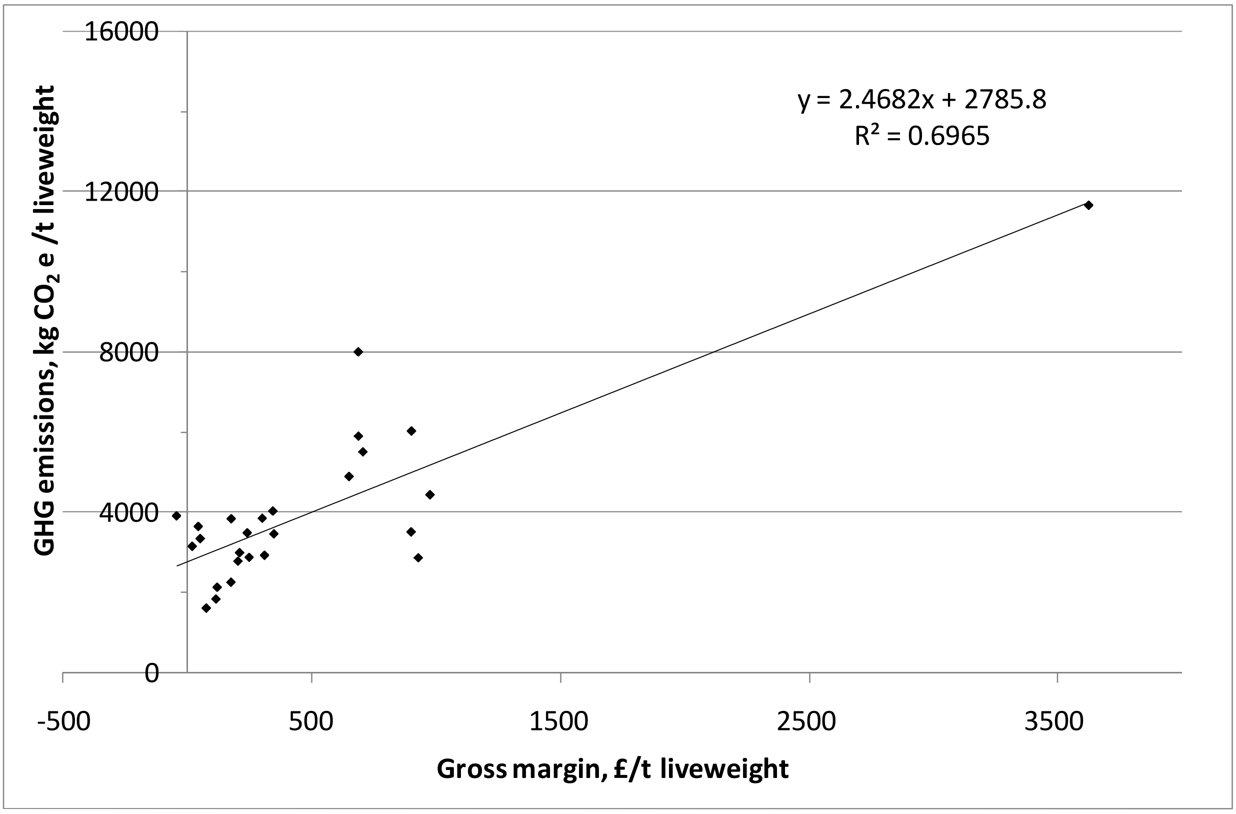


Figure 31 Energy use & gross margin per unit commodity for eggs

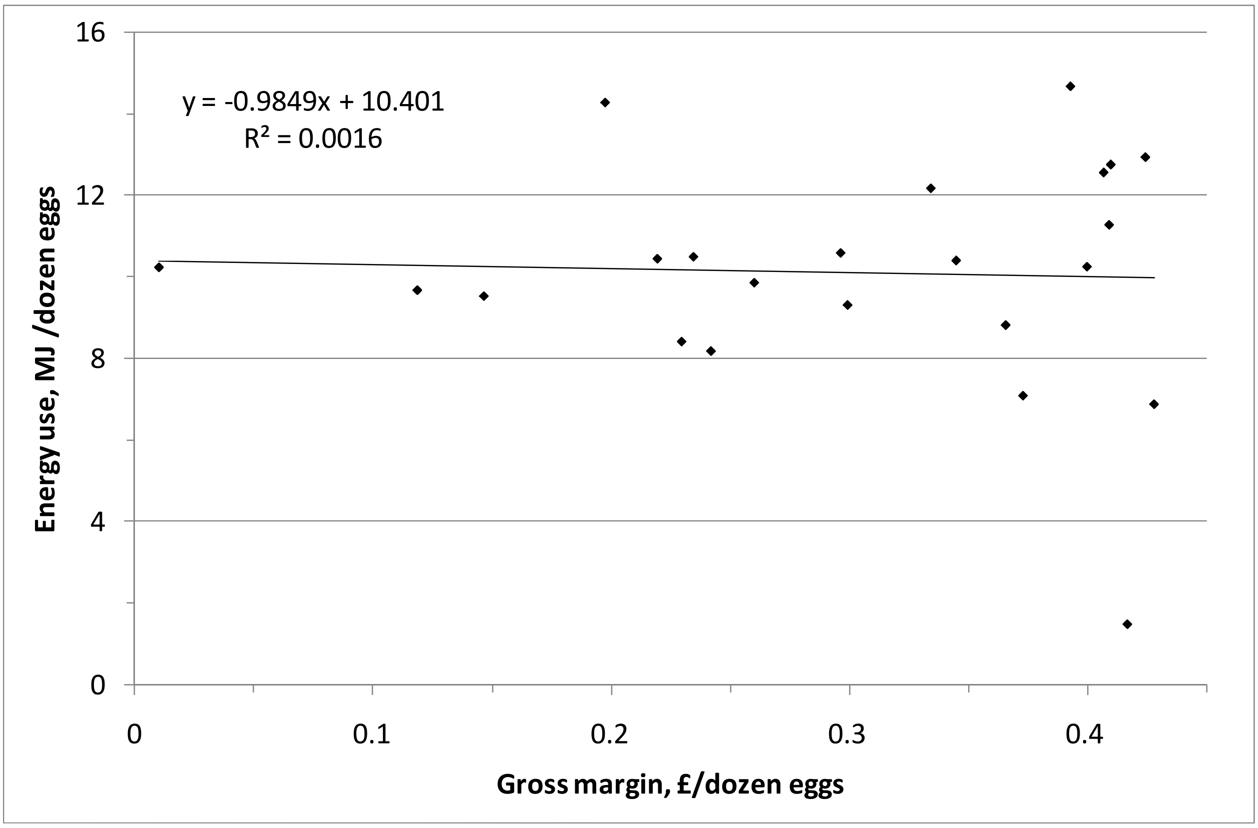


Figure 32GHG emissions & gross margin per unit commodity for eggs

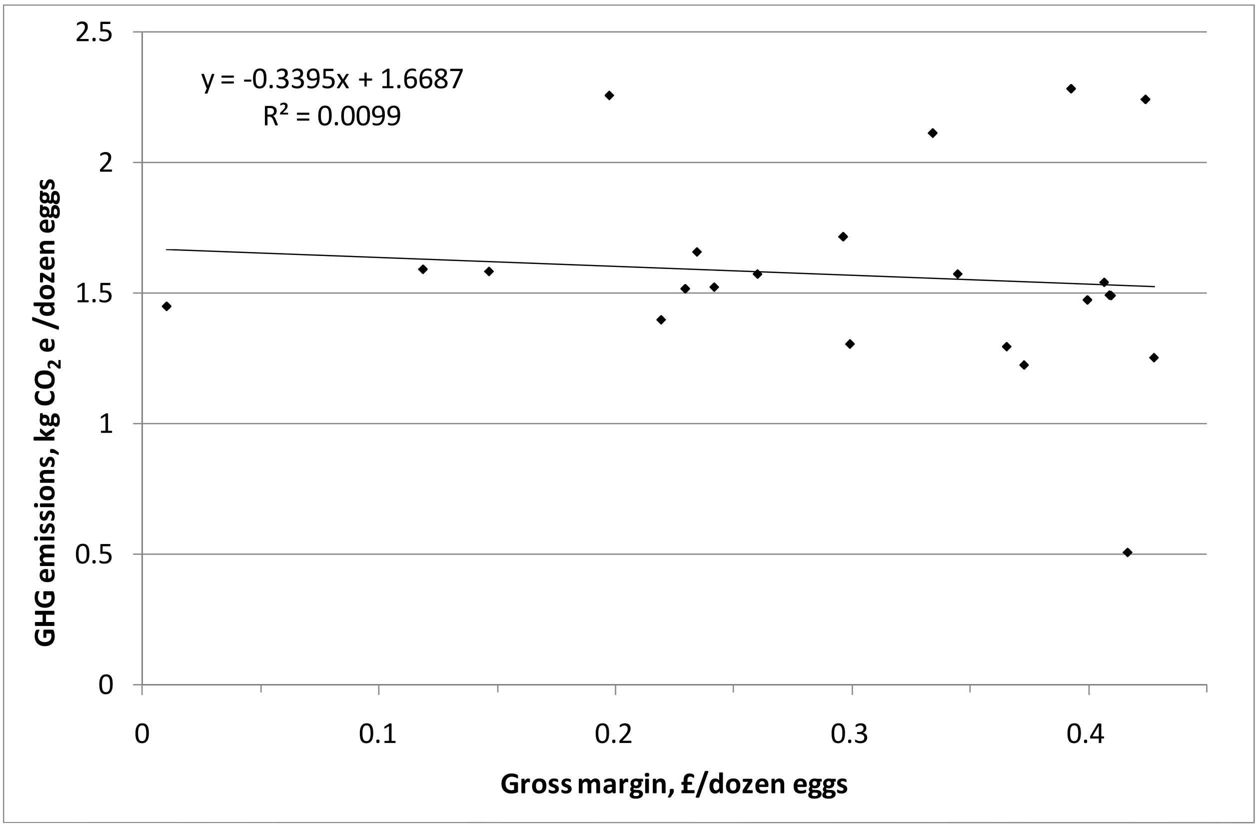


Figure 33 Energy use & gross margin per unit commodity for poultry

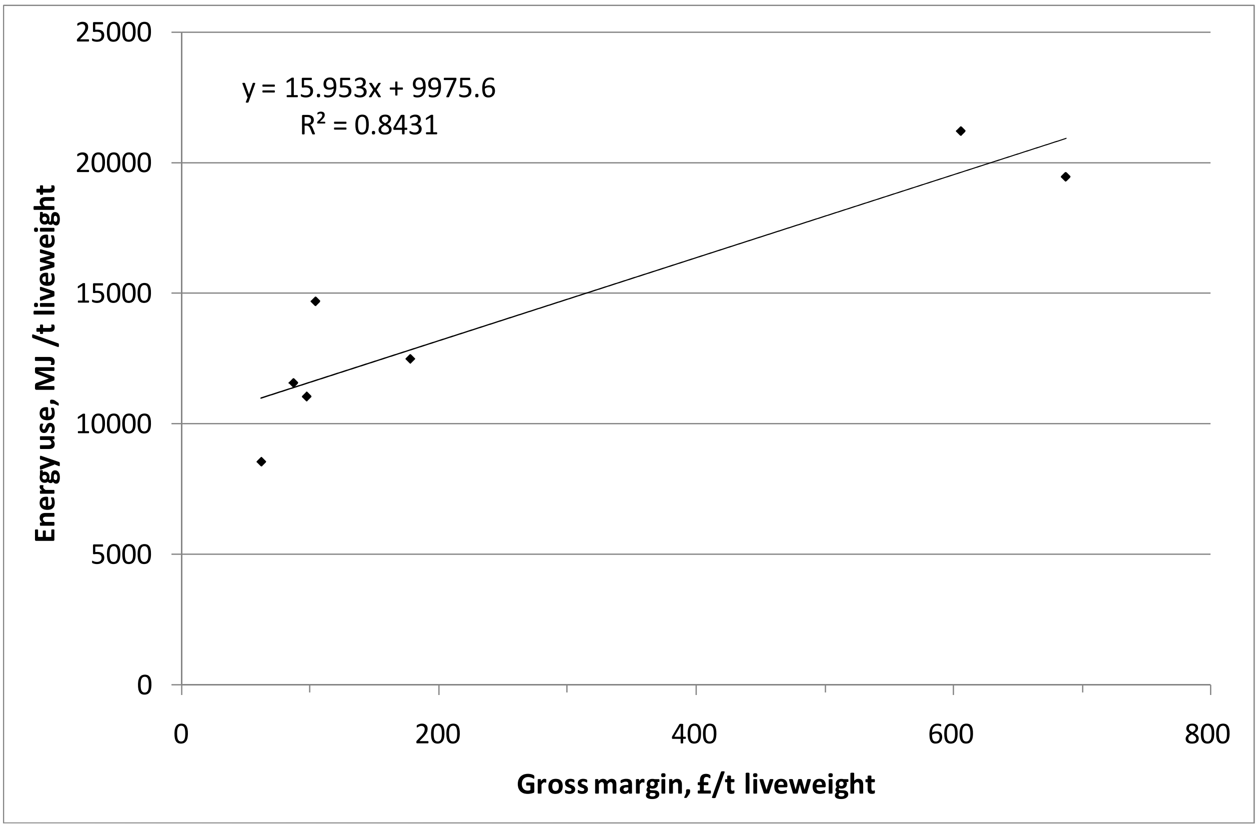


Figure 34 GHG emissions & gross margin per unit commodity for poultry

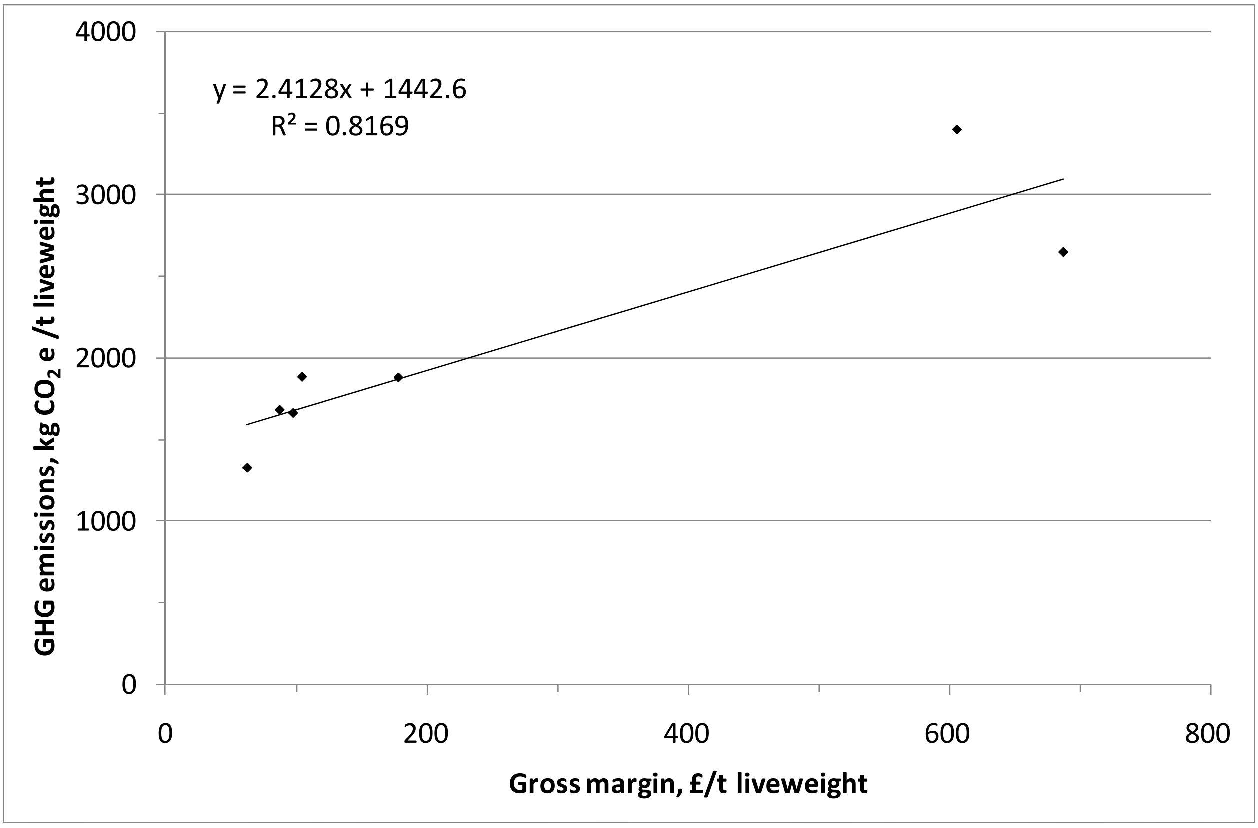


Figure 35 Energy use & gross margin per unit commodity for winter wheat

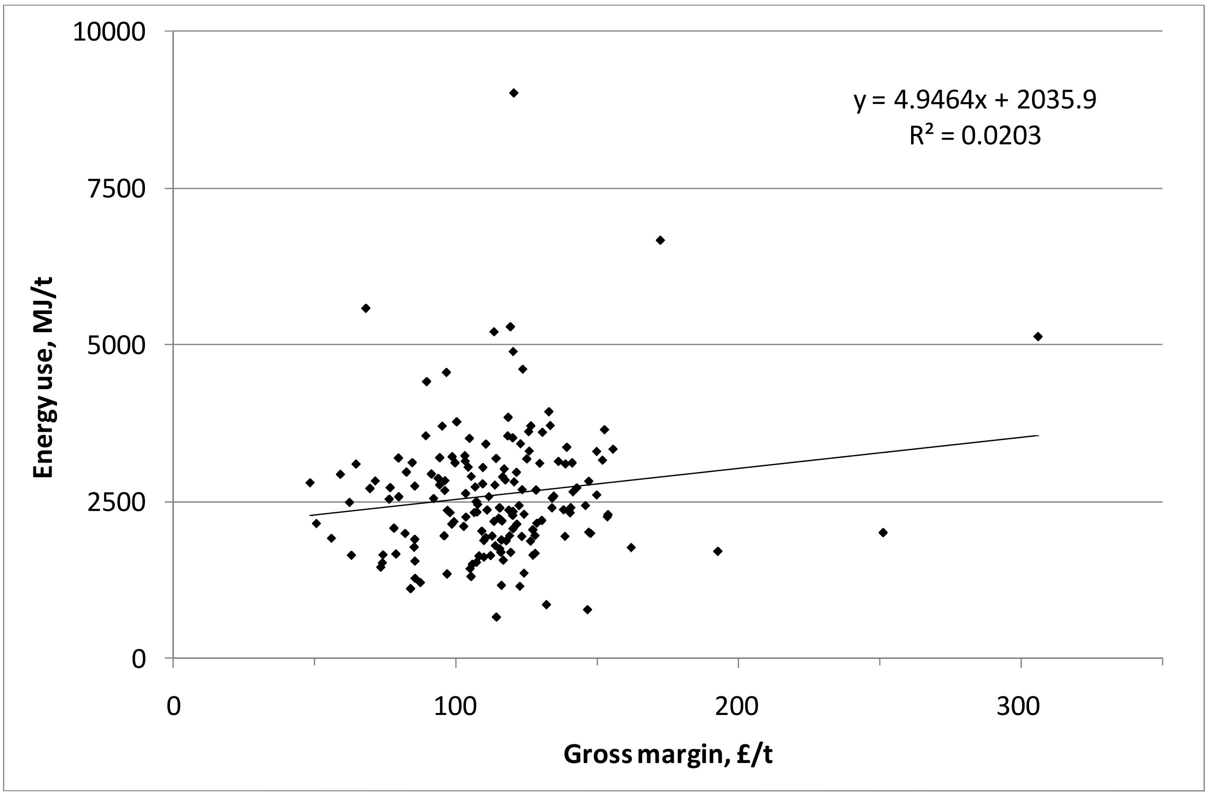


Figure 36 GHG emissions & gross margin per unit commodity for winter wheat

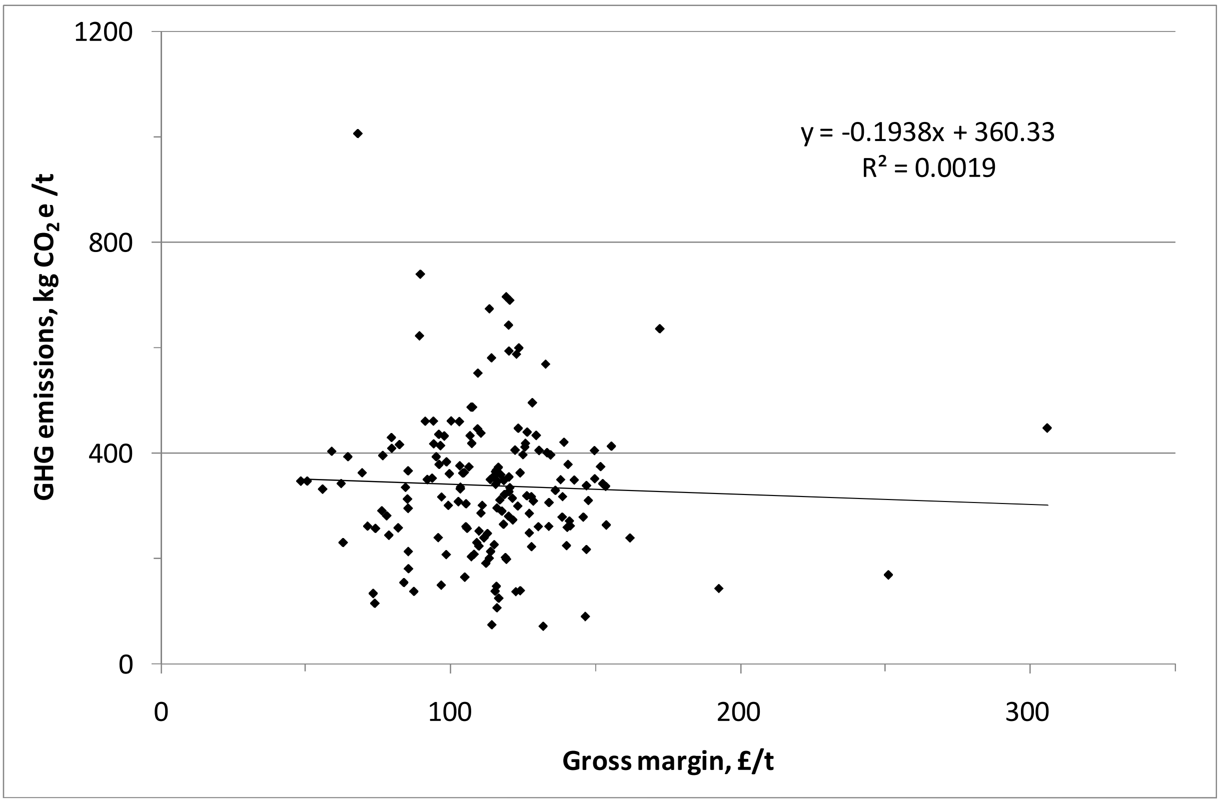


Figure 37 Energy use & gross margin per unit commodity for winter barley

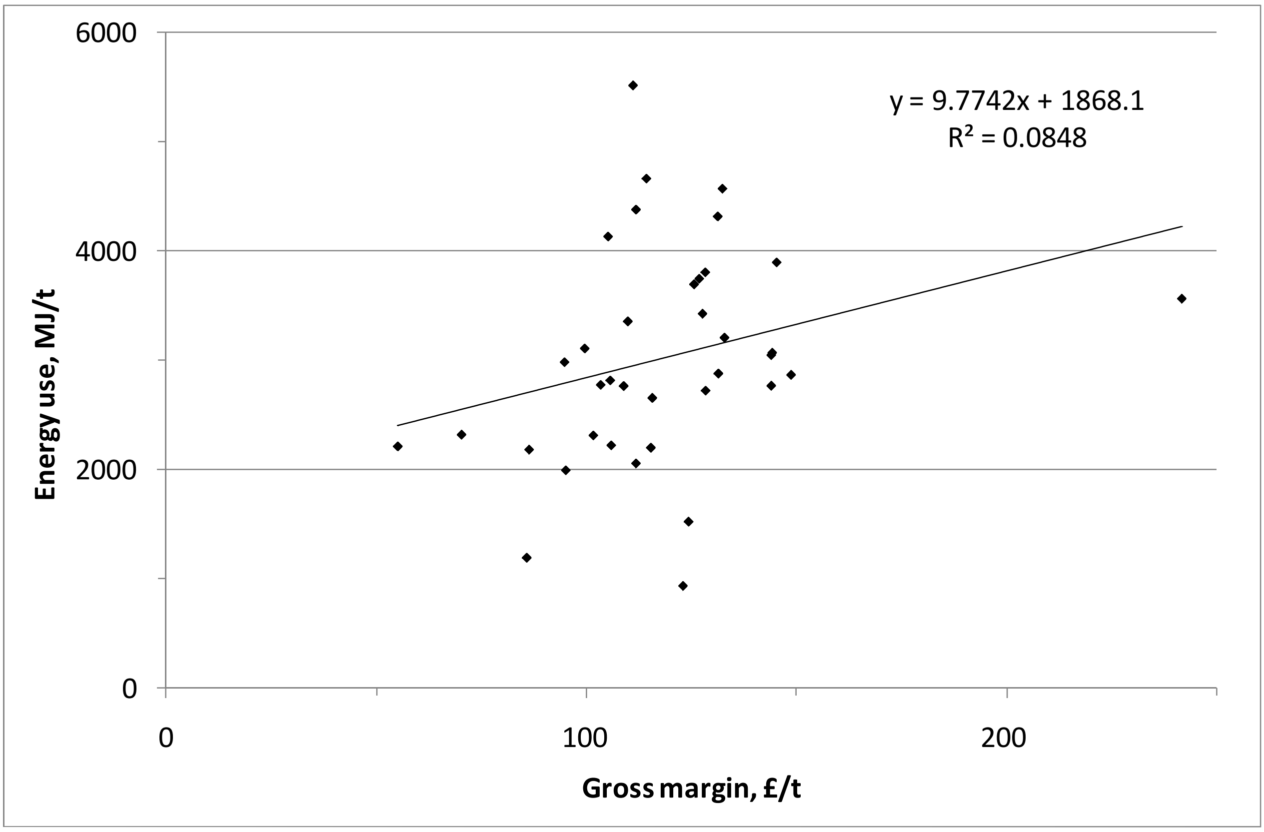


Figure 38 GHG emissions & gross margin per unit commodity for winter barley

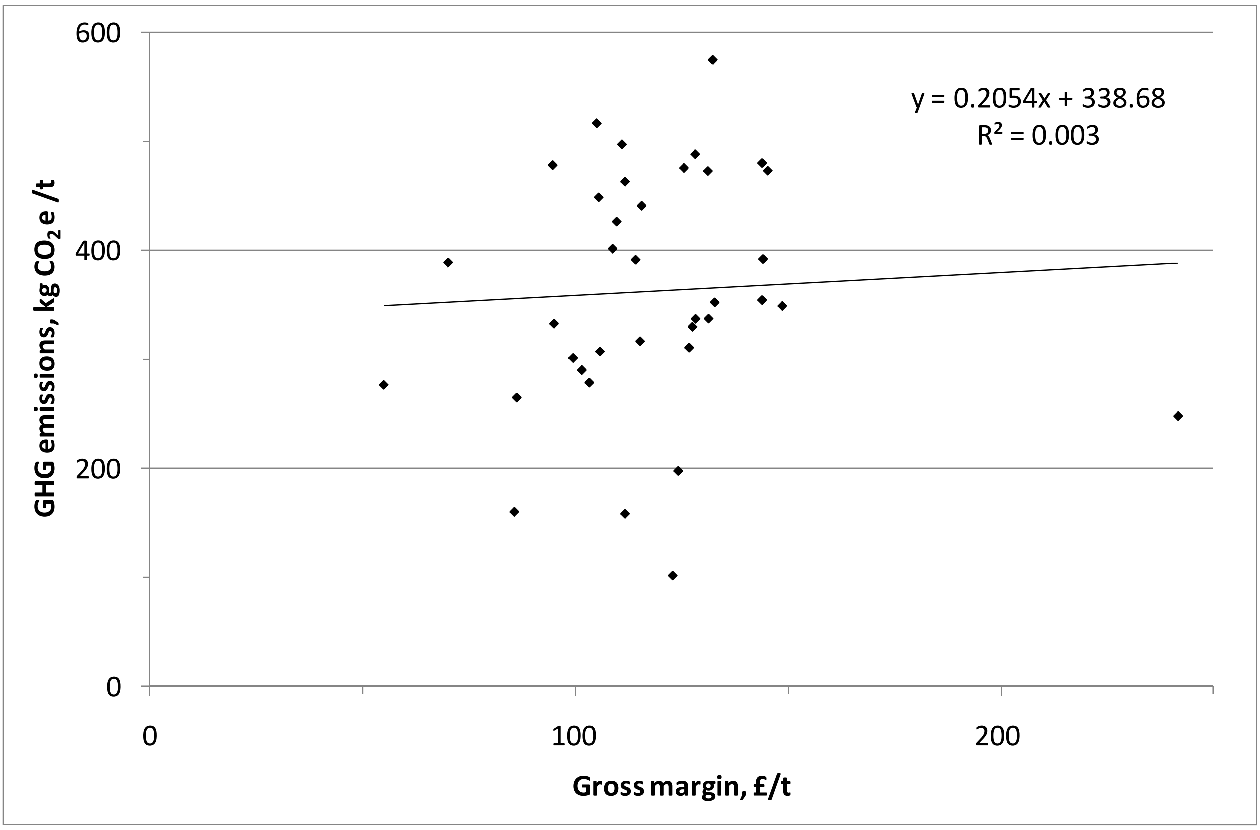


Figure 39 Energy use & gross margin per unit commodity for ware potatoes

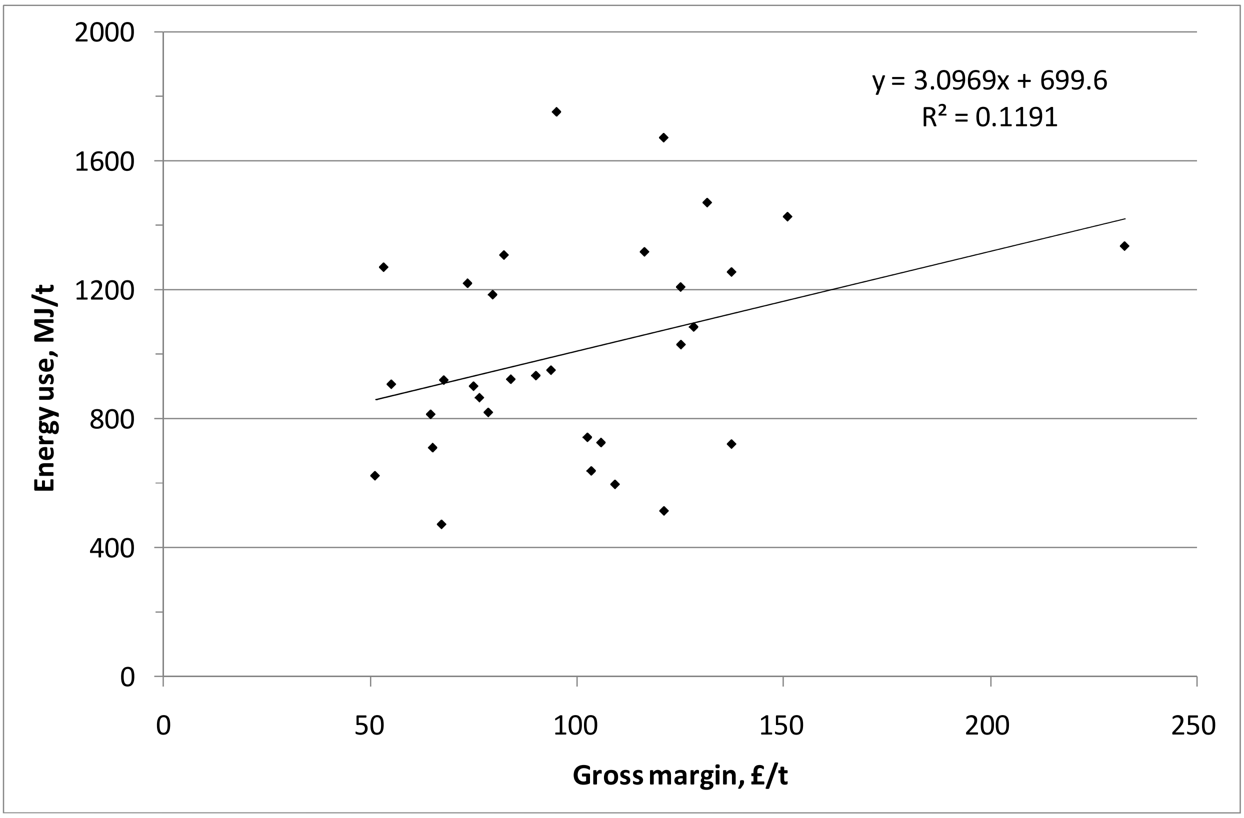


Figure 40 GHG emissions & gross margin per unit commodity for ware potatoes

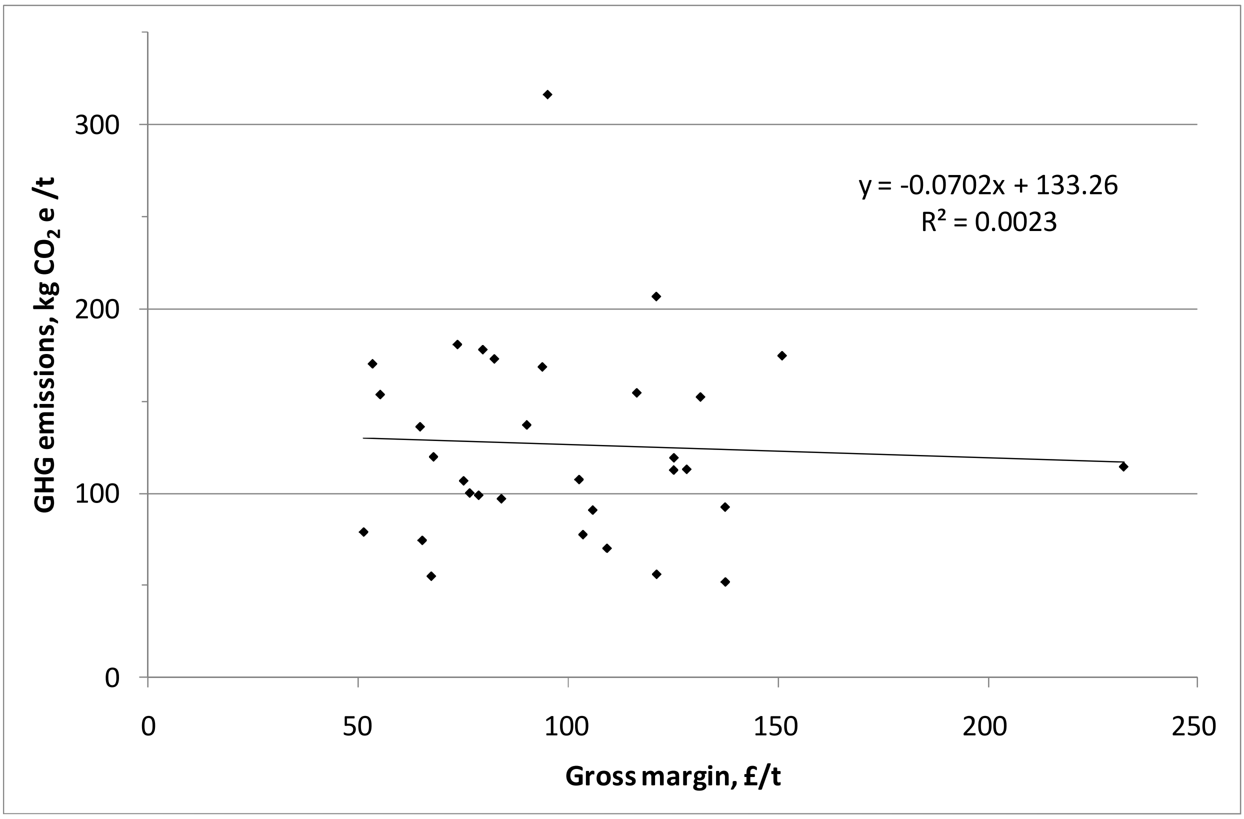


Figure 41 Energy use & gross margin per unit commodity for sugar beet

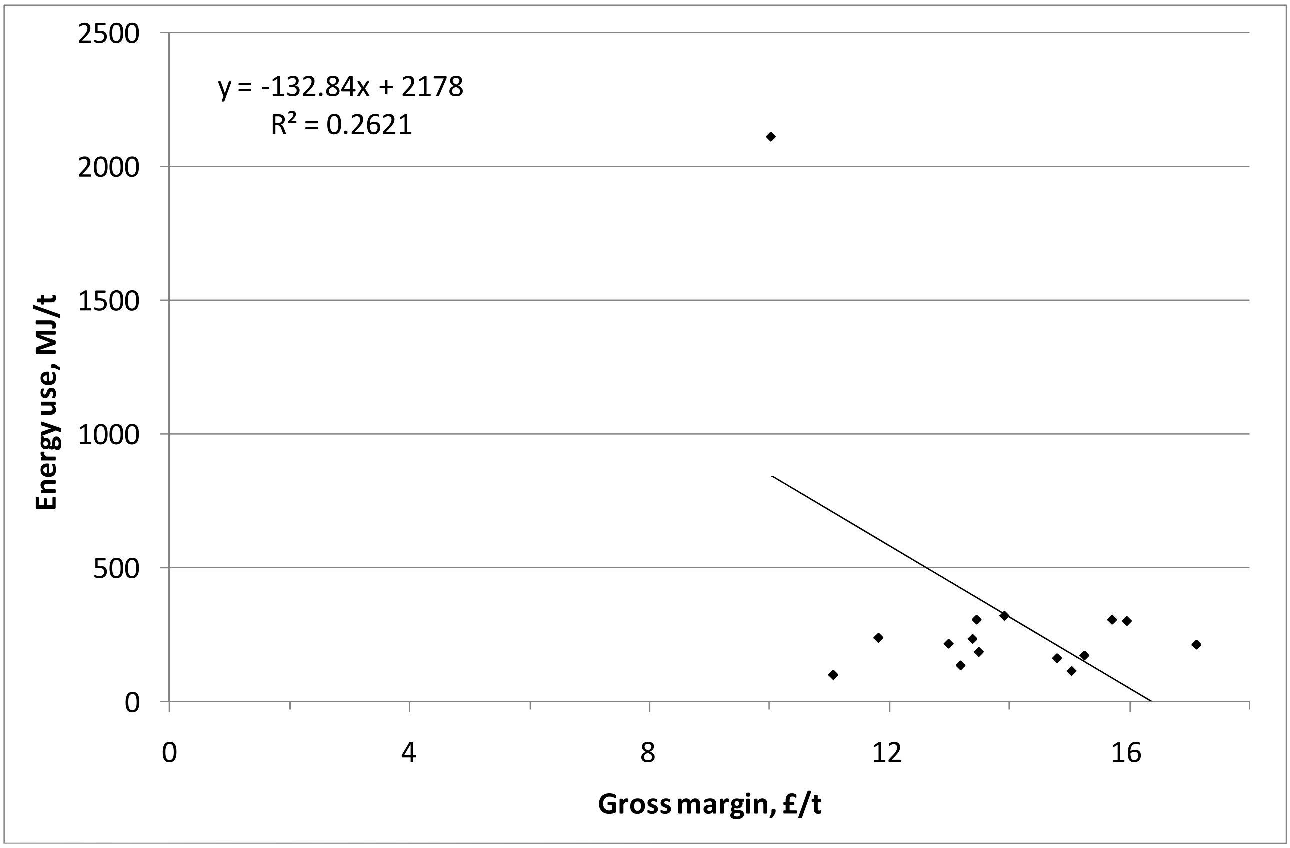


Figure 42 GHG emissions & gross margin per unit commodity for sugar beet

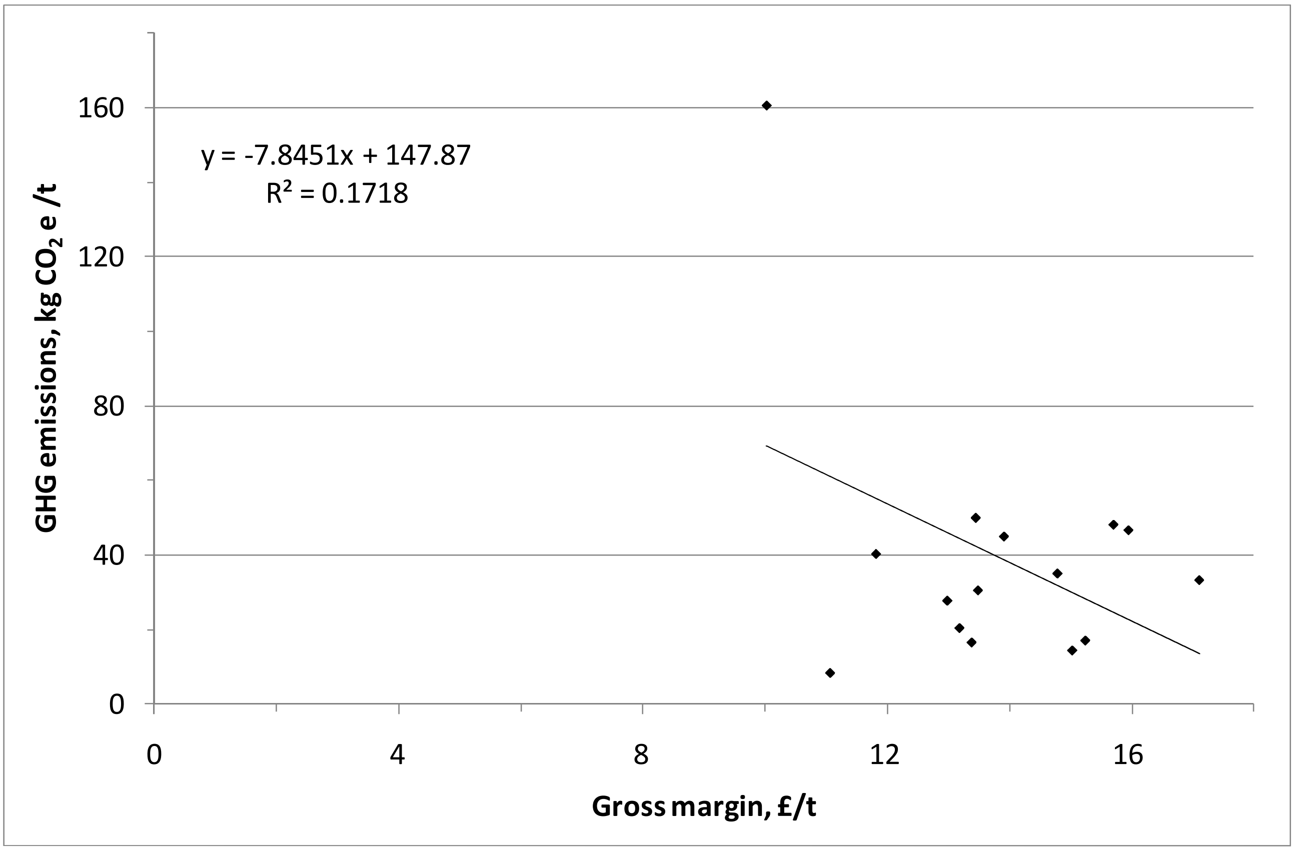


Figure 43 Energy use & gross margin per unit commodity for winter oilseed rape

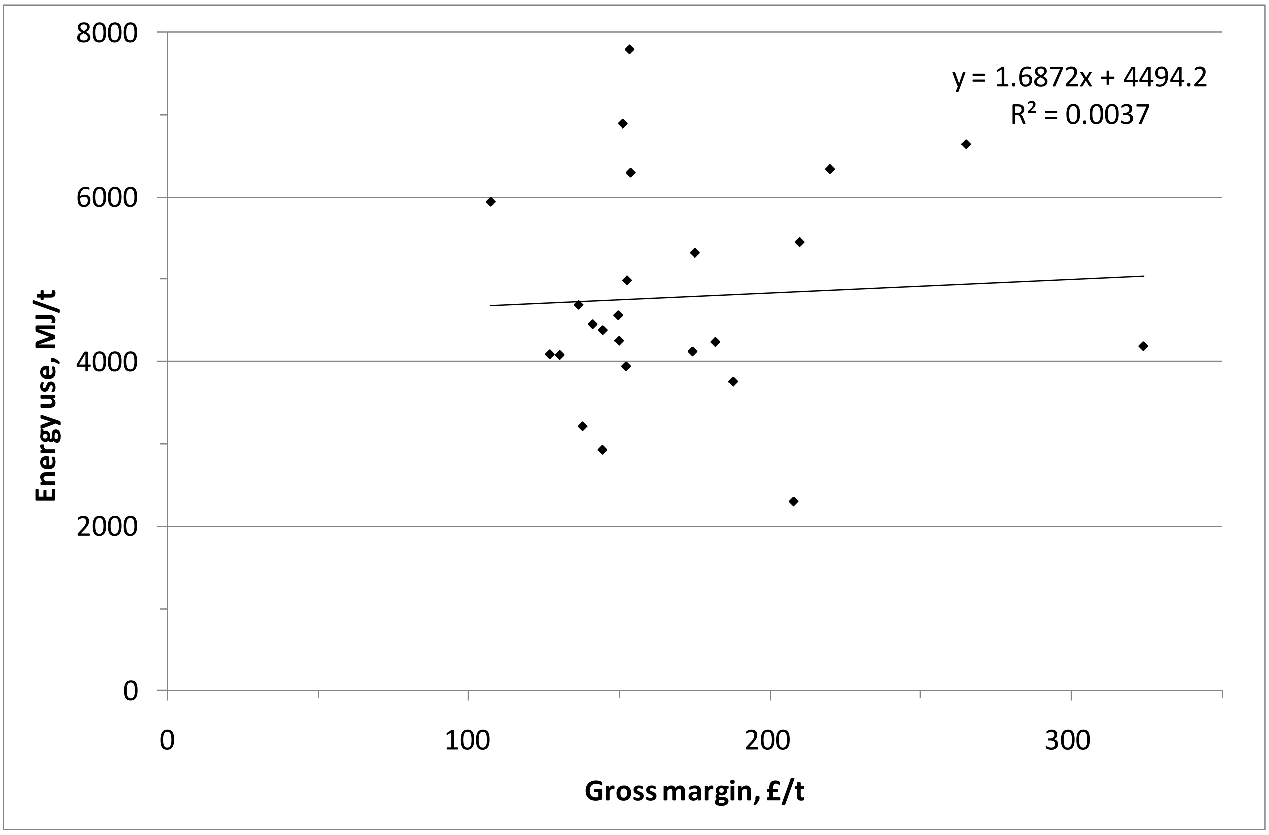
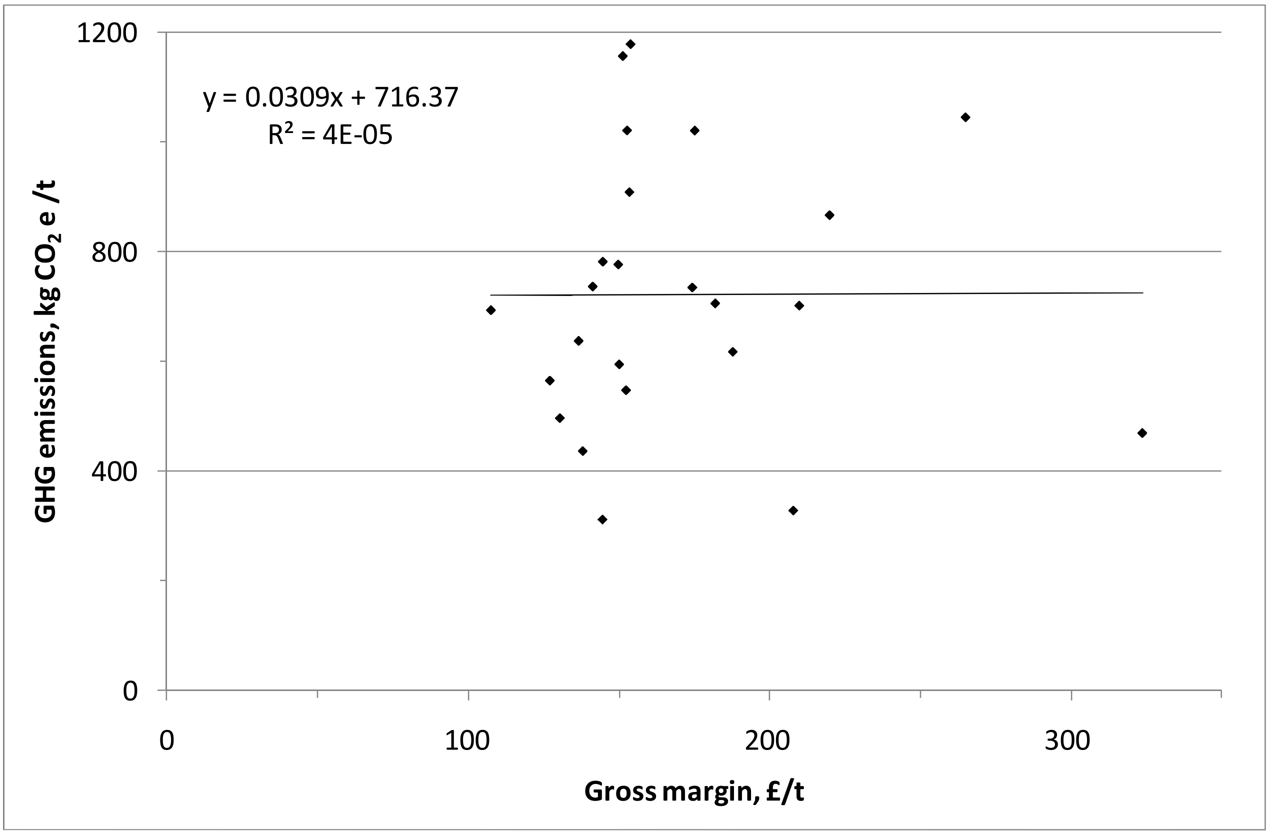


Figure 44 GHG emissions & gross margin per unit commodity for winter oilseed rape



More analysis on milk

The possible effects were investigated further, concentrating mainly on milk production. The influence of farm size was negligible (Figure 45 and Figure 46). There were relatively few small farms and the performance of these was concentrated in the centre of the spread of data. The medium scale farms covered most of the spread of large farms, which were numerically dominant, but the scatter was great so that no clear trend was detectable. A minority of dairy farms were registered organic and managed. The gross margins of these farms were in the upper half of the range. The energy use for organic was in the lower part of the range of all farms (which is consistent with results from LCA), while the GHG emissions were well within the range of all farms (Figure 48 and Figure 47). The one difference between the organic and non-organic farms is that there are significant correlations between both energy use and GHG emissions with gross margin and that the slopes were both negative. So, the implication for organically produced milk is that better economic performance can go along with better environmental performance.

Figure 45 Energy use & gross margin per unit commodity for dairy, effect of farm size

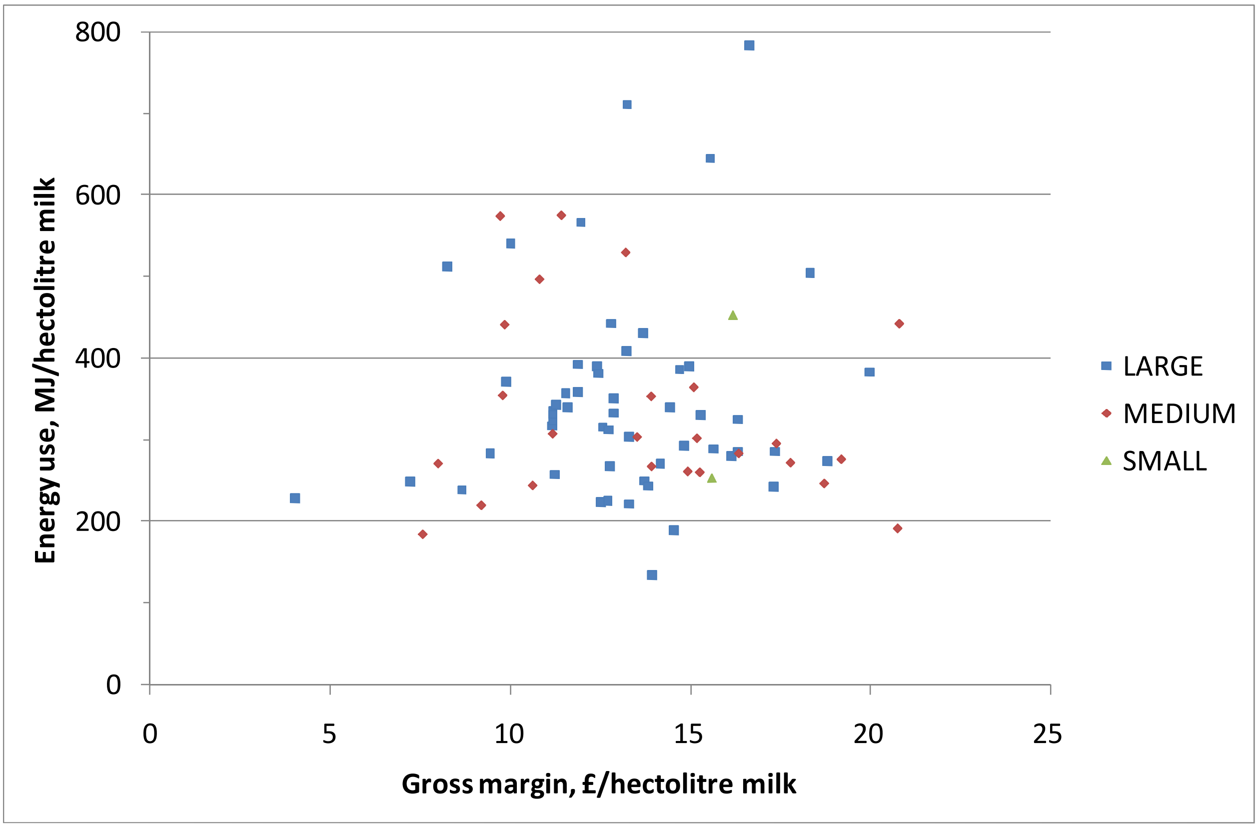


Figure 46 GHG emissions & gross margin per unit commodity for dairy, effect of farm size

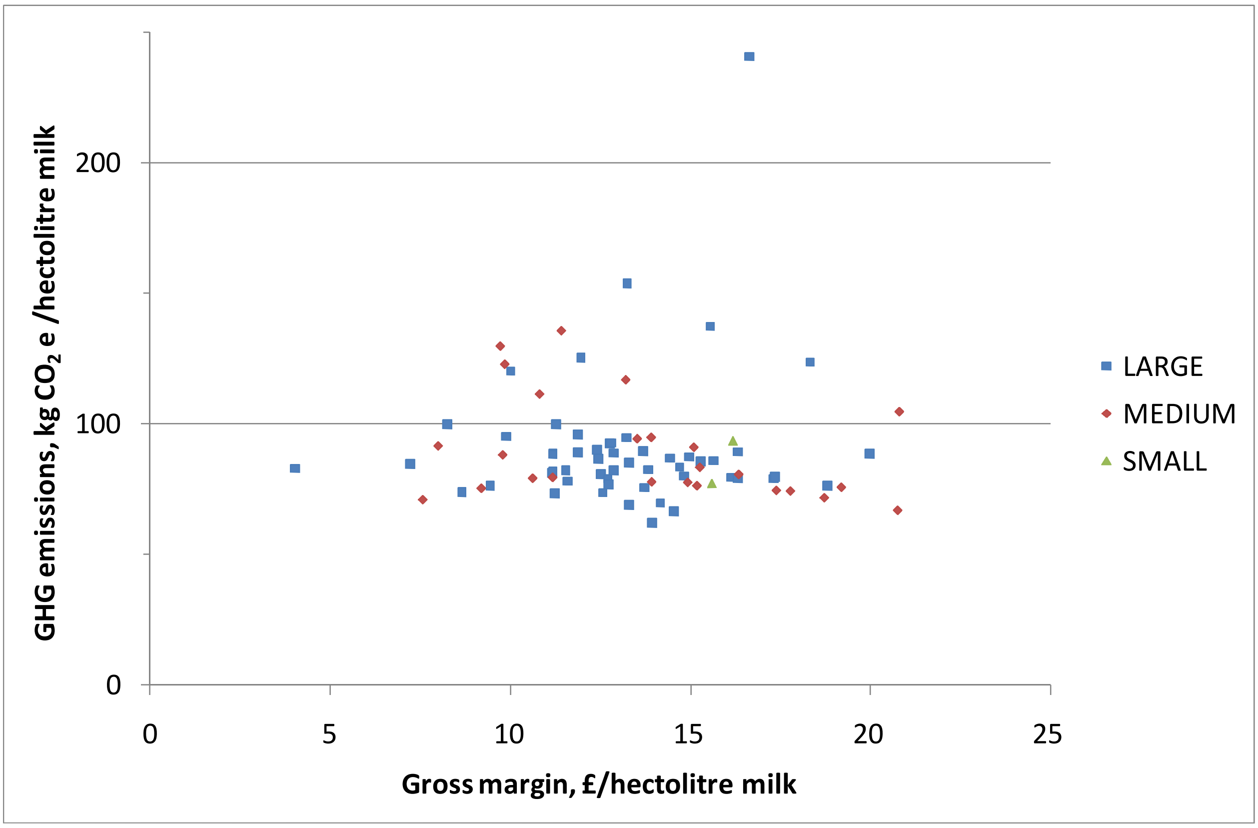


Figure 47 Energy use & gross margin per unit commodity for dairy, organic and non-organic

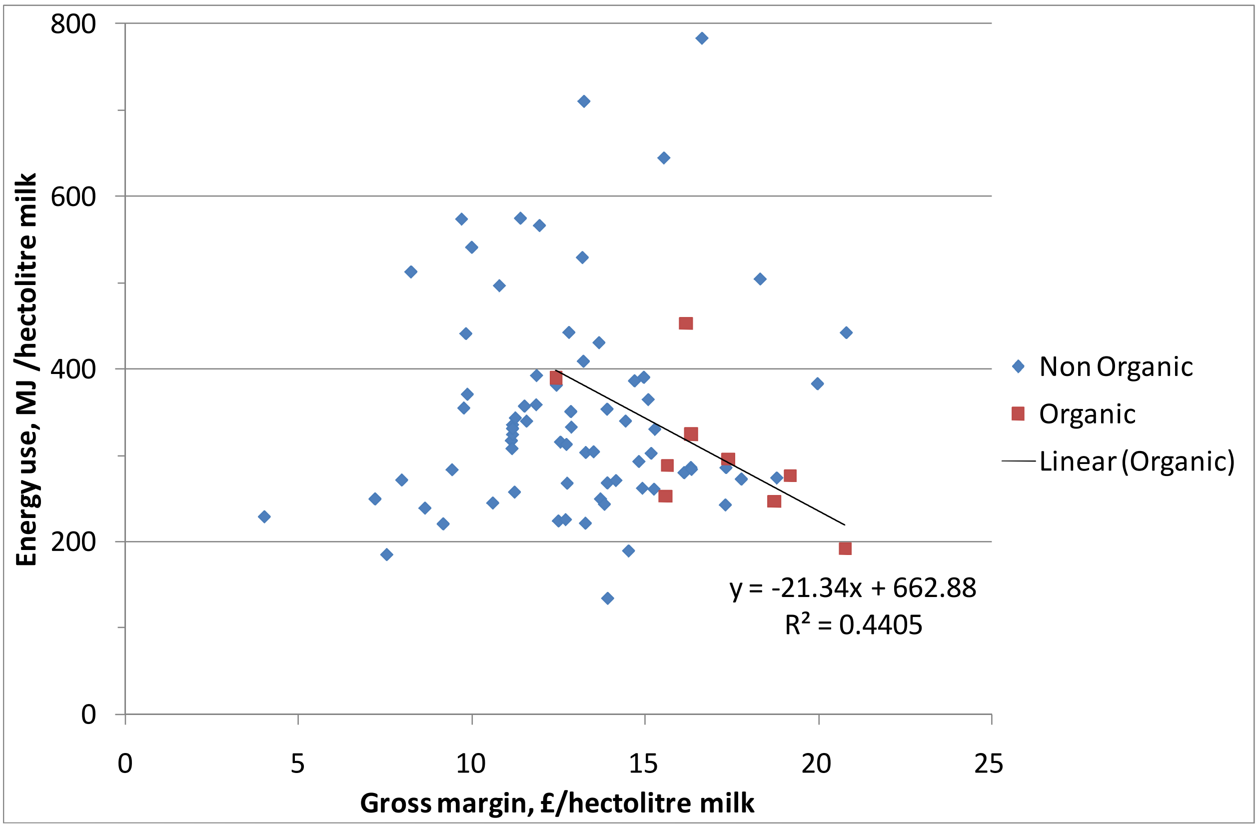
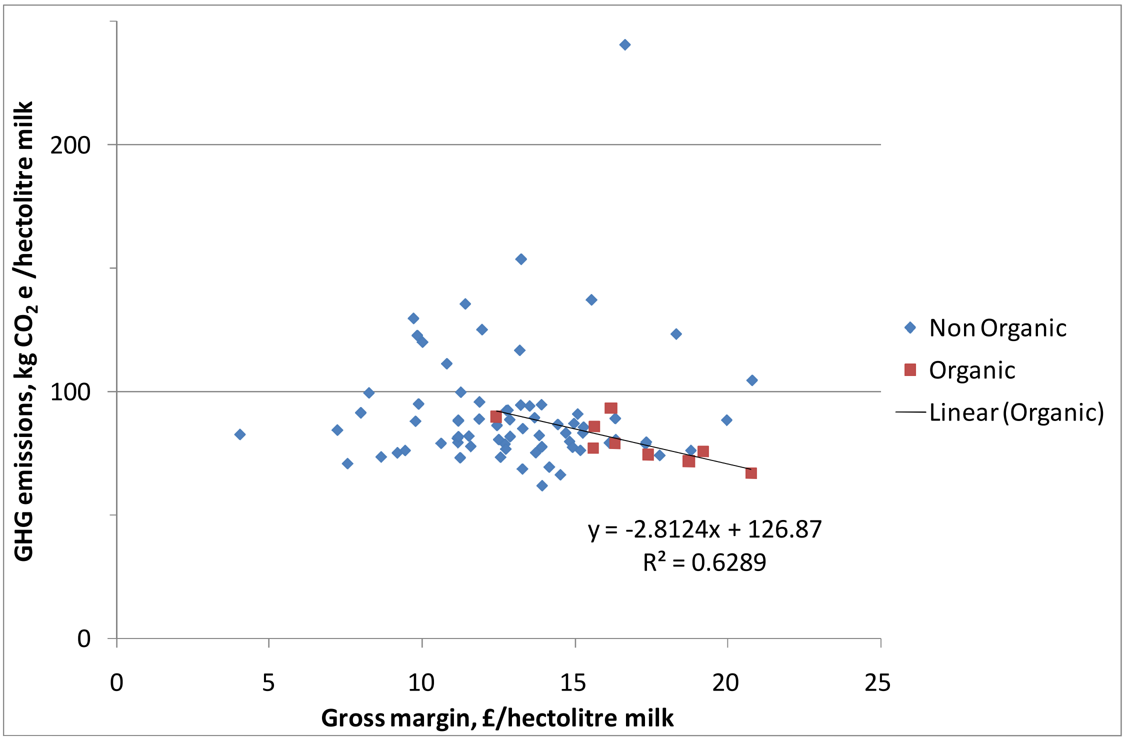
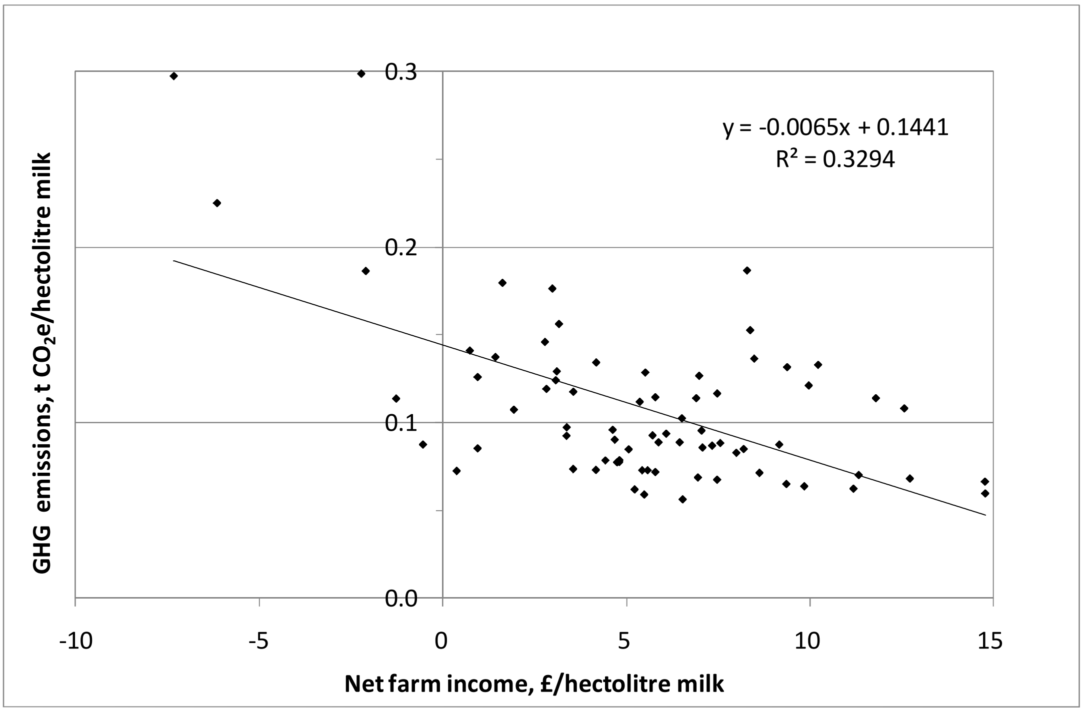


Figure 48 GHG emissions & gross margin per unit commodity for dairy, organic and non-organic



Another approach was taken with milk, which was to correlate GHG emissions and net income per unit milk. This was more promising than the relationship with gross margin and the correlation was significant when applied to all farms (Figure 49). This had a negative slope, which was statistically significant, even though the regression coefficient (r^2) was relatively low at 0.33. This is an encouraging example of where increasing economic performance is linked directly with increasing environmental performance. One caveat is that the slope is influenced by some outliers.

Figure 49 GHG emissions versus net income per unit milk production on dairy farms



Organic and non-organic wheat

Organically produced wheat was compared with non-organic wheat. There were only four farms in the sample, but it is clear from the gross margin that organic wheat is profitable, with three farms having higher gross margins than the main body of data (Figure 50 and Figure 51). The energy use and GHG emissions were well within the spread of data. Unlike organic milk, there was not an obvious negative slope, but there are too few points to be conclusive about the apparent positive slope of gross margin with energy use and GHG emissions.

Figure 50 Energy use & gross margin per unit commodity for winter wheat, organic & non-organic

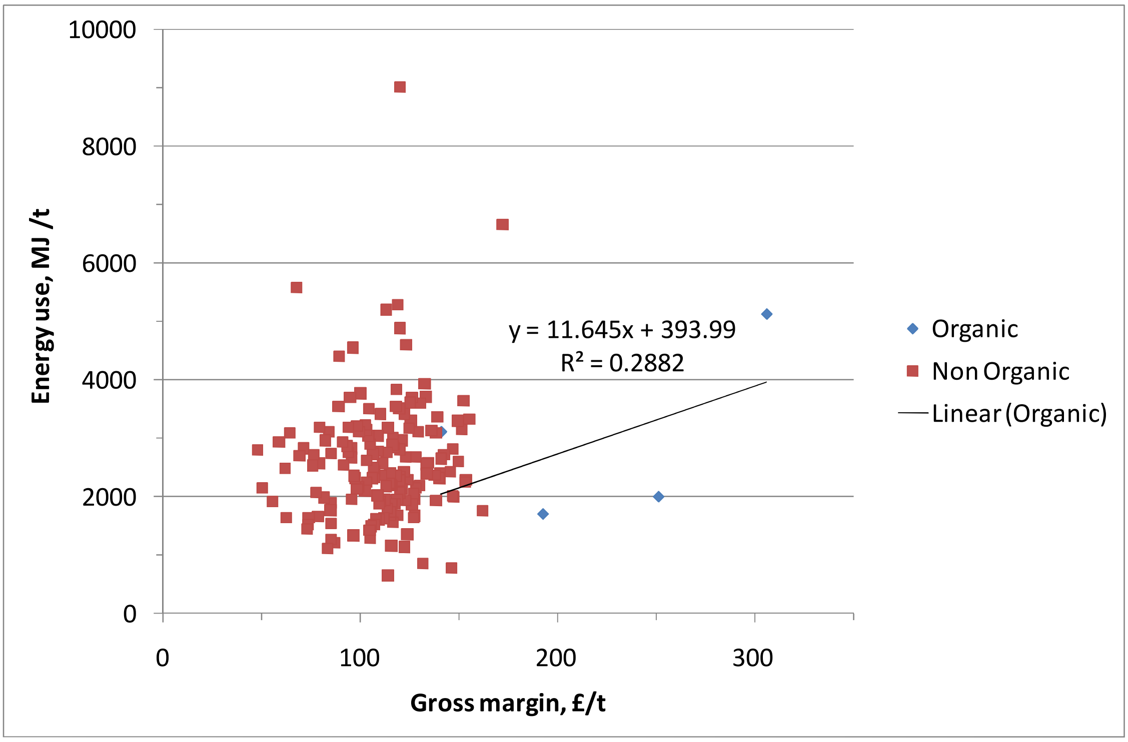
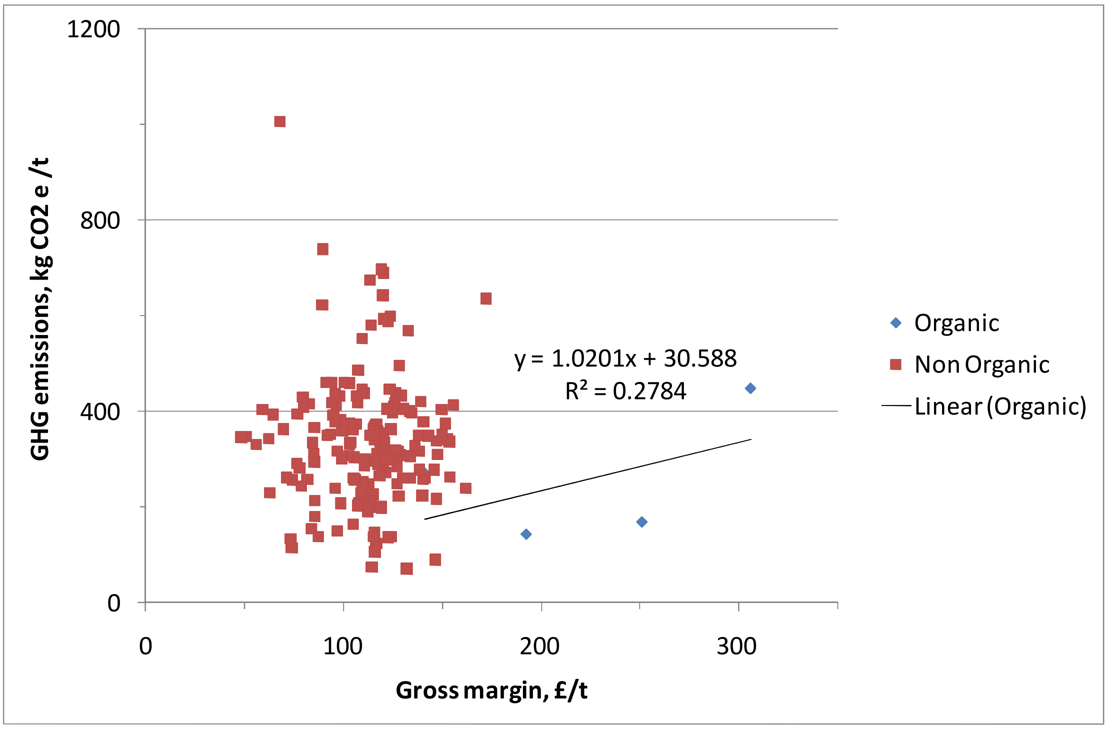


Figure 51 GHG emissions & gross margin per unit commodity for winter wheat, organic & non-organic



Fully housed (indoor) and free range (outdoor) egg production was compared. The results were that the spread of both gross margin and energy use or GHG emissions were larger for outdoor than indoor production (Figure 52 and Figure 53). This probably results from the considerable optimisation in mainstream egg production reducing technical performance more than in free range systems.

Figure 52 Energy use & gross margin per unit commodity for eggs, fully housed (indoor) & free range (outdoor)

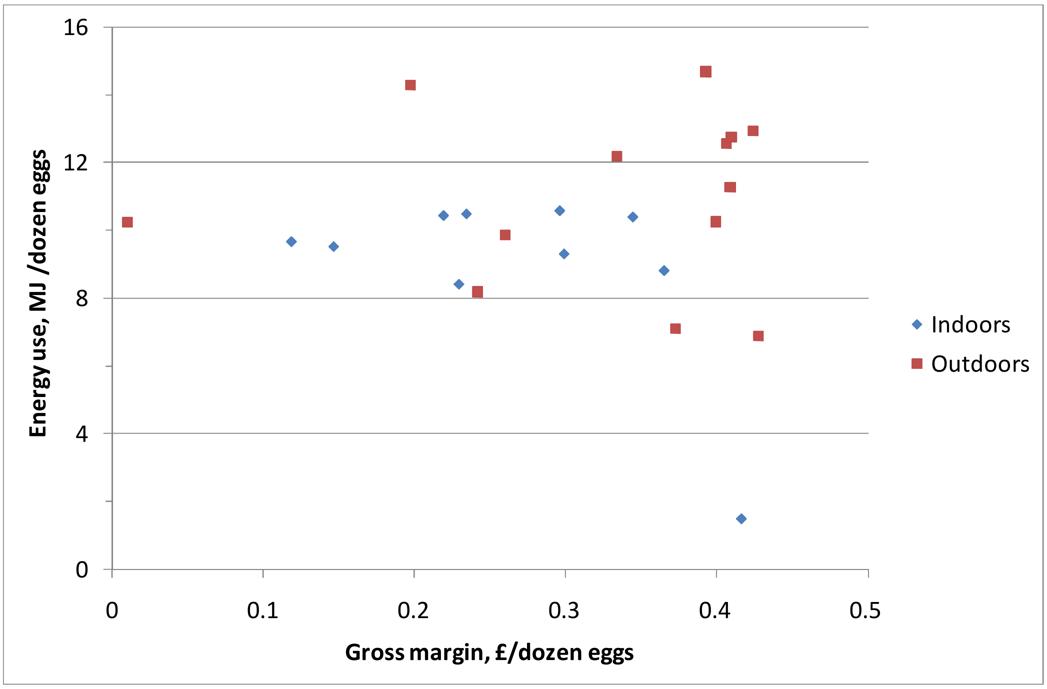
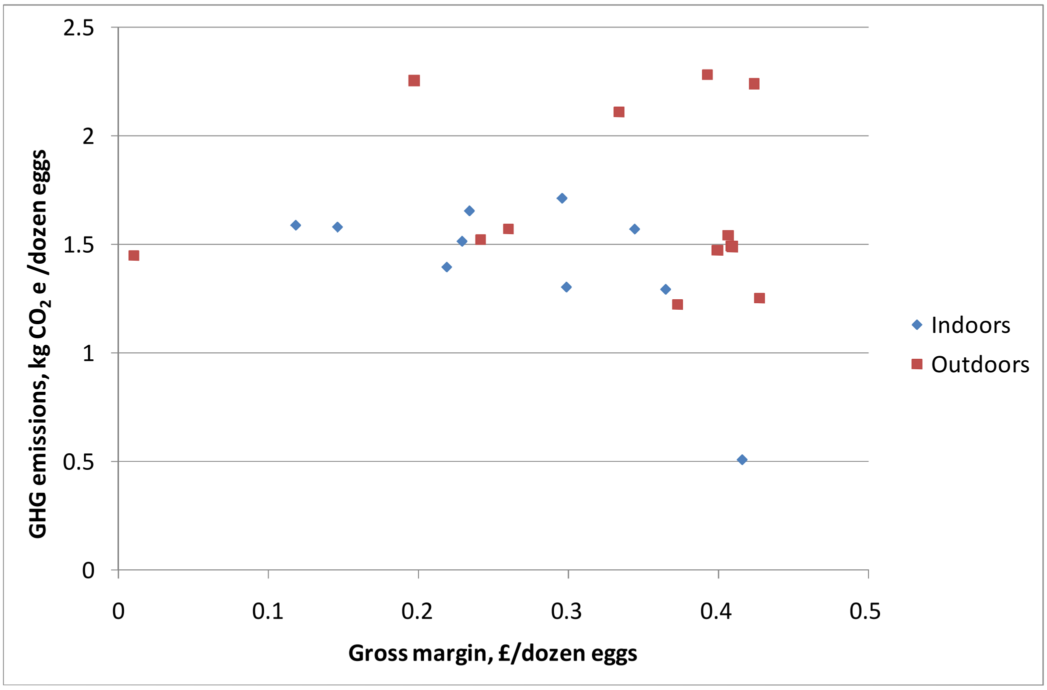


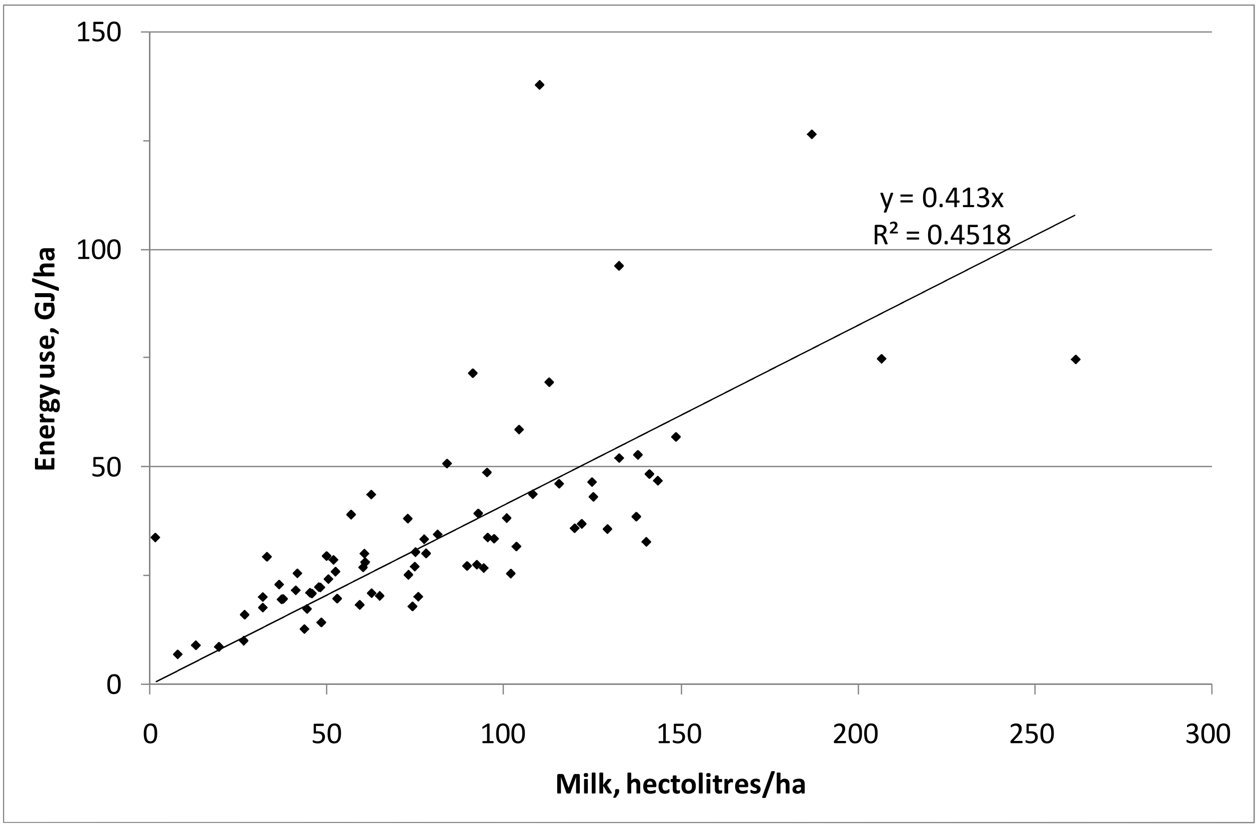
Figure 53 GHG emissions & gross margin per unit commodity for eggs fully housed (indoor) & free range (outdoor)



Milk yield and energy use per hectare

There was a better relationship between milk yield per ha and energy use per ha (Figure 54). This is entirely understandable as increasing inputs, such as N fertiliser increases grass yield and hence milk yield.

Figure 54 Dairy farms energy use versus milk production per ha



On-farm emissions and energy use for wheat and milk

A sub-set of relationships were explored to see if the GHG emissions and energy use that were incurred on farms were more closely related to economic performance. Winter wheat was examined first and the indirect energy use from embedded energy and GHG emissions in fertiliser and pesticide manufacturing were excluded. This meant that the energy use and GHG emissions were located largely on the farm (GHG from electricity generation occurs at the power station, but demand comes from the farm). The situation for milk production is more complex. The only unequivocal source embedded energy that could be excluded was fertiliser and pesticide manufacture. Other factors varied from farm to farm, so that false comparisons would be made with due care, e.g. some farms use energy to grow feed crops, while others buy feeds in. Hence, feed imports need to be included to ensure that the energy use per unit milk is uniformly calculated across farms.

The results have not appreciably changed the outcomes of the analyses that included all energy use and emissions. There were again no significant relationships between gross margin per unit of output and either energy use or GHG emissions per unit output (Figure 55 to Figure 58). The main difference between these and the previous analyses is that the values for energy use and GHG emissions were reduced with exclusion of embedded materials. This was by a factor of about a half for wheat, but the effect was considerably smaller for milk.

Other investigations were also made (although not illustrated). Applying the gross margin per cow rather than per hectolitre milk or per ha rather than per t wheat did not provide any significant relationships. If anything, it provides confirmation that there is much variation in performance between farms.

Figure 55 GHG emissions per unit winter wheat vs. gross margin per unit winter wheat. Only on-farm GHG emissions included.

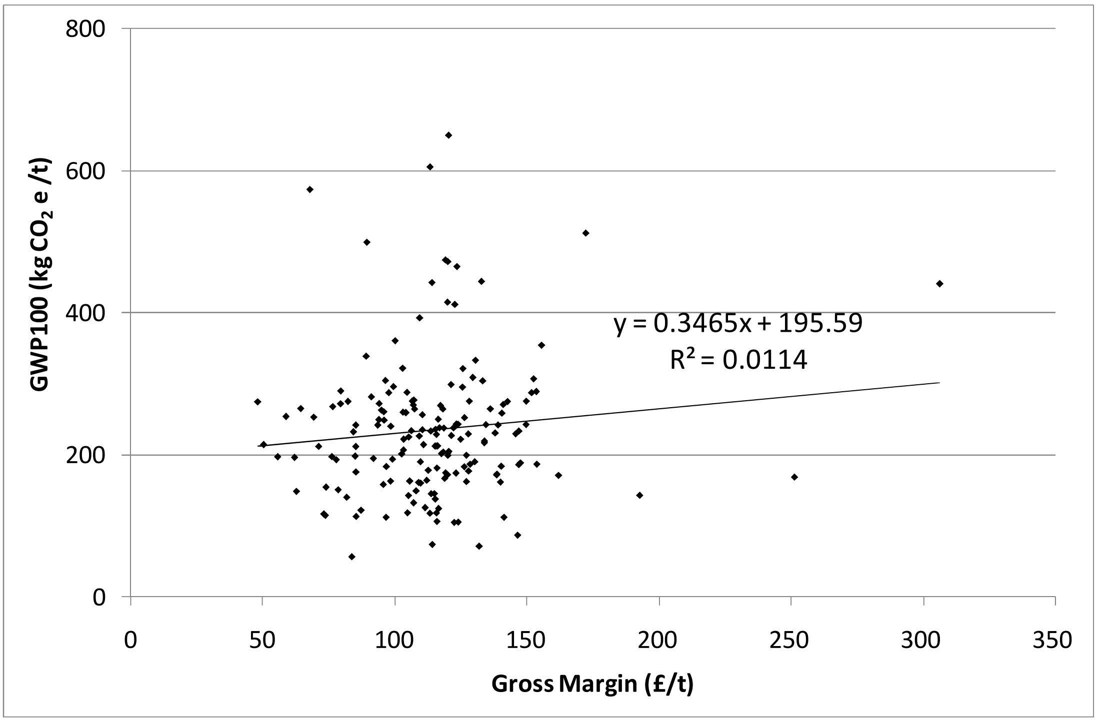


Figure 56 Energy use per unit winter wheat vs. gross margin per unit winter wheat. Only on-farm energy use included.

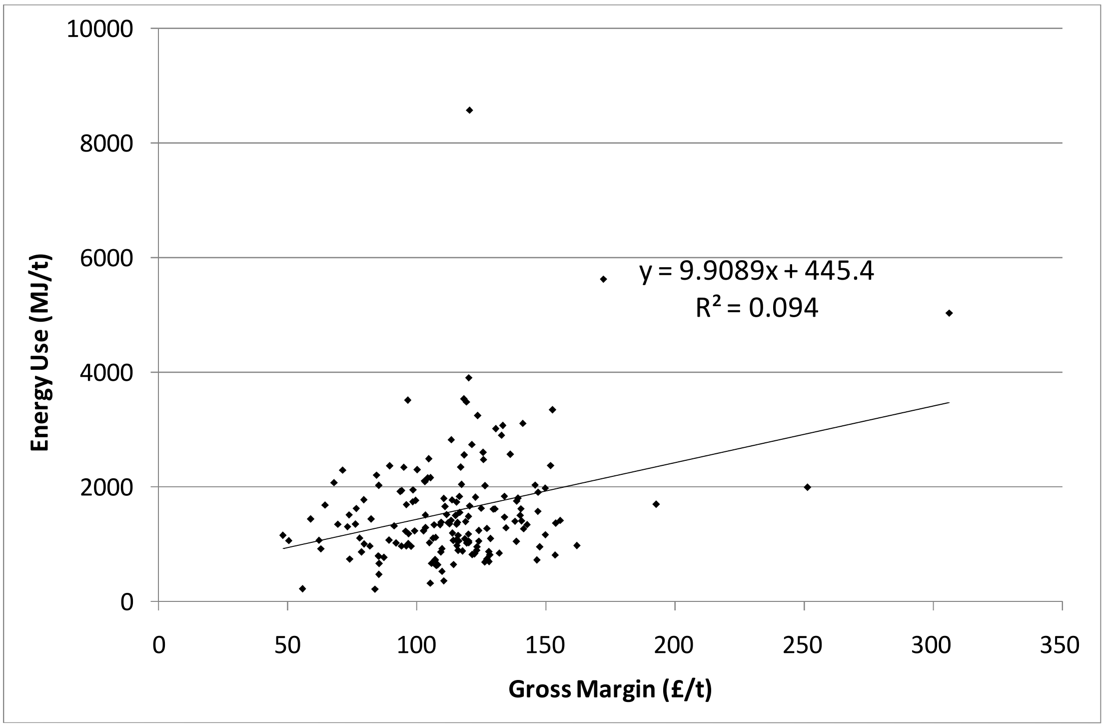


Figure 57 Energy use per unit milk vs. gross margin per unit milk. Fertiliser manufacturing energy excluded

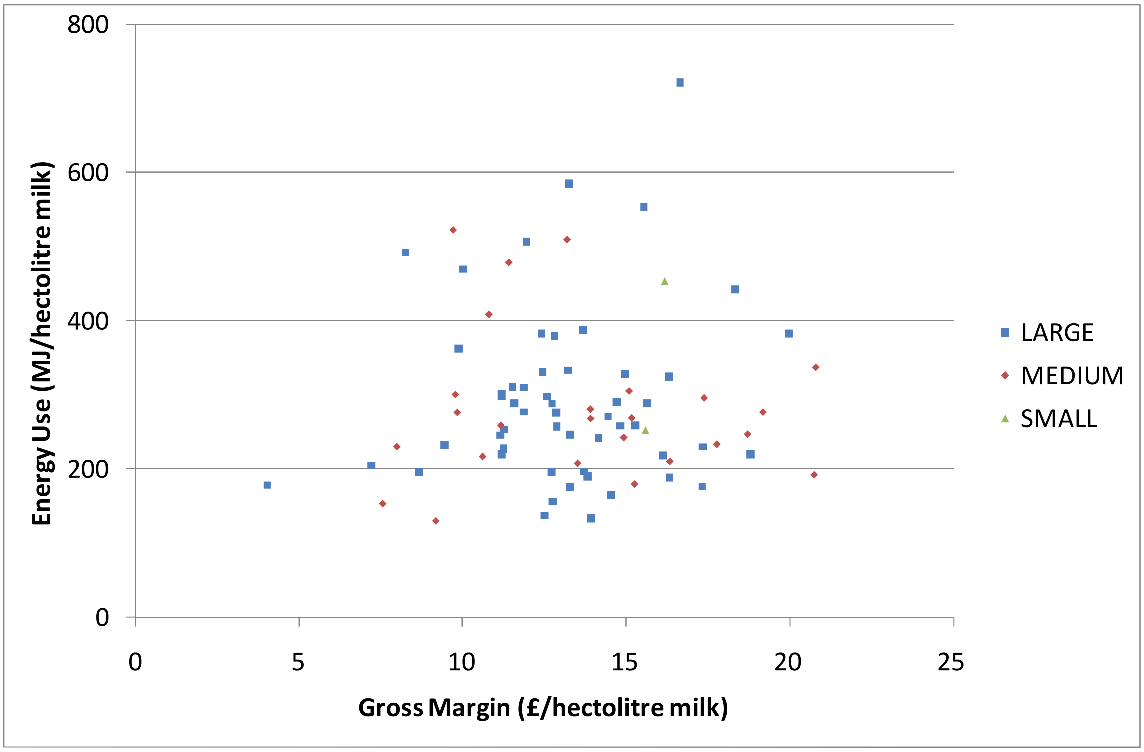
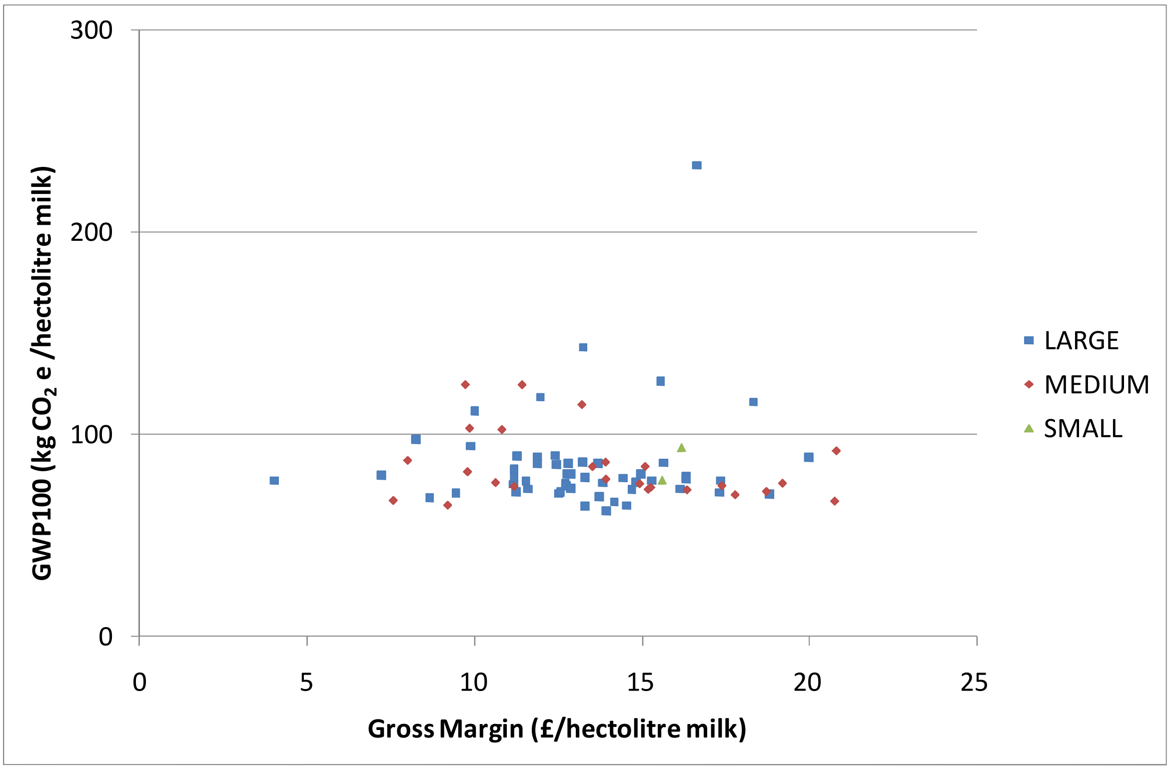


Figure 58 GHG emissions per unit milk vs. gross margin per unit milk. Fertiliser manufacturing energy excluded



Discussion on environmental and economic performance

It is somewhat disappointing that there seemed to be so little relationship between farm financial performance and energy use or GHG emissions. Nonetheless, this part of the study has shown the scatter (sometimes very wide) of both energy use and income per ha or physical unit of output. The mere fact that there ranges shows that there is scope for improvement in both financial and environmental performance. The significant, although weak, negative slope for milk production and energy accords with other reports of increased profitability and financial performance (Kite Marketing and Kingshay Trust *pers. comm*.).

This part of the study has still illustrated some very useful features of farm types. Energy use and GHG emissions per ha are systematically different between farm types. Energy use per ha and milk yield are highly correlated and are now quantified. There are clear differences in energy and emissions per ha with indoor and outdoor pig farms, although the range is wide. Indoor poultry production seems to be well optimised and with relatively little variation in environmental performance between the farms examined, while the range for outdoor production was much greater.

One area in which there was not enough data to make a worthwhile analysis was of organic production. This was because of the very limited data available, with small numbers of farms of different types and relatively high diversity of outputs. There is no fundamental reason why the analysis can not be applied to organic systems; it just needs more data.

6. Energy and emissions per ha

One feature that emerged in this analysis is the generally strong linear relationship across farm types between normalised energy use and GHG emissions. It was most obvious for horticultural and poultry units, in which there is a relatively high direct fuel use (Figure 59). There was a highly significant linear relationship between energy use and GHG emissions per ha across all farm types (Table 50). The fits were very good for high energy activities like specialist mono-gastric production and horticulture. They were inevitably poorer for other farming activities where enteric methane emissions and field emissions of N_2O play a relatively greater role (Table 50). This, nonetheless, provides the ability to produce a quick estimate from data that is relatively easy to derive. Examples for pigs, dairy and cereals illustrate the range of fits (Figure 60 to Figure 62).

Figure 59 Relationship between energy use and GHG emissions per ha for all farm types

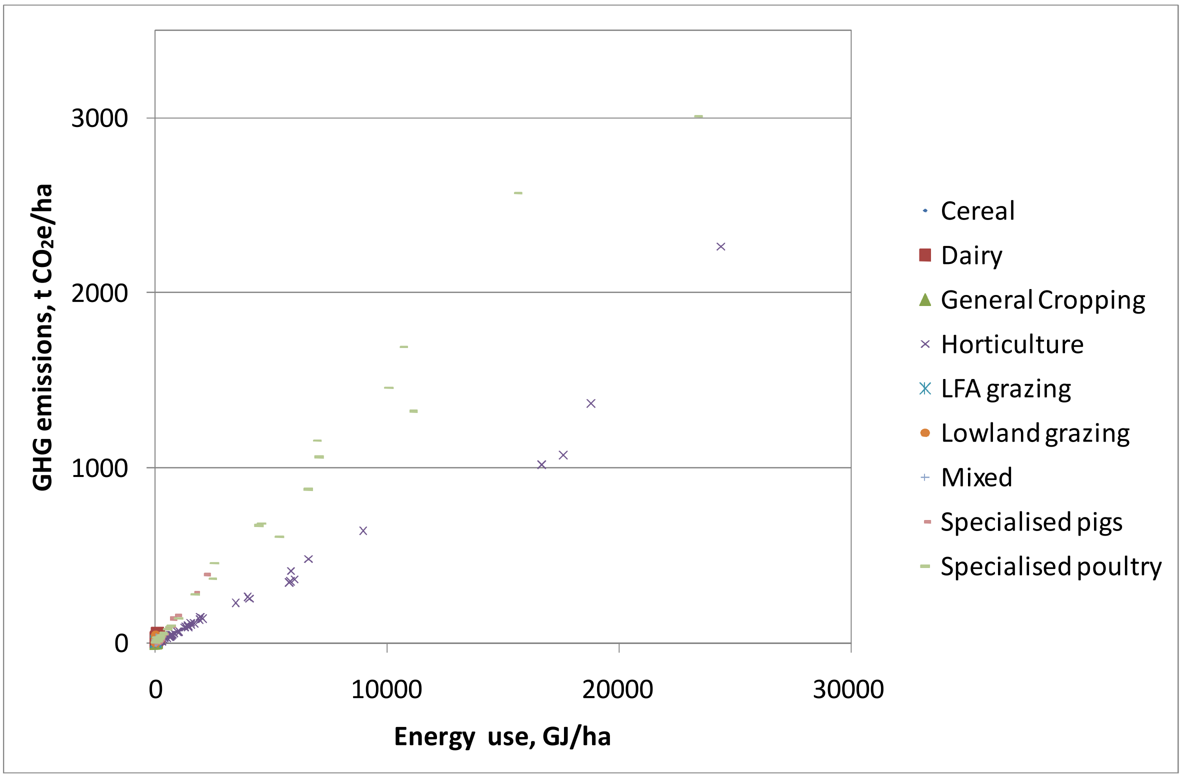


Table 50 Summary of regression between energy use per ha and GHG emissions per ha across farm types. The regressions and slopes were all significant at p<.001. There are ordered by decreasing quality of fit.

Farm type	Variance accounted for	Standard Error of regression	Slope, t CO_2e/GJ	Standard Error of slope
Specialist pigs	99%	10	0.181	0.0033
Specialist poultry	98%	101	0.141	0.0027
Horticulture	97%	59	0.0746	0.0014
Dairy	90%	1.27	0.219	0.0037
LFA grazing	69%	0.96	0.390	0.0266
Mixed	61%	1.79	0.236	0.0123
Lowland grazing	56%	1.35	0.355	0.0178
General cropping	53%	0.82	0.144	0.0059
Cereals	52%	0.72	0.178	0.0059

Figure 60 Energy use and GHG emissions per unit area for specialist pig farms.

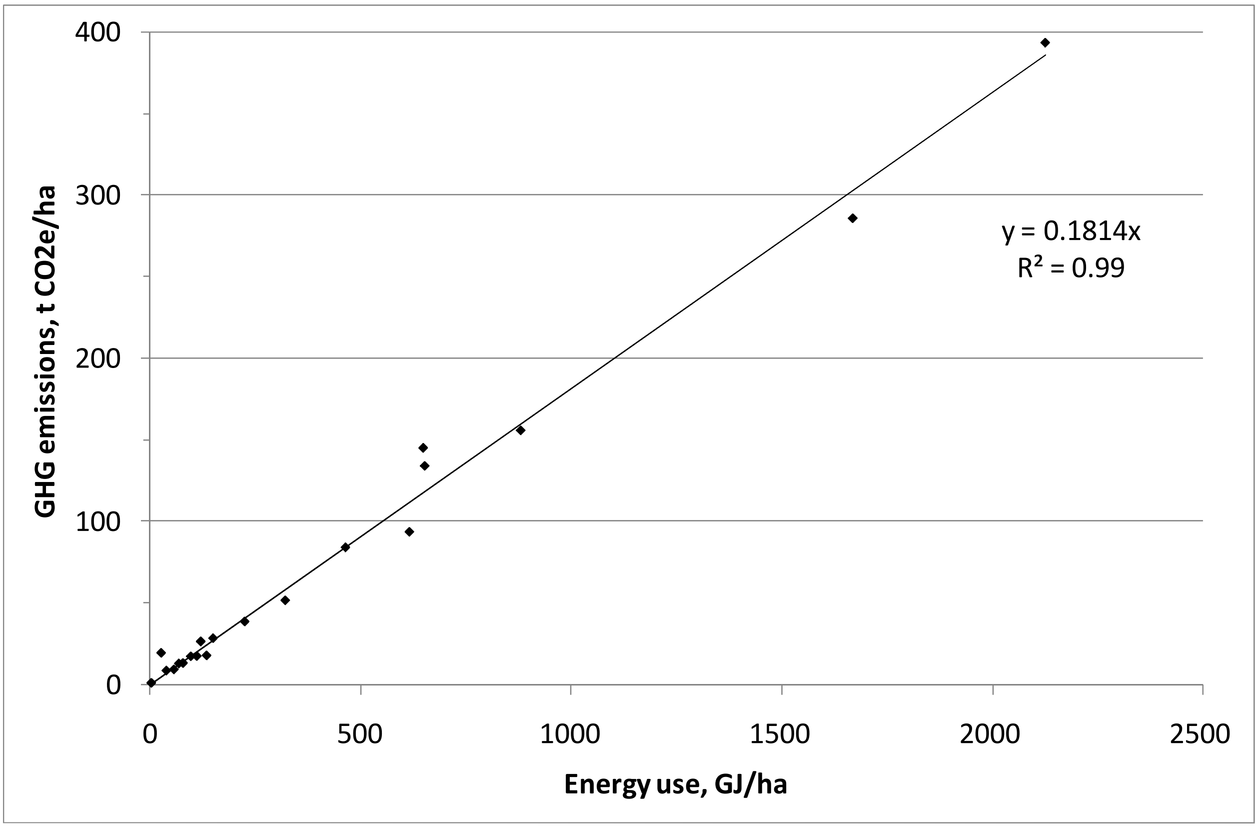


Figure 61 Energy use and GHG emissions per unit area for specialist dairy farms.

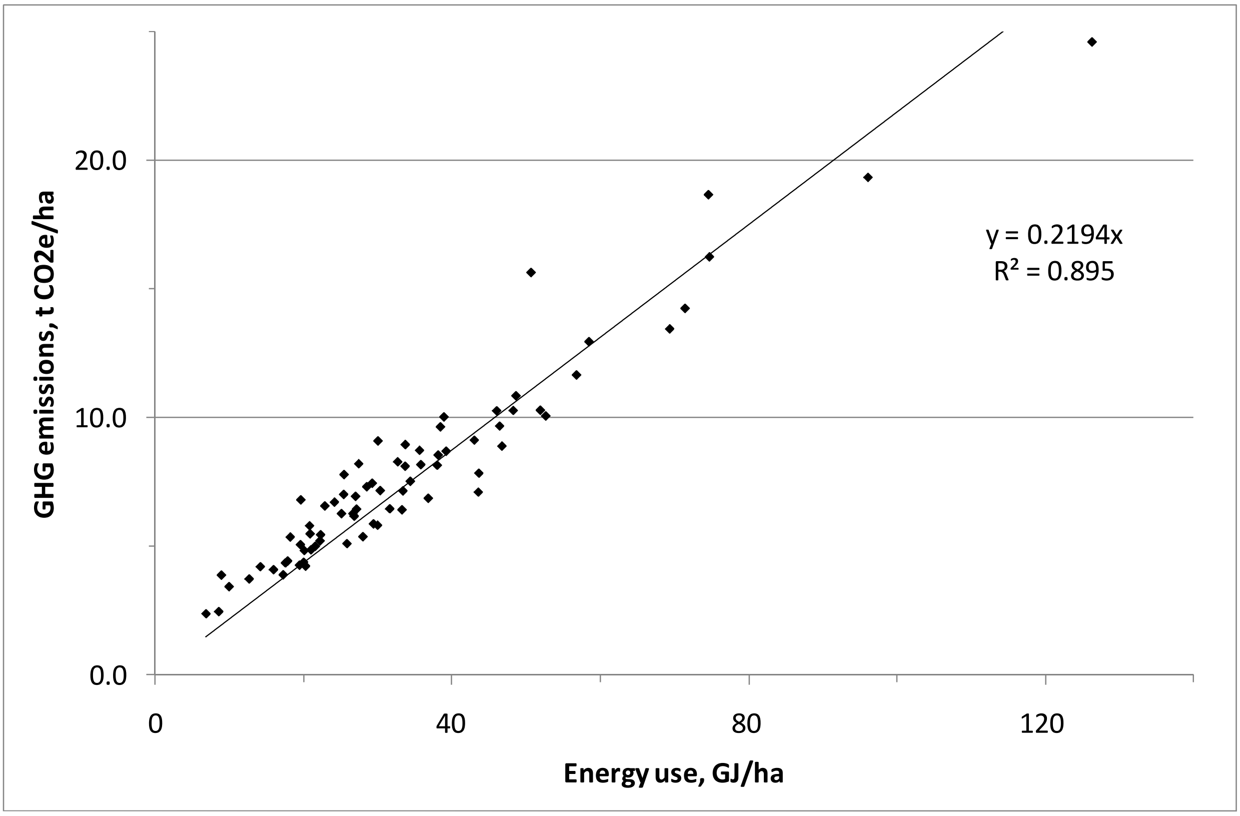
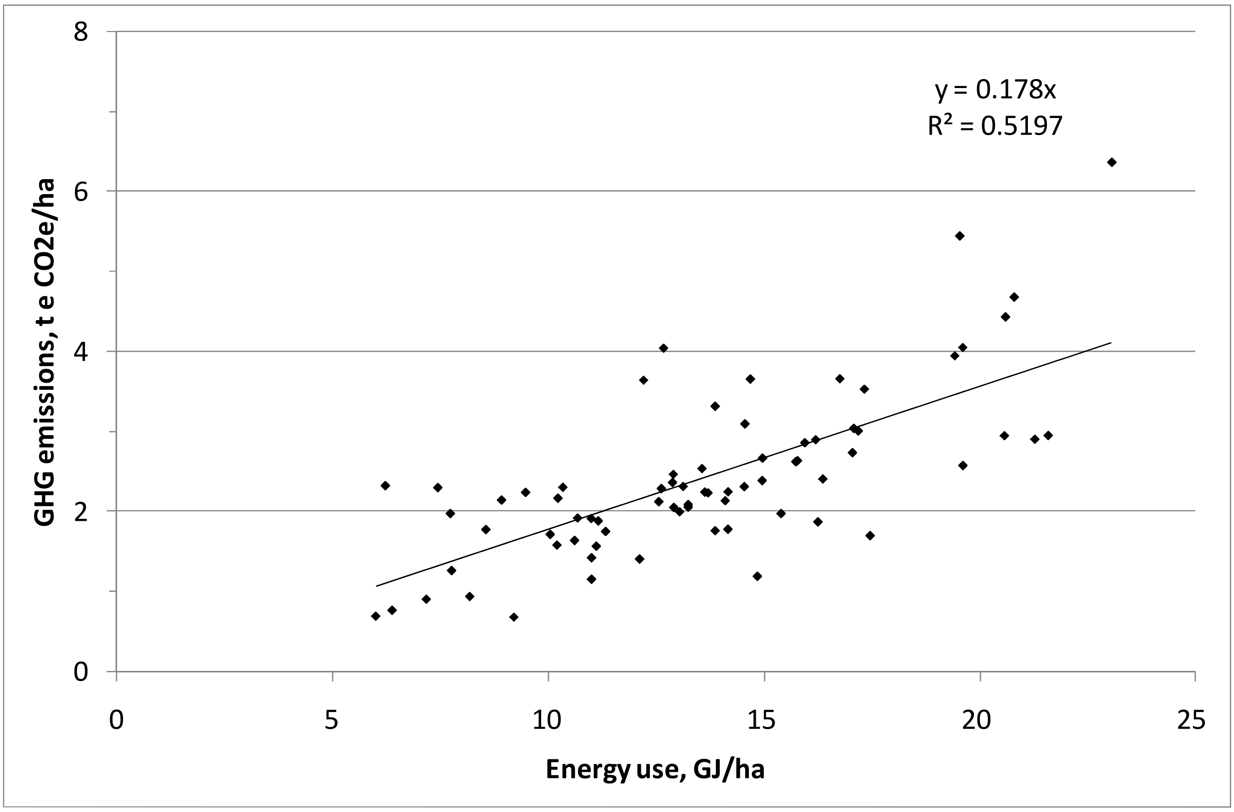


Figure 62 Energy use and GHG emissions per unit area for specialist cereal farms.



7. Data envelopment analysis

Introduction

Data envelopment analysis (DEA) is a method to measure the relative efficiency of multiple decision-making units (DMUs) when the production process presents a structure of multiple disparate inputs and outputs. The DEA method was formally developed by Charnes, Cooper and Rhodes (1978). The advantage of the procedure is its ability to compare the efficiency of DMUs with very different levels of disparate inputs and outputs, in this case cereals, root crops, ruminants, non-ruminants, and grassland on farms. The strength of this method is that it makes no *apriori* assumptions about the importance or weight of any of these disparate input or outputs.

In this case DEA will be applied to determine the relative efficiency of each farmer (i.e. the decision making unit, DMU). Efficiency (E) is defined as the emission per weighted sum of outputs per unit of energy or GWP:

$$E_j = \frac{\sum \{weights\}_{ij} \times \{Outputs\}_{ij}}{Energy_j}$$

where *i* is the output such as wheat and *j* is the DMU number. The principle of the procedure is that it chooses the weights individually for each DMU which maximise their efficiency-score, subject to the constraint that no other DMU using those same weights can have an efficiency-score greater than 1. Once all DMUs have been so analysed, the DMUs that have an efficiency of 1 form a Pareto-efficient frontier and are efficient relative to their peers. A lower value represents the level of inefficiency relative to their peers. A typical very simplified outcome is illustrated in Figure 63, in which farm efficiencies of two enterprises form an efficiency frontier. This is simplified in that only one frontier is presented, whereas in the analysis of the FBS data, an n-dimensional surface is created. Although many calculations are needed, the solution is found by linear programming, which is computationally efficient.

Figure 63 is presented as an output orientated model with the greatest radial expansion of output per unit of input being the points furthest from the origin where the Pareto efficient frontier lies. The efficiency calculated by this model is known as technical output efficiency. It is equally possible to formulate the problem with an input orientation where the task is find the maximum radial contraction of inputs per unit output giving a Pareto frontier closest to the origin. This is known as technical input efficiency. Where, it is assumed that there are no economies of scale, that is constant returns to scale, then technical input and output efficiency are the same.

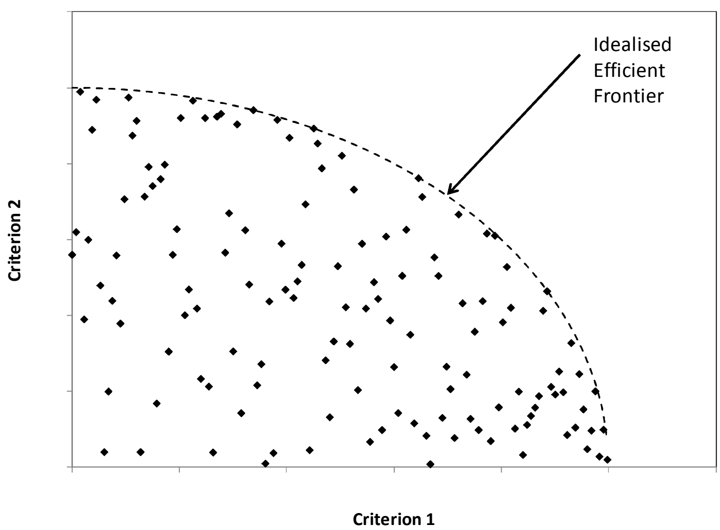


Figure 63 Hypothetical example of Data Envelopment Analysis

The procedure is frequently used to compare the efficiency of units with very different levels of inputs and outputs such as schools or bank branches. The main output is the identification of the most efficient farms and a relative ranking of other farms.

DEA Method

We adopt the DEA model for assessing technical input efficiency (Thanassoulis, 2001: 66). Take a set of N DMUs (j=1....N) using m inputs to generate r outputs where x_{ij} and y_{rj} are the levels of the i^{th} input and r^{th} output respectively. The technical efficiency of DMU j_0 is defined as k_0 and is determined by the following linear programming model

$$\min k_0 - \epsilon\left[\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right]$$

Subject to

$$\sum_{j=1}^{N} \lambda_j x_{ij} - k_0 x_{ij0} + S_i^- = 0 \qquad i = 1 \ldots m$$

$$\sum_{j=1}^{N} \lambda_j y_{rj} - S_r^+ = y_{rj0} \qquad r = 1 \ldots s$$

$$\lambda_j \geq 0, j = 1 \ldots N, S_i^-, S_r^+ \geq 0\ \forall i \text{ and } r, k_0 \text{ free}, \epsilon \text{ is a non-Archimedean infinitesimal}$$

Where λ_j is weight each DMU (j=1...N) will have in calculating the inputs and outputs of the composite DMU j_0*. Each of the criteria can have a slack denoted by S_i^- and S_r^+, which represents the distance from the constraint

The model is not solved by introducing the non Archimedean infinitesimal, but rather a two stage optimisation is used. First k_0 is minimised then with that held constant the sum of the slacks, S_i^- and S_r^+, is maximised.

In this form, the DEA model is said to be Constant Returns to Scale (CRS) and the average productivity is not a function of scale/farm size. In the CRS model technical input efficiency equals technical output efficiency. The alternative formulation is known as Variable Returns to Scale (VRS) and it requires an additional constraint, $\sum_{j=1}^{N} \lambda_j = 1, \forall N$, that is the sum of the weights equals 1 (Banker *et al*. 1984). In the VRS case technical input efficiency does not equal technical output efficiency. The VRS model prevents DMU from up scaling or down scaling to find a referent point for efficiency measurement.

It is worth noting throughout the following sections on results that when a unit is referred to as efficient it has a score (technical input efficiency) of one and lies on the Pareto frontier where it is impossible to improve one criterion without some other criteria deteriorating. In theory it is possible to have a set of DMUs with a technical input efficiency of 1 that do not lie on the Pareto frontier because they are dominated in at least one dimension, but not all dimensions by a peer on the Pareto frontier. Anything with DEA technical input efficiency of <1 is deemed inefficient. The efficient set is only relatively efficient to the inefficient set. DEA tells nothing about absolute efficiency and the capacity of the efficient set to improve.

A worked example

To illustrate the DEA method we have developed several sets of test data. In the first dataset random data was generated for three vectors, Global Warming Potential 100 years (GWP), hectares of land required, and total gross margin. The DEA is conducted using the input oriented VRS model. The results are shown in Figure 64 revealing the spread of the data in the production possibilities set, the location of the Pareto efficient or non dominated set and the boundary that is assumed to run through them to envelop all DMUs. Contrasting to Figure 63, Figure 64 is presented as the minimisation of input per unit of output. In this case we are seeking the smallest amount of the inputs land and GWP per unit of total gross margin and this lies closest to the origin of the graph. The technical input efficiency of each DMU is taken on a radial line from the DMU to the origin and is the ratio of the distance from the origin to the Pareto boundary over the distance from the origin to the DMU. To calculate radial efficiency the DEA method assumes the Pareto frontier extends beyond the outlying efficient DMUs to envelop all DMUs (dotted line in Figure 64)

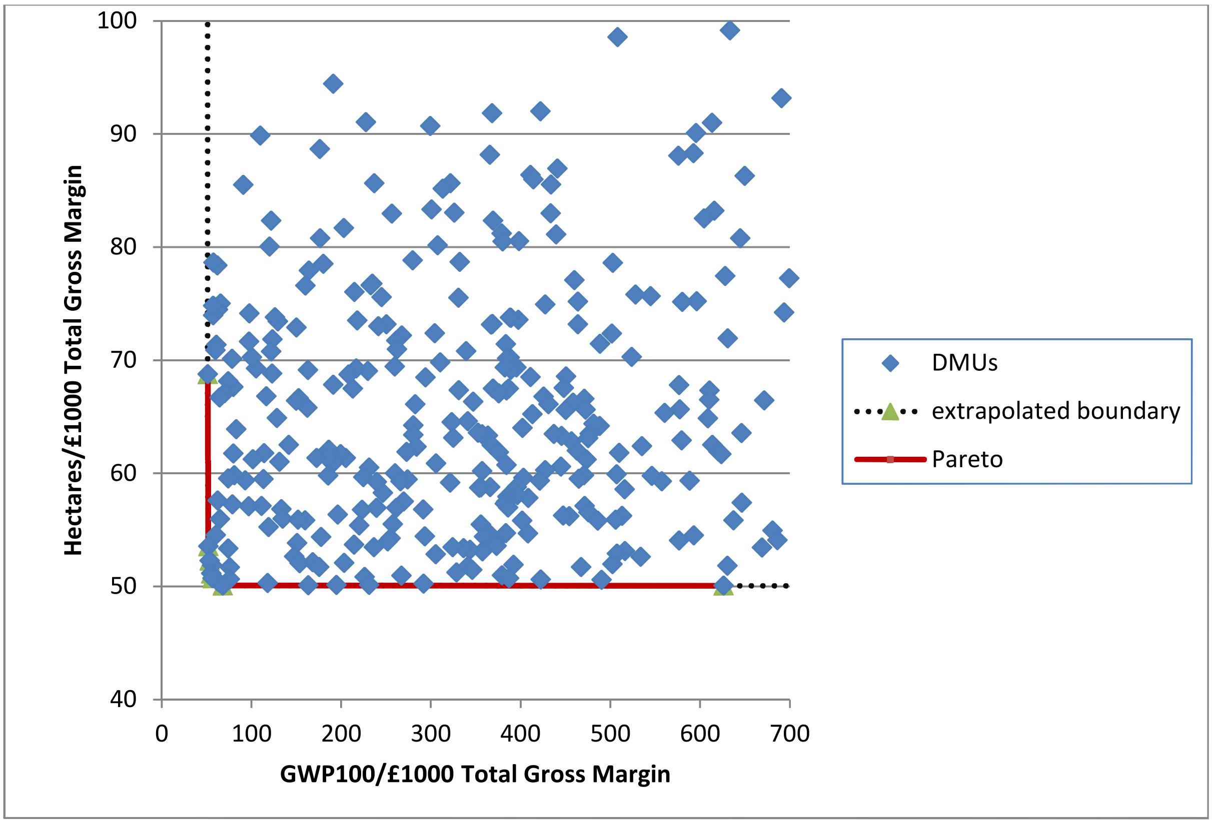


Figure 64 A randomly generated DMU dataset showing the location of the Pareto set and frontier

Next, a data set of 482 farm Decision Making Units (DMUs) was simulated, which is the same number of DMUs as those that report financial information in the FBS energy dataset. Five crops are simulated, wheat, barley, rape, beans and potatoes. Each can be grown on a random area between 0 and 100 hectares and generating a gross margin of £500/ha, £425/ha, £445/ha, £430/ha, and £1600/ha respectively. Thus, a farm can be between 0 and 500 hectares with five gross margin outputs, one for each crop. On the input side of the model we have a single emission vector of greenhouse gases with 50kg/ha from wheat, 45kg/ha from barley, 70kg/ha from rape, 25kg/ha from beans, and 125kg/ha from potatoes.

Unlike Figure 64, this example DEA model has greater than three dimensions and it is thus much harder to present the results graphically.

In this first case all the DMUs are efficient, E=1, as each has the same technical relationship between inputs and outputs regardless of amounts grown. Each DMU can take a set of weights that makes its output mix look ideal without making any other DMU look better.

Next, one DMU is taken and the emission of greenhouse gases from potatoes is modelled 250 rather than 125kg/ha. The DEA successfully identifies this DMU and returns a technical input efficiency of 0.7. In this case the inefficient unit has been dominated by efficient peers.

Next the DMUs are split into two sets so that the first 141 have low GHG emissions for Potatoes (125 kg/ha) and the rest have high ones (250kg/ha). Most of the inefficient DMUs are detected. However, some seem efficient because they are not dominated by a member of low GHG set in their neighbourhood in other words for that particular combination of outputs.

To further demonstrate this idea of dominance 241 farms were generated as a low GHG and high GHG potatoes pairs to make 482 DMUs. In this case every high GHG case is exactly dominated by its low GHG case and has a relative efficiency of 0.7.

If we introduce a second input vector (to be minimised) that reflects, say rainfall above 600 mm mean and generate a set where the first 141 have low GHG potatoes and the rest have high GHG potatoes (as in the case previously) and assign 100mm extra rainfall to the second set then the efficiency scores are unchanged by the second input. This is because it is modelled as an undesirable and thus they can't assign any weight on it to better their existing efficiency scores. However, if the first set has the 'poor' 100 rainfall value then all DMUs can take weights that make them relatively efficient as they all have a good and a bad value in one or other input. As rainfall is an exogenous input that is beyond management control then a requirement could be to only compare units that have the same level and introduce an equality constraint, such that each virtual efficient DMU must have the same rainfall. Then each DMU from each set is now efficient even if the second set have both the higher GHGs and the higher rainfall.

Data, such as the FBS energy survey will contain the effects of chance. We now define a set of 141 with low GHG potatoes and a second set where the GHG emissions are now;

wheat = 30 +rnd *20,
barely = 25 + rnd * 20,
rape = 50 + rnd * 40,
beans = 20 + rnd * 10, and
potatoes = 220 + rnd * 60.

In this case, some of the second set dominate the first set as the first 4 crops have lower emissions despite the larger potato emissions. Of the first 141 the mean relative efficiency is 0.92 of which 54 are efficient and of the second set the mean relative efficiency is 0.89 of which 84 are efficient.

Exploratory DEA analysis of FBS data

The sole input vector is either

- Total direct and indirect Greenhouse Gas emission as the 100 year Global Warming Potential (GWP), kgCO_2 eqv., or
- total direct and indirect energy (MJ)

in order to maximise the discrimination power of the model. The output vectors are based on the production of quantities of commodity:

Cereals (t),
Oilseeds (t),
Combinable legumes (t),
Potatoes (t),
Sugar beet (t),
Horticultural revenue (£)*,
Milk (hectolitres),
Eggs (no),
Cattle Liveweight (kg),

Sheep Liveweight (kg),
Pig Liveweight (kg), and
Poultry Liveweight (kg).

*Not uniformly reported in physical units so revenue used instead and includes: ornamentals, top fruit, soft fruit, salads and herbs, other, and vegetables

All negative values are replaced by zero.

Due to the need to have a homogenous population for the DEA a number of potentially unrepresentative DMUs are removed. In both models 71 DMUs are removed because they have no outputs measured in these criteria. A further 92 DMUs are removed because over 20% of the energy use arises from contracting. Some animal liveweight outputs were calculated as negative and 21 poultry, 5 cattle, 1 pig, and 1 sheep DMUs have had that output set to zero.

Exploratory Results

The DEA was conducted using the input oriented VRS model. Figure 65 shows the histogram of DEA scores for both model formulations with 38 (GWP) and 33 (Energy) of the 347 DMUs forming the efficient set of distinct classes of farm with respect to these measures. In other words there is no other farm with their particular combination of the above commodity quantities which has lower GWP or Energy input.

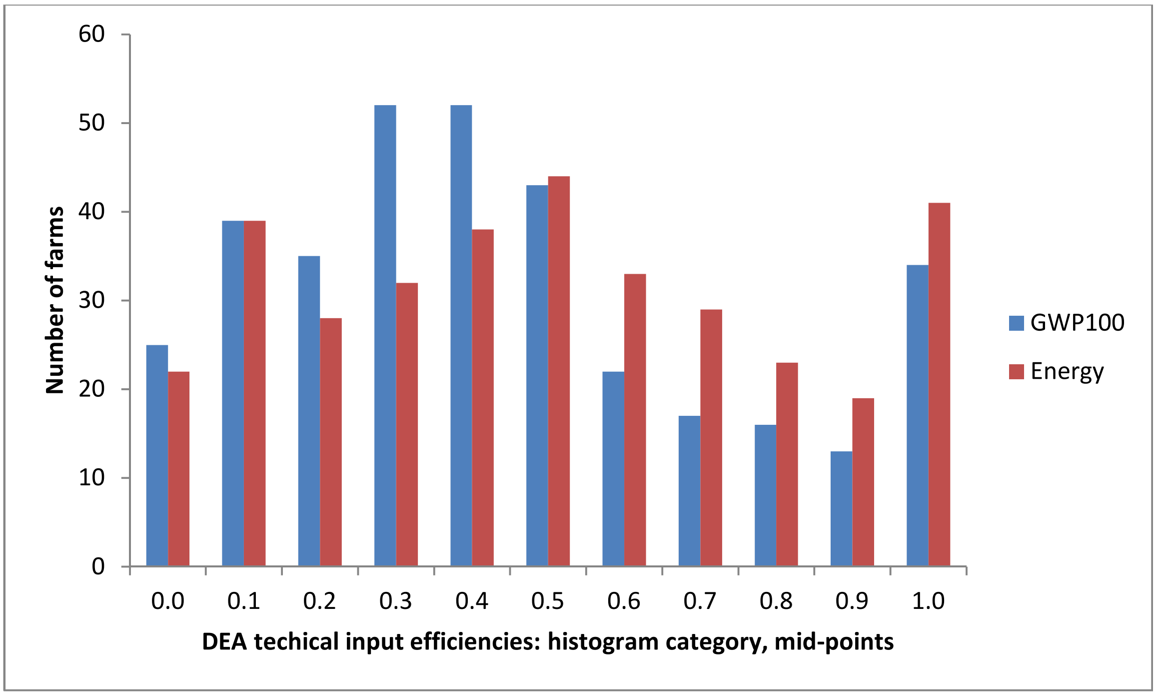


Figure 65 Histogram of technical input efficiency scores, assuming variable returns to scale (VRS) for models based on either total Global Warming Potential (GWP) or total Energy showing broadly similar profiles

Table 51 identifies each of the relatively efficient DMUs from each DEA formulation together with how often each DMU is a peer to a relatively inefficient one. Many of the DMUs are relatively efficient in both formulations. Additionally, some DMUs act as peers to a large set of relatively inefficient ones. Provided that these DMUs are not in some way outliers they are candidates for best practice benchmarking. One such outlier might be DMU 288, which is a small organic horticulture holding which is peer to 215 other farms. Thus, this is removed and the energy formulation is run again (Table 51) showing a slightly more diverse set of efficient DMUs

Table 51 DMUs that are efficient in the GWP and Energy DEA VRS formulation showing that many DMUs are efficient in both formulations. To consider the effect of a possible outlier the Energy formulation is run without DMU 288 and shows a slightly more diverse set of efficient DMUs.

DMU	Energy		GWP		Energy –No DMU 288						
DMU	Efficient	Times a peer	Efficient	Times a peer	Efficient	Times a peer	Type	Area	Organic?	Total adjusted agricultural area, ha	Proportion of fuels from contracting
23	Y	1	Y	2	Y	1	Cereals	North East		882	2%
53	Y	1	Y	1	Y	1	Cereals	East Midlands		146	10%
132			Y	98			Cereals	Yorks & Humb		42	20%
336	Y	10	Y	24	Y	9	Cereals	East of England		451	5%
348	Y	1	Y	1	Y	1	Cereals	East of England		1597	0%
359	Y	12	Y	13	Y	14	Cereals	East of England		33	4%
441	Y	153	Y	151	Y	126	Cereals	South West		1944	15%
306	Y	3	Y	7	Y	3	Dairy	East of England		272	7%
401			Y	45			Dairy	West Midlands		114	7%
402	Y	2	Y	6	Y	2	Dairy	South East		382	6%
505	Y	16			Y	16	Dairy	South West		66	7%
397					Y	14	Dairy	West Midlands	Y	78	9%
196	Y	7	Y	2	Y	7	General cropping	West Midlands		85	8%
215	Y	19	Y	30	Y	14	General cropping	East Midlands		86	15%
222	Y	5	Y	36	Y	5	General cropping	East Midlands		385	0%
254	Y	1	Y	8	Y	1	General cropping	East of England		640	0%
281	Y	3	Y	2	Y	3	General cropping	East Midlands		864	2%
284	Y	2	Y	2	Y	2	General cropping	East of England		839	4%
307	Y	3	Y	3	Y	3	General cropping	East Midlands		2137	2%
327	Y	10			Y	10	General cropping	East of England		124	0%
333	Y	9			Y	13	General cropping	East of England		65	0%
345	Y	1	Y	1	Y	1	General cropping	East of England		353	15%
361	Y	11	Y	10	Y	11	General cropping	East of England		959	0%
368	Y	16	Y	17	Y	15	General cropping	East of England		705	1%
426	Y	35	Y	36	Y	30	General cropping	West Midlands		194	9%
283					Y	2	General cropping	East Midlands		54	18%
22	Y	30	Y	27	Y	33	Horticulture	North West		57	0%
288	Y	179	Y	215	#	#	Horticulture	East of England	Y	9	0%
366			Y	2			Horticulture	East of England		164	0%
295					Y	53	Horticulture	East Midlands		9	13%
19	Y	6	Y	9	Y	6	LFA grazing livestock	North East		204	13%
47	Y	39			Y	30	LFA grazing livestock	Yorks & Humb	Y	87	15%
62	Y	23			Y	20	Lowl'd graz'g live'k	South East		95	7%
210	Y	49	Y	80	Y	48	Lowl'd graz'g live'k	East Midlands		87	6%
332	Y	95			Y	101	Lowl'd graz'g live'k	East of England		36	17%
374			Y	44	Y	117	Lowl'd graz'g live'k	West Midlands		26	5%
42	Y	20	Y	18	Y	18	Mixed	Yorks & Humb		66	10%
214	Y	40			Y	28	Mixed	East Midlands		227	16%
304	Y	23			Y	21	Mixed	East of England		65	11%
371	Y	3	Y	2	Y	3	Mixed	South West		1278	19%
383	Y	52	Y	15	Y	44	Mixed	South East		49	15%
392	Y	1			Y	1	Mixed	South West		536	2%
180	Y	5	Y	5	Y	5	Specialist poultry	West Midlands		0	20%
303	Y	15	Y	15	Y	10	Specialist poultry	East of England		0	0%
321	Y	25	Y	25	Y	23	Specialist poultry	East of England		22	0%

Figure 66 continues to consider what happens if the possible outlier, DMU 288, is removed from the energy formulation of the model and it shows that the DEA score tends to be raised and less scattered.

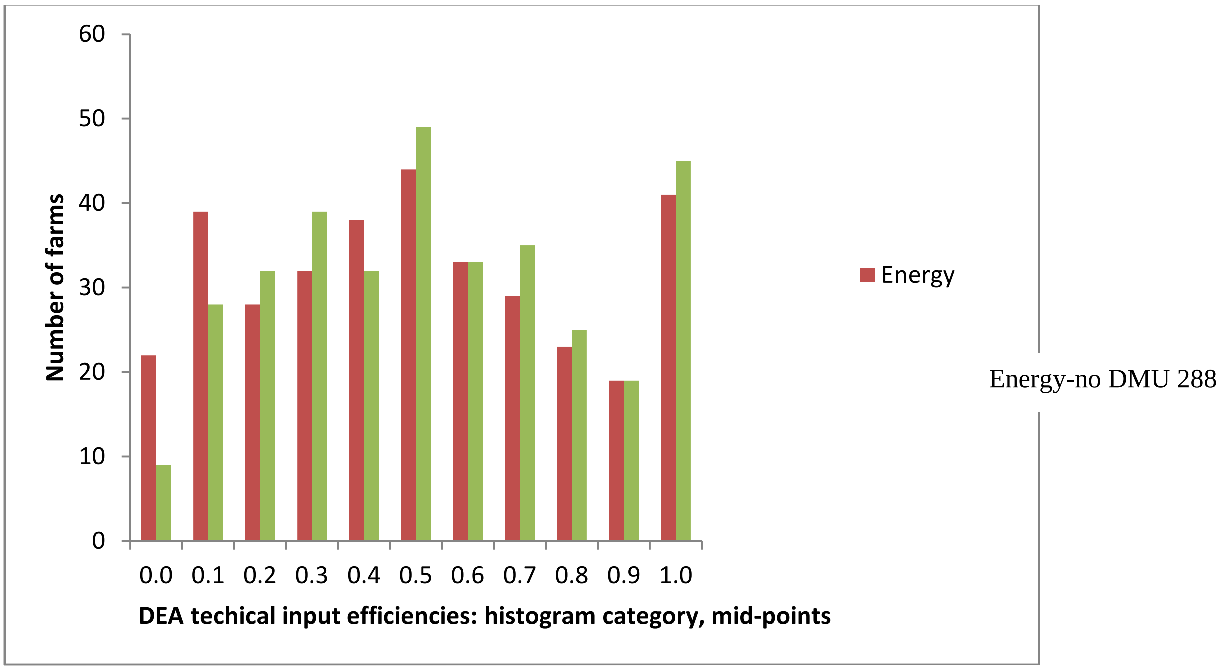


Figure 66 Histogram of DEA technical input efficiency scores for the Energy formulation with and without DMU 288 showing that the efficiency scores are moved to the right when a possible outlier is removed.

Figure 67 shows a comparison between the GWP and Energy formulation, assuming constant returns to scale (CRS), and reveals a similarly close correspondence to the VRS case.

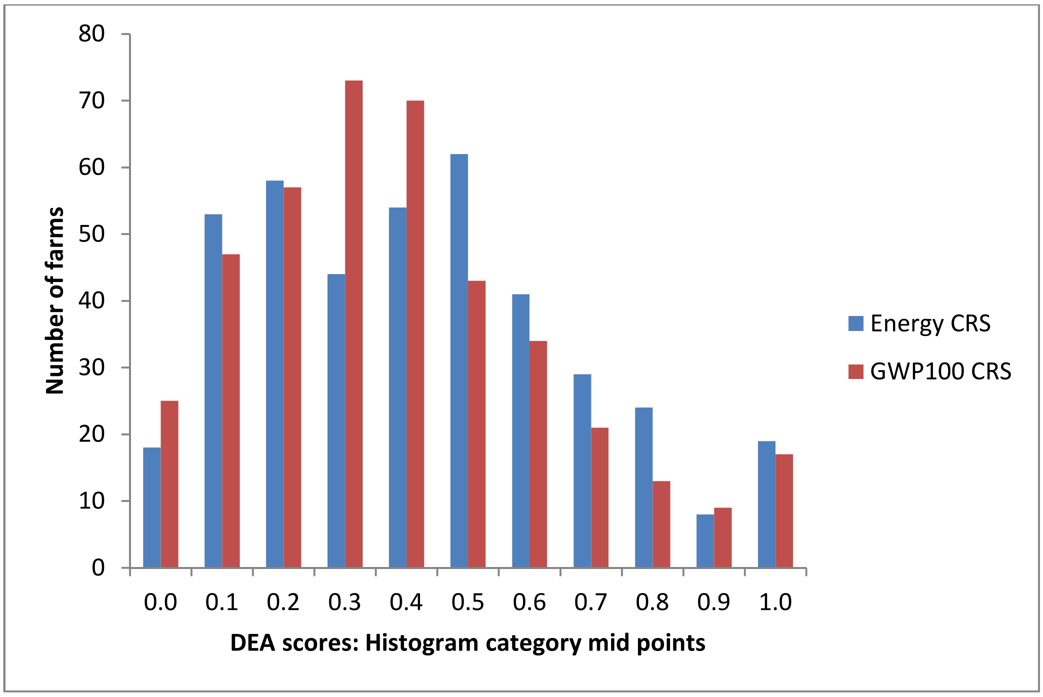


Figure 67 Histogram of DEA scores showing close correspondence between Energy and GWP formulations under constant returns to scale (CRS)

As a rule, CRS scores are always the same as or less than the VRS scores hence the small efficient set on the CRS case. Figure 68 illustrates this point that there is a very high agreement between VRS and CRS scores.

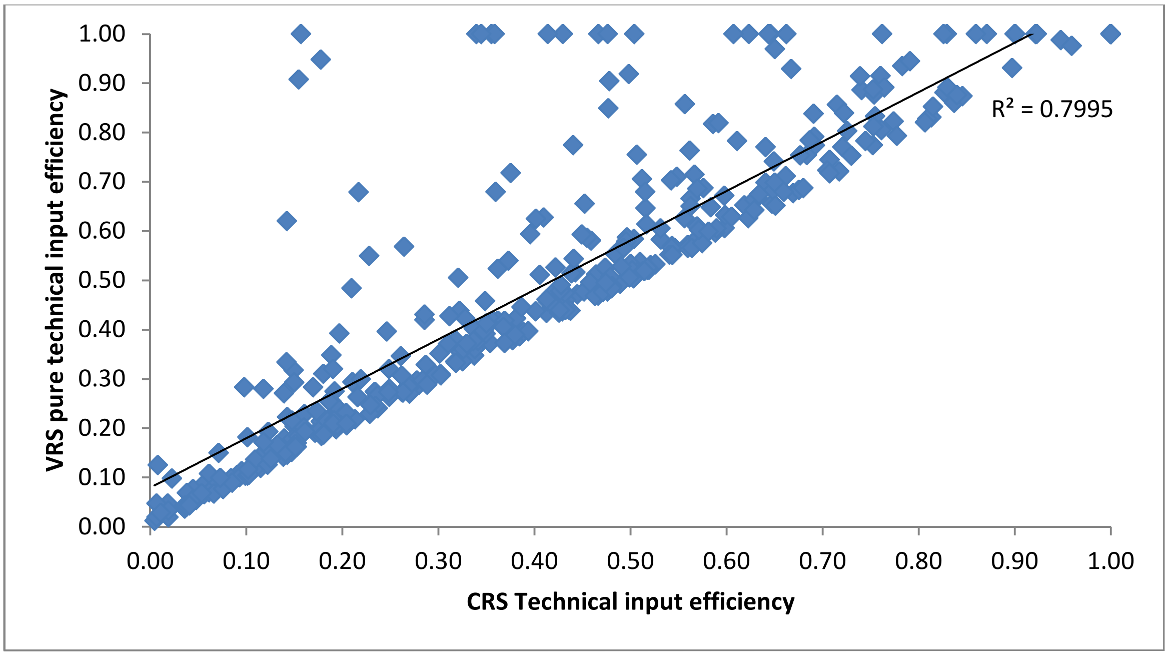


Figure 68 Scatter diagram of VRS and CRS models using the energy formulation showing a strong degree of similarity with some VRS score having a much lower CRS score

Summary

The DEA scores are broadly comparable if either GWP or Energy is used as the input vector, with many DMUs being efficient in both models. This is a bit non-intuitive until one considers that this study quantified indirect as well as direct energy inputs. In agriculture, the majority of greenhouse gas emissions (GWP) arise from nitrogenous fertiliser usage (N_20 emissions) or methane due to rumen digestion or the anaerobic decay of manures. Indirect (off-farm) energy inputs are very important in the production of nitrogenous fertilisers which are also in turn sequestered off-farm in the form of imported feed stuffs.

The results also suggest that one has to be wary of very efficient outliers as they dictate the position of the frontier against which all others are judged.

A revised DEA model

The initial analysis revealed that there was not much difference between the formulations based on energy or GWP. It also revealed that DMU 288 was a significant outlier. These factors have been taken into account to select a revised population of DMUs and criteria. Horticulture has also been revisited and broken down into two to differentiate salad and herb revenue from other horticulture revenue as this former group of horticulturalists seems to be very heavy users of heated glass compared to the rest.

The revised formulation now contains 409 DMUs. The exclusions are DMU 288, seven with no countable outputs, and 94 with over 20% of energy arising from contracting. The livestock live-weight production calculations for 21 poultry, 6 cattle, 1 pig, and 1 sheep DMUs were negative and these have been made zero.

The DEA is conducted using input oriented constant returns to scale model, which gives identical results to the output formulation in this case.

Results

The histogram of DEA technical input efficiency scores for the revised model is shown in Figure 69. It again has a characteristic efficient population (42) followed by a gap and then the bulk of the DMUs

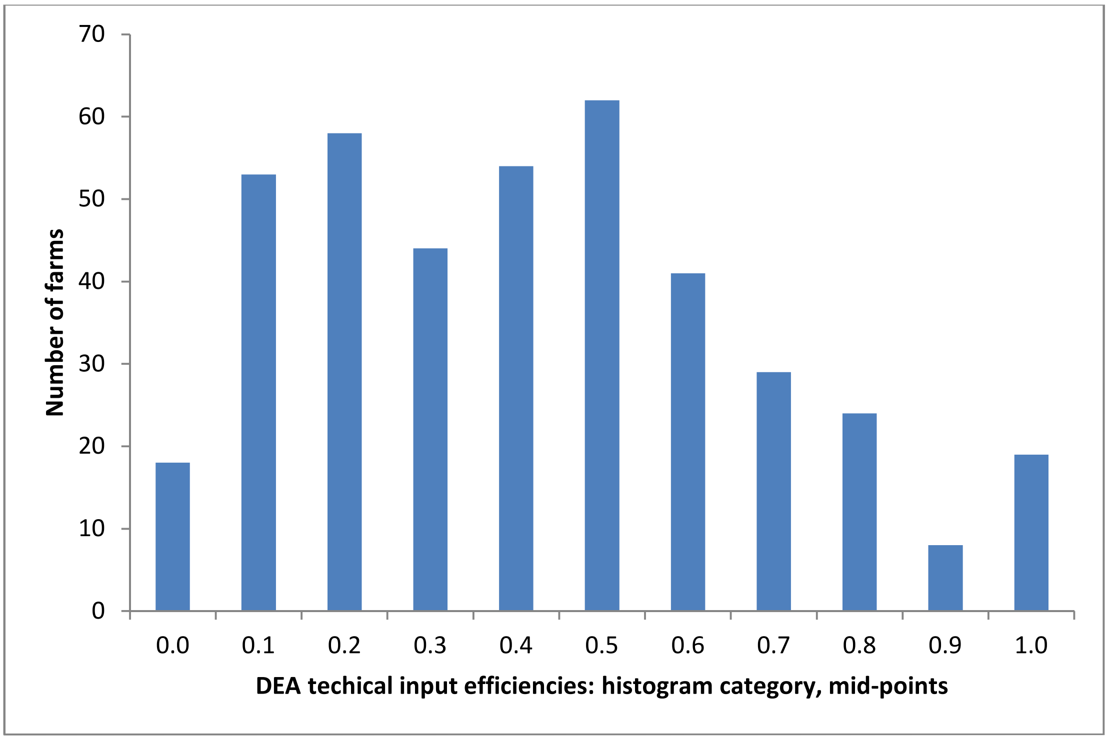


Figure 69 Histogram of DEA technical input efficiency scores for the revised model based on total energy use

The Pareto efficient set

Table 52 lists all 18 of the efficient DMUs together with their farm types, organic status, the number of time each is a peer, and the criteria levels of each. Most farm types have a peer group except for specialist pigs whose peers would seem to be pig units on arable farms. The greater then number of times a DMU is a peer then the more it dominates the industry and is thus a benchmark candidate that might reflect widespread practice.

Table 53 looks more closely at the role each Pareto efficient DMU has as a peer to the inefficient DMUs. The information is organised by farm type and details how much of the peer is used and the mean weight (λ) given to it. It is clear that the farm typologies are not mutually exclusive as inefficient DMUs use peers from more than their own farm type. The specialists tend to use mostly their own kind but the picture is much more mixed when the general farm types are considered.

Of practical concern might be the case of Dairy and Specialist pigs that have no peers of their own kind and thus use peers from general farm types. The risk is that their efficiency is being measured against a reference with a more divers set of outputs, say, pigs with arable or dairy with fat stock. The following subsection looks in more detail at the inefficient DMUs and their peers

Table 52 The 18 Pareto efficient DMUs showing their farm type, the number of times each is a peer and their criteria levels (2 significant figures)

DMU	Type	Organic	No. times a peer	Energy 000GJ	Milk hl	Eggs 000 No	Cattle t lwt	Sheep t lwt	Pig t lwt	Poultry t lwt	Cereals t	Oilseeds t	Legumes t	Potatoes t	Sugarbeet t	Salad £	Hortic £000
336	Cereals		6	6800	0	0	0	0	1200	0	1900	330	120	0	3700	0	0
359	Cereals		18	270	0	0	0	0	0	0	78	0	29	0	0	0	0
441	Cereals		162	9900	0	0	4.8	0	0	0	7500	1100	750	0	0	0	0
283	General cropping		4	500	0	0	0	0	0	0	94	0	0	150	380	0	49
222	General cropping		7	2500	0	0	0	0	0	0	830	250	0	200	980	0	45
196	General cropping		12	1600	0	0	0	0	0	0	280	77	0	930	0	0	0.340
333	General cropping		15	510	0	0	0	0	0	0	160	0	0	0	840	0	0
215	General cropping		36	760	0	0	0	0	0	0	320	19	35	0	1000	0	0
426	General cropping		39	6200	0	0	0	0.51	0	0	1300	0	0	4000	0	0	0
320	Horticulture		23	270	0	0	0	0	0	0	0	0	0	0	0	88000	58
381	Horticulture		104	1700	0	0	0	0	0	0	0	0	0	0	0	0	1500
47	LFA grazing livestock	Y	67	320	0	0	13	25	0	0	0	0	0	0	0	0	0
62	Lowland grazing livestock		38	210	0	0	3.4	17	0	0	0	0	0	0	0	0	0
332	Lowland grazing livestock		128	170	0	0	18	0	0	0	0	0	0	0	0	0	0
304	Mixed		26	690	0	0	8.4	6.3	230	0	0	0	0	0	0	0	0
214	Mixed		48	2100	9500	0	11	0	0	0	470	100	3.5	0	0	0	0
303	Specialist poultry		20	8600	0	0	0	0	0	16000	0	0	0	0	0	0	0
321	Specialist poultry		26	1100	0	790	0	0	0	0	0	0	0	0	0	0	0

Table 53 An investigation, by farm type, into the role that each Pareto efficient DMU has in being a peer to an inefficient unit showing that often the main peer is a farm of the same type, but can also be drawn from the more general types.

	Farm type of inefficient DMUs with the number of times (count) each peer is chosen and the mean weight (Av. λ) of it																	
	Cereals		Dairy		General crop'g		Horticulture		LFA graz'g lives'k		Lowl'd graz'g livest'k		Mixed		Special't pigs		Special't poultry	
Peers by type	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**	**Count**	**Av. λ**
Cereals																		
211			1	0.55														
336					2	0.09							1	0.00	2	0.06		
359	7	2.09	1	0.32	3	0.28	1	4.05					3	0.47			2	0.33
441	64	0.16	1	0.01	41	0.09	8	0.03	1	0.00	8	0.00	30	0.05	5	0.03	2	0.03
General cropping																		
196					11	1.04												
215	6	2.19			27	2.45	1	0.06					1	0.43				
222	2	0.24			4	0.47												
283					1	5.85	2	1.20										
333					12	2.24	1	0.22					1	4.35				
426	3	0.04	1	0.01	27	0.33	3	0.13			1	0.00	3	0.03				
Horticulture																		
320	2	0.15			3	0.18	17	5.90										
328			1	0.59														
381	2	0.04			18	0.07	82	0.25			1	0.00						
LFA grazing livestock																		
46	6	0.57	15	0.33	4	0.52			12	0.90	14	0.62	12	0.79			3	0.09
Lowland grazing livestock																		
62	6	1.46	5	0.56	5	0.83	1	0.91	6	1.02	8	0.68	4	2.54			2	0.30
332	24	1.29	31	0.79	15	1.25			9	0.97	19	0.97	23	2.44	1	0.17	4	1.31
Mixed																		
42			1	0.38														
214			43	0.72	1	1.21					1	0.01	2	1.13				
304	1	0.00	1	0.12	4	0.61							3	1.46	16	0.88		
Specialist poultry																		
303	1	0.00			1	0.00							1	0.00			16	0.06
321	1	0.00			1	0.34	1	0.00					2	0.20			20	1.10

A selection of inefficient DMUs and improvements

Table 54 through to Table 58 give the target improvements of a selection of inefficient DMUs from a number of farm types. The tables identify each of the peers and the weights they have in forming the ideal criteria outcomes by weighted proportion. This ideal outcome is reported along with the initial or raw criteria levels.

The most convincing peer group comparisons are in Table 54 to Table 56 where the DEA has found convincing peers that produce equivalent outputs for a fraction of the total energy input of the inefficient DMU. This is a telling insight for those inefficient farms and warrants further investigation with the peer group serving as the benchmark farms to the inefficient ones. Two of the examples show a simple up (Table 55) or down (Table 54) scaling of a much more efficient peer

Table 54 Investigating the recommended improvement of DMU 450, a Horticulture farm type with technical input efficiency of 0.23

DMU No	Peer proportion	Energy MJ	Hortic £
450	raw	110000	22000
381	*0.015*	*1,700,000*	*1,500,000*
450	ideal	26,000	22000

Figure 70 shows a more detailed investigation of the difference in energy in between DMU 450 and its peer. The direct forms of energy are proportionally less with the efficient peer once scaled. The inefficient DMU has a small amount of additional indirect energy input mostly in the form of the manufacture of farm equipment. The horticultural farm type is a very broad class so perhaps the explanation lies in exactly what is produced, but it so happens both produce ornamentals rather than one vegetables and the other salads/herbs. However, ornamentals could include anything from orchids to outdoor daffodils with vastly different financial values and production requirements. A harder look at the nature of ornamentals and other horticultural outputs could help yield robust comparable typologies. DEA starts a process that identifies these questions.

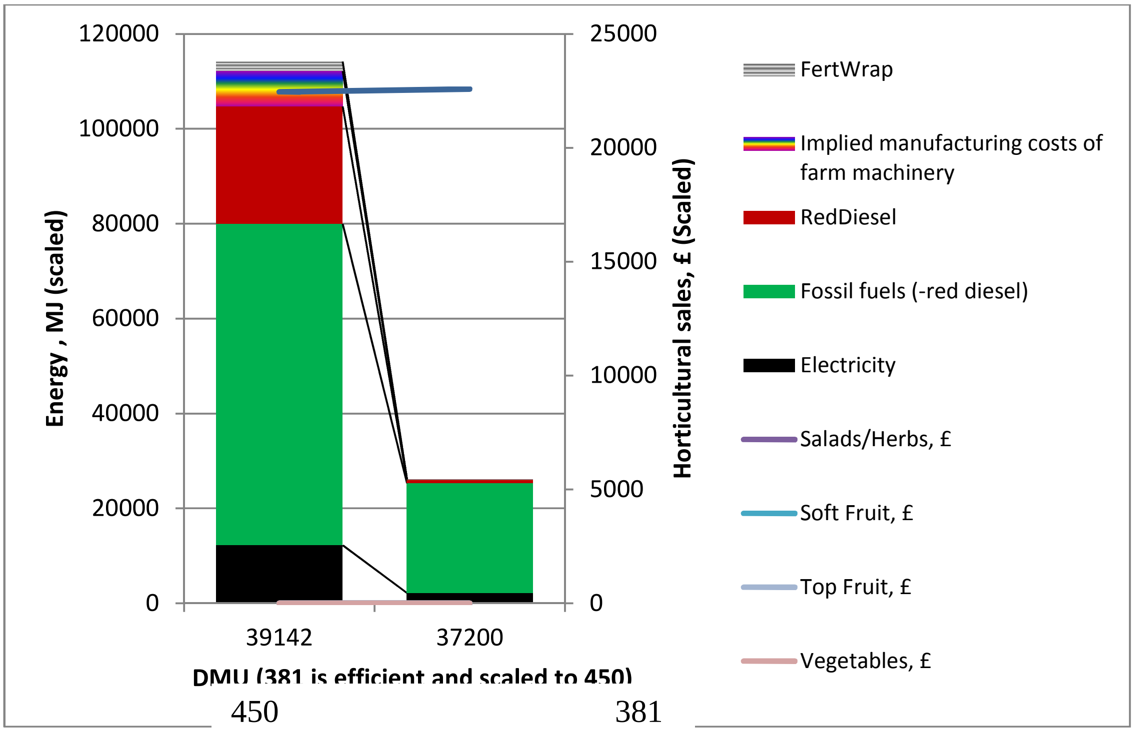


Figure 70 Detailed exploration of the energy inputs of DMU 450 relative to its peer, showing proportionally less direct energy use and a near absence of indirect energy use in the peer for identical kind of sales (ornamentals)

Table 55 Investigating the recommended improvement of DMU 331, a Specialist poultry farm type with technical input efficiency of 0.14

DMU No	Peer proportion	Energy MJ	Eggs No
331	raw	17000000	1600000
321	*2.1*	*1100000*	*790000*
331	ideal	2400000	1600000

Figure 71 shows a detailed investigation into the energy inputs of DMU 331 relative to its peer. The peer uses proportionally less direct energy. Major result is that DMU 331 has major indirect energy inputs in the forms of bought feeds and purchased poultry that are virtually absent in the efficient peer. It could be that the flock change over lies just outside the reporting 12 months of DMU 321. It could be that the pullets are produced within the farm. Similarly for feed it could be that feed is produced within the farm, but then one would expect to see fertiliser inputs? For want of a good explanation it would seem wise to treat DMU 321 as an outlier and reconsider the efficiency of DMU 331.

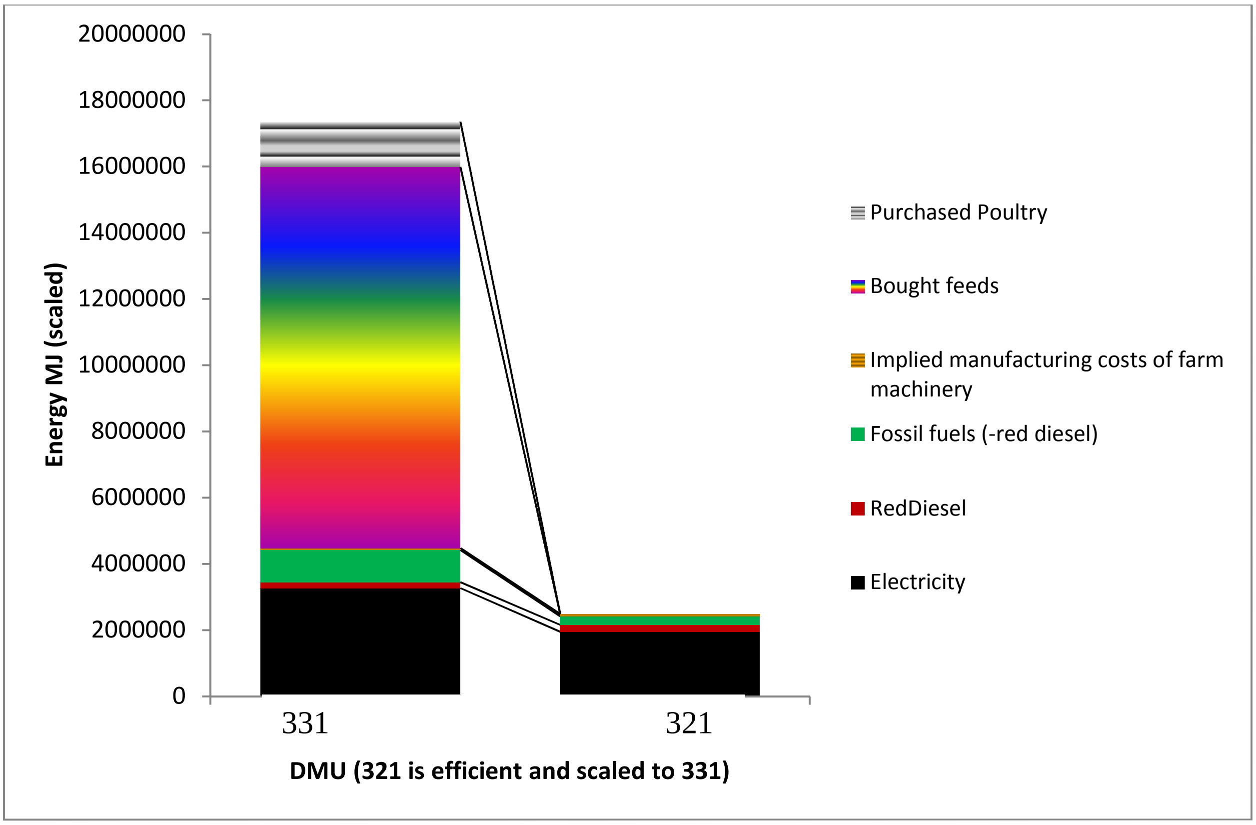


Figure 71 Detailed look at the Energy input into DMU 331 and its peer, showing both a proportional reduction in direct energy use and a major difference in indirect energy use

Table 56 Investigating the recommended improvement of DMU 145, a LFA grazing livestock farm type with technical input efficiency of 0.43

DMU No	Peer proportion	Energy MJ	Cattle kg lwt	Sheep kg lwt
145	raw	660000	19000	12000
332	*0.73*	*170000*	*18000*	*0*
47	*0.48*	*320000*	*13000*	*25000*
145	ideal	280000	19000	12000

Figure 72 shows a detailed investigation of the energy inputs into DMU 145 relative to its two peers. The results show a proportional reduction in all forms of energy. The peers seem to offer good benchmarks for DMU 145.

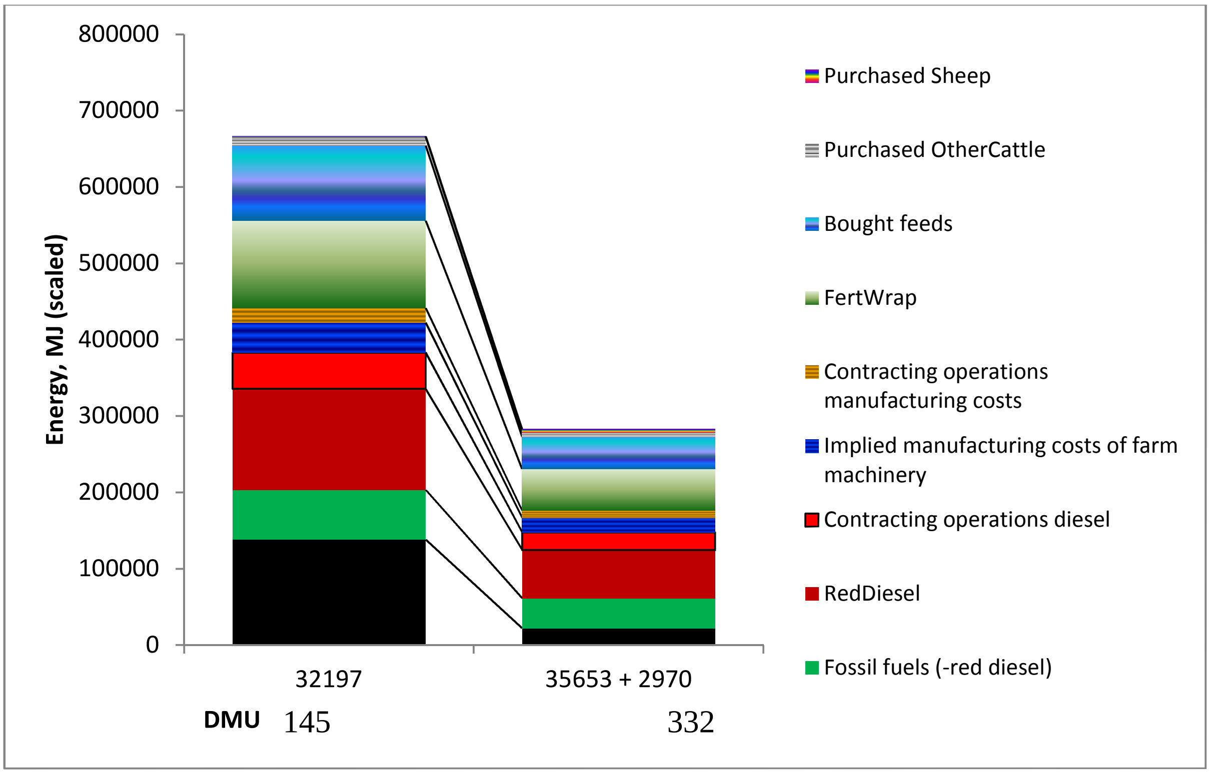


Figure 72 Detailed investigation into the energy inputs into DMU 145 relative to its peers, showing across the board proportional reduction in direct and indirect energy inputs

There is a lot of heterogeneity between farms and this shows up in Table 57 to Table 58. In these cases peers are chosen that introduce a new outputs and in these cases it may pay to re-analyse them to restrict the properties of the peer group, say no new outputs, but that may reduce discrimination to the point that these farms with these combinations of outputs become unique and thus relatively efficient by definition. Table 57 show an efficient dairy unit being constructed from dairy and grazing farms, which may not be reasonable as the 25t of wheat required is drawing in a lot of other arable products. A similar problem of a little arable sold is also bringing in other arable products in the lowland grazing case shown in Table 58.

Table 57 Investigating the recommended improvement of DMU 1709, a Dairy farm type with technical input efficiency of 0.52

DMU No	Peer proportion	Energy GJ	Milk hl	Cattle kg lwt	Sheep kg lwt	Cereals t	Oilseeds t	Legumes t
5	raw	4800	9300	45000	5900	25.0	0	0
332	*1.7*	*170*	*0*	*18000*	*0*	*0*	*0*	*0*
214	*0.98*	*2100*	*9500*	*11000*	*0*	*470*	*100*	*3.50*
47	*0.24*	*320*	*0*	*13000*	*25000*	*0*	*0*	*0*
5	ideal	2500	9300	45000	5900	470	100	3.44

Table 58 Investigating the recommended improvement of DMU 39538, a Lowland grazing livestock farm type with technical input efficiency of 0.41

DMU No	Peer proportion	Energy GJ	Cattle kg lwt	Sheep kg lwt	Cereals t	Oilseeds t	Legumes t
483	raw	1000	17000	32000	7.6	0	0
47	1.28	320	13000	25000	0	0	0
332	0.050	170	18000	0	0	0	0
441	0.001	99000	4800	0	7500	1100	750
483	ideal	440	17000	32000	7.6	1.2	0.8

Table 59 and Table 60 show this effect of multiple outputs in the peer group further. In both cases it is the same peer which draws in other outputs namely cattle and legumes in addition to the requisite cereals and oilseeds

Table 59 Investigating the recommended improvement of DMU48, a General cropping farm type with technical input efficiency of 0.54

DMU No	Peer proportion	Energy GJ	Cattle kg lwt	Cereals t	Oilseeds t	Legumes t
48	raw	2200	0	910	100	0
441	0.12	9900	4800	7500	1100	750
48	ideal	1200	580	910	140	91

Table 60 Investigating the recommended improvement of DMU 205, a Cereals farm type with technical input efficiency of 0.63

DMU No	Peer proportion	Energy GJ	Cattle kg lwt	Cereals t	Oilseeds t	Legumes t
205	raw	1400	0	330	110	0
441	0.094	9900	4800	7500	1100	750
205	ideal	9300	450	710	110	71

We next examine whether these efficiency scores can be explained by specific exogenous factors. Data Envelopment Analysis is not often used in this role but rather it is used to inform managers of efficiency problems. The DEA scores are not normally distributed so the best way to look for difference is to inspect visually the means and score distributions. Given sufficient data quantity and quality it is possible to use some statistical techniques, such as *Tobit* regression or non parametric ANOVA, but such approaches are not universally agreed in the literature.

Effect of organic status

One fascinating question is does organic agriculture deliver environmental benefits per unit of production when compared to non organic systems. Figure 73 shows the histogram plot of both farming systems and shows that whilst 2 (10%) of the organic farms are efficient, 17 (4.4%) of the non organic ones are as well. The two are similar and the population sizes are very different. This observation is confirmed by as statistical analysis of the technical input efficiency scores in Table 61, which is further broken into farm type in Table 62. Overall there is no consistent trend..

Given more data one could separate out the two groups and conduct separate DEA analysis and return each farm back into the joint population of farms as its ideal self within its sub group, thus all management inefficiencies have been removed. When DEA is conducted on this joint pool any differences in scores are a due entirely to the difference in policy between them

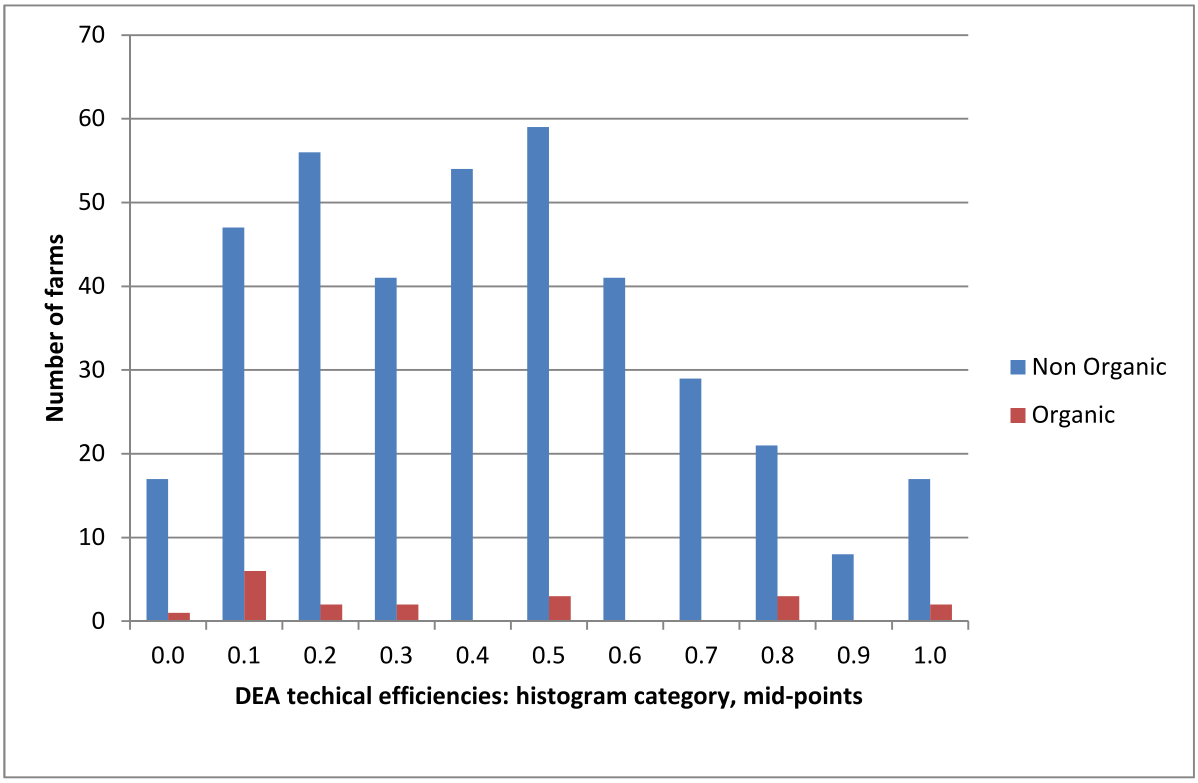


Figure 73 Histogram of technical efficiency scores of organic and non organic farms

Table 61 Statistical analysis of DEA technical input efficiency scores for organic and non-organic farms showing a slight advantage to non organic farms but from very different population sizes

Organic status	Count	Minimum	Mean	Maximum
FALSE	390	0.00	0.42	1.00
TRUE	19	0.02	0.40	1.00

Table 62 Statistical analysis of technical input efficiency scores of organic and non organic farms by farm types showing that organic might have the edge for dairy and LFA grazing livestock farm types

	Organic status			
	FALSE		TRUE	
Farm Type	count	mean	count	mean
Cereals	69	0.49		
Dairy	41	0.59	3	0.87
General cropping	62	0.62	3	0.37
Horticulture	98	0.30	1	0.10
LFA grazing livestock	14	0.33	2	0.88
Lowland grazing livestock	26	0.46	3	0.28
Mixed	30	0.45	3	0.29
Specialist pigs	16	0.22		
Specialist poultry	34	0.16	4	0.06

Effect of Farm Type

Another breakdown analysis of the DEA scores is to look at the effect of farm types. Figure 74 shows the histogram plots for farm types. Mixed farming is held in common to both charts. Specialist poultry and horticulture are dominated by lower scoring units probably because their outputs have not been readily characterised on a consistent criteria or have a very efficient outlier.

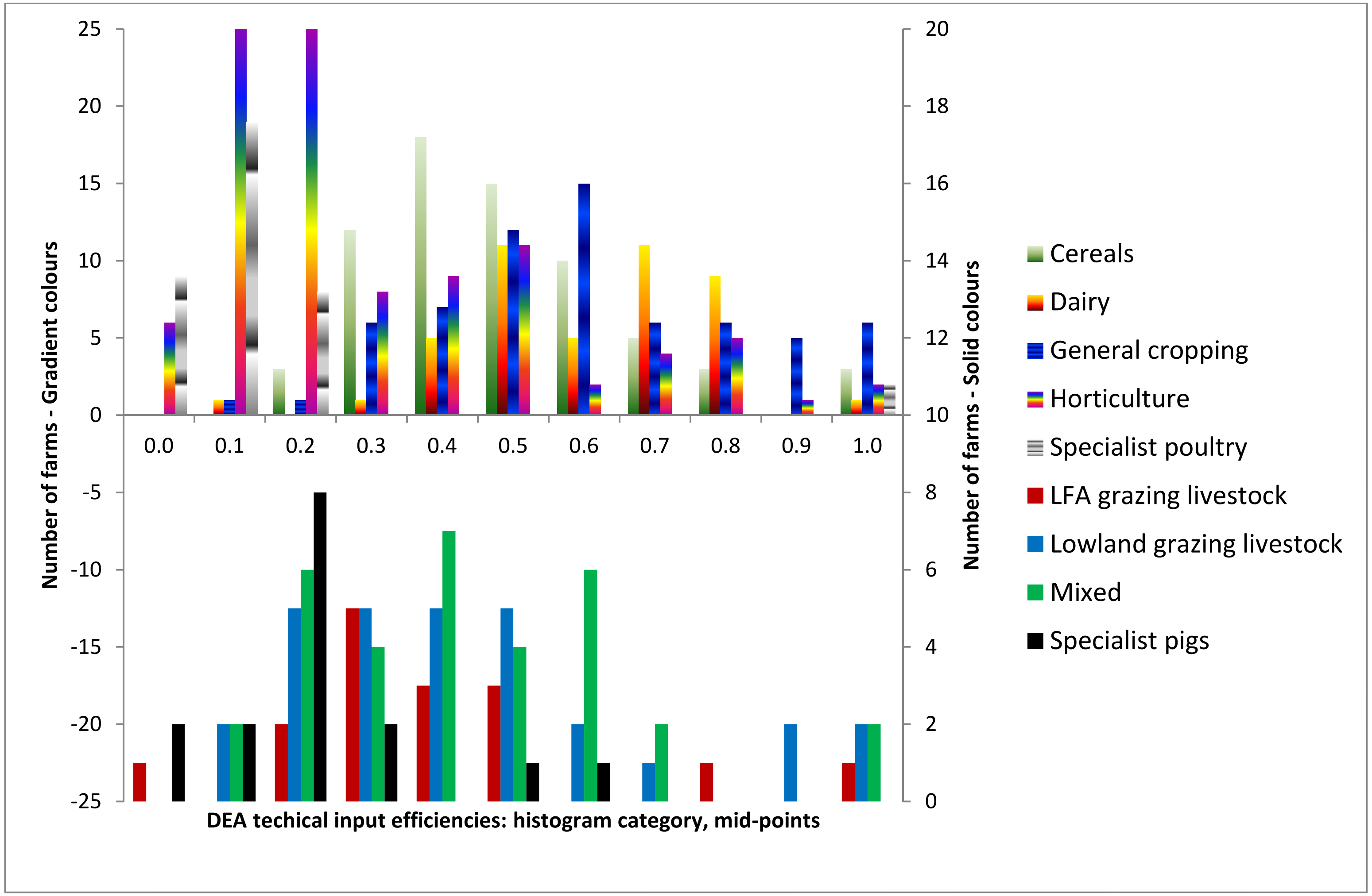


Figure 74 histogram plots of DEA scores for farm types

Table 63 shows the statistical analysis of the farm type DEA scores. All except dairy and specialist pigs have efficient examples. Farms that might be characterised by only one output, such as specialist pigs, specialist poultry and horticulture seem lower scoring on average.

Table 63 Statistical analysis of farm type DEA scores, showing that most farm types contain an efficient unit

Farm Type	count	Minimum	Mean	Maximum
Dairy	44	0.15	0.61	0.96
General cropping	65	0.09	0.60	1.00
Mixed	33	0.16	0.49	1.00
Cereals	69	0.12	0.44	1.00
LFA grazing livestock	16	0.12	0.43	1.00
Lowland grazing livestock	29	0.01	0.40	1.00
Horticulture	99	0.01	0.30	1.00
Specialist pigs	16	0.02	0.22	0.64
Specialist poultry	38	0.00	0.15	1.00

Effect of region

Another interesting question is whether region, as in latitude, makes a difference to efficiency scores.

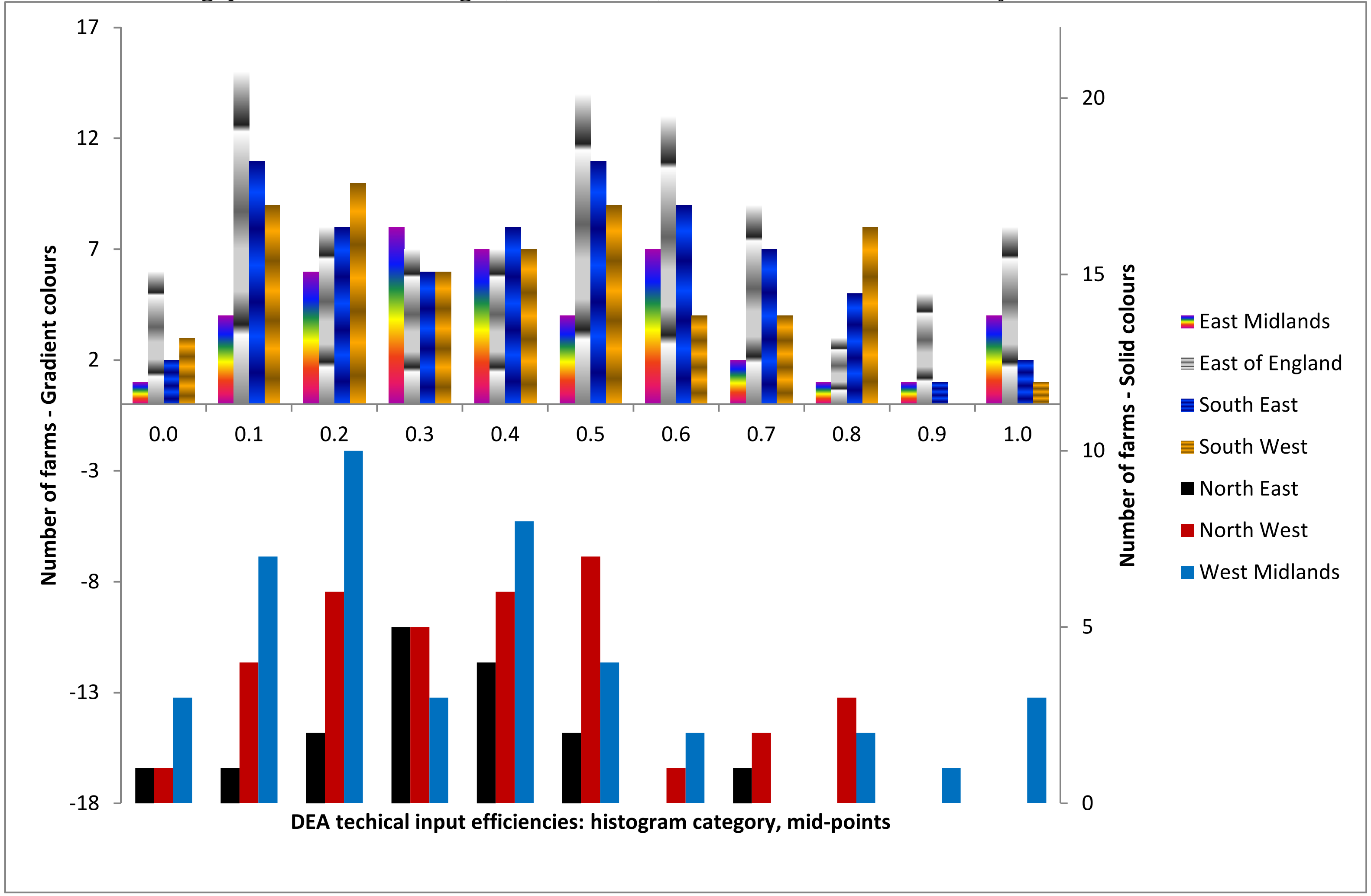


Figure 75 shows the histogram plots of DEA scores by region and reveals that most profiles are broadly similar with a few efficient farms and a majority of middling to poorer ones. East of England is noteworthy as it contains three peaks at 0.1, 0.5-0.6, and the frontier. The southwest is more uniform and neither the North East or North West contain efficient DMUs

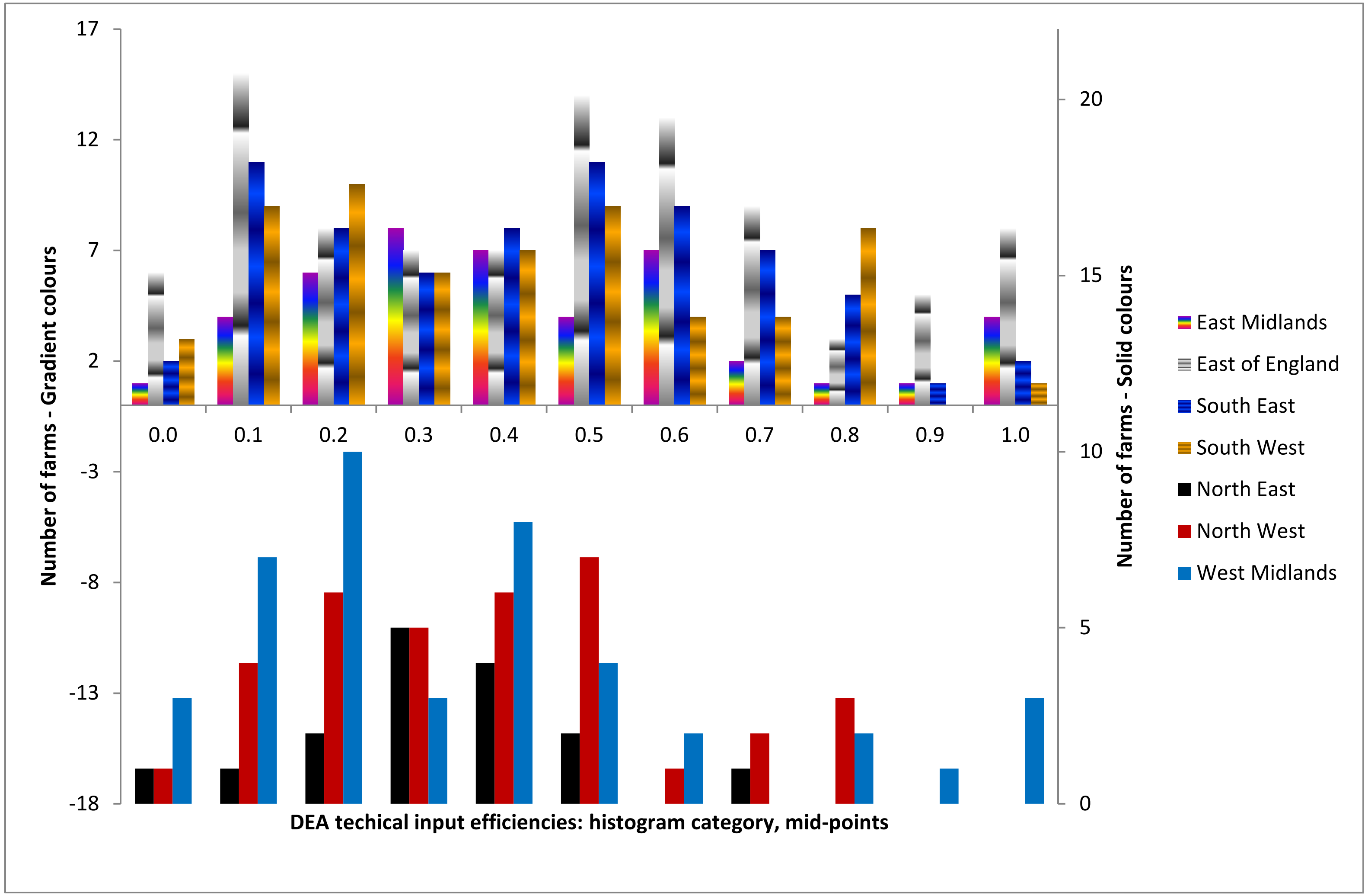


Figure 75 Histogram plots of DEA score by NUTS2 regions

Table 64 shows the statistical analysis of these scores and if there is as a trend it is very weak and slightly south east-north west trend. Table 65 further considers the effect of region on DEA score by considering the average DEA score of different farm types.

Table 64 shows the statistical analysis of these scores and if there is as a trend it is very weak and slightly south east-north west trend.

Row Labels	Count	Minimum	Mean	Maximum
East of England	95	0.00	0.47	1.00
Yorkshire & the Humber	44	0.04	0.45	1.00
East Midlands	45	0.04	0.44	1.00
South East	70	0.04	0.42	1.00
North East	16	0.02	0.40	1.00
South West	61	0.05	0.38	0.81
North West	35	0.01	0.36	1.00
West Midlands	43	0.01	0.33	0.70

Table 65 Mean DEA scores by region and farm type showing some evidence of different farm types being efficient in different regions (italics denotes the farm types with highest efficiency in that region)

Region	Count	Min.	Mean	Max.
East of England	**95**	**0.00**	**0.47**	**1.00**
Cereals	20	0.24	0.56	1.00
Dairy	2	0.44	0.54	0.65
General cropping	*25*	*0.33*	*0.66*	*1.00*
Horticulture	23	0.01	0.30	1.00
Lowland grazing livestock	3	0.14	0.59	1.00
Mixed	5	0.32	0.54	1.00
Specialist pigs	6	0.02	0.20	0.64
Specialist poultry	11	0.00	0.26	1.00
East Midlands	**45**	**0.04**	**0.45**	**1.00**
Cereals	9	0.28	0.52	0.77
Dairy	1	0.43	0.43	0.43
General cropping	13	0.31	0.61	1.00
Horticulture	13	0.07	0.23	0.50
LFA grazing livestock	1	0.31	0.31	0.31
Lowland grazing livestock	2	0.45	0.69	0.92
Mixed	*3*	*0.50*	*0.70*	*1.00*
Specialist pigs	2	0.04	0.14	0.25
Specialist poultry	1	0.10	0.10	0.10
South East	**70**	**0.04**	**0.42**	**1.00**
Cereals	16	0.16	0.49	0.76
Dairy	*3*	*0.47*	*0.67*	*0.83*
General cropping	6	0.09	0.54	0.75
Horticulture	27	0.04	0.36	1.00
Lowland grazing livestock	7	0.35	0.59	1.00
Mixed	5	0.16	0.40	0.66
Specialist pigs	2	0.19	0.23	0.26
Specialist poultry	4	0.06	0.09	0.12
South West	**61**	**0.02**	**0.40**	**1.00**
Cereals	4	0.30	0.55	1.00
Dairy	15	0.15	0.62	0.85
General cropping	4	0.23	0.42	0.75
Horticulture	15	0.06	0.31	0.83
LFA grazing livestock	*2*	*0.53*	*0.64*	*0.75*
Lowland grazing livestock	7	0.15	0.31	0.51
Mixed	7	0.12	0.39	0.61
Specialist pigs	1	0.18	0.18	0.18
Specialist poultry	6	0.02	0.08	0.15
Yorks &the Humber	**44**	**0.04**	**0.44**	**1.00**
Cereals	9	0.23	0.41	0.59
Dairy	*5*	*0.47*	*0.66*	*0.79*
General cropping	9	0.37	0.49	0.60
Horticulture	8	0.10	0.35	0.75
LFA grazing livestock	3	0.43	0.64	1.00
Lowland grazing livestock	1	0.42	0.42	0.42
Mixed	3	0.35	0.52	0.64
Specialist pigs	3	0.19	0.30	0.50
Specialist poultry	3	0.04	0.11	0.22
North East	**16**	**0.05**	**0.38**	**0.81**
Cereals	5	0.34	0.35	0.37
Dairy	1	0.38	0.55	0.81
LFA grazing livestock	*6*	*0.78*	*0.79*	*0.81*
Lowland grazing livestock	2	0.11	0.25	0.46
Mixed	1	0.26	0.28	0.29
Specialist poultry	1	0.15	0.15	0.15
North West	**35**	0.19	0.32	0.43
Cereals	2	0.05	0.11	0.18
Dairy	13	**0.01**	**0.36**	**1.00**
General cropping	2	0.28	0.37	0.43
Horticulture	*6*	*0.47*	*0.76*	*0.96*
LFA grazing livestock	3	0.27	0.65	1.00
Lowland grazing livestock	1	0.04	0.17	0.43
Mixed	3	0.40	0.40	0.40
Specialist poultry	5	0.12	0.39	0.86
West Midlands	**43**	0.14	0.32	0.65
Cereals	4	0.15	0.23	0.30
Dairy	4	0.01	0.12	0.21
General cropping	6	**0.01**	**0.33**	**0.70**
Horticulture	7	0.30	0.39	0.52
LFA grazing livestock	*1*	*0.70*	*0.70*	*0.70*
Lowland grazing livestock	6	0.01	0.27	0.48
Mixed	6	0.26	0.27	0.27
Specialist pigs	2	0.38	0.38	0.38
Specialist poultry	7	0.14	0.14	0.14

Effect of farm size and number of outputs

One question is possible about scale efficiencies. Do larger farms use their inputs and capital more effectively or not? It is hard to separate farm size from the effect of an increased number of different output steams on the DEA model. Table 66 shows the how the more different output streams a DMU has the greater its likely technical input efficiency. This is due to the increased chance that the DMU does not have peers with that combination and proportion of outputs. This is not evidence for any claims that generalisation is superior to specialisation *per se*.

Table 66 Technical input efficiency scores showing the effect increasing number of outputs on increasing efficiency score and correlated to increasing number of outputs is farm size.

No. of outputs	Count	Mean ha	Minimum	mean	Maximum
1	131	22	0.01	0.35	1.00
2	82	126	0.10	0.55	1.00
3	80	181	0.07	0.57	1.00
4	62	211	0.07	0.58	1.00
5	41	302	0.13	0.61	1.00
6	10	222	0.27	0.62	1.00
7	3	1200	0.55	0.85	1.00

To further explore the interplay between farm areas, number of output streams produced, and the technical input efficiency a scatter plot is shown in Figure 76 and a correlation analysis is shown in Table 67. There seems to be almost two populations. One population is below 500 ha and very variable and the other a space set above 500ha. There could be a weak case for efficiencies of scale. There is certainly not enough evidence to worry about the assumption of constant returns to scale assumed in selecting this DEA model. To get a better idea of any scale effects it would be necessary to aggregate the output streams into constant number perhaps using value. Given a large enough dataset one could look only at the subset of say 3 outputs and use *Tobit* regression to identify any trend.

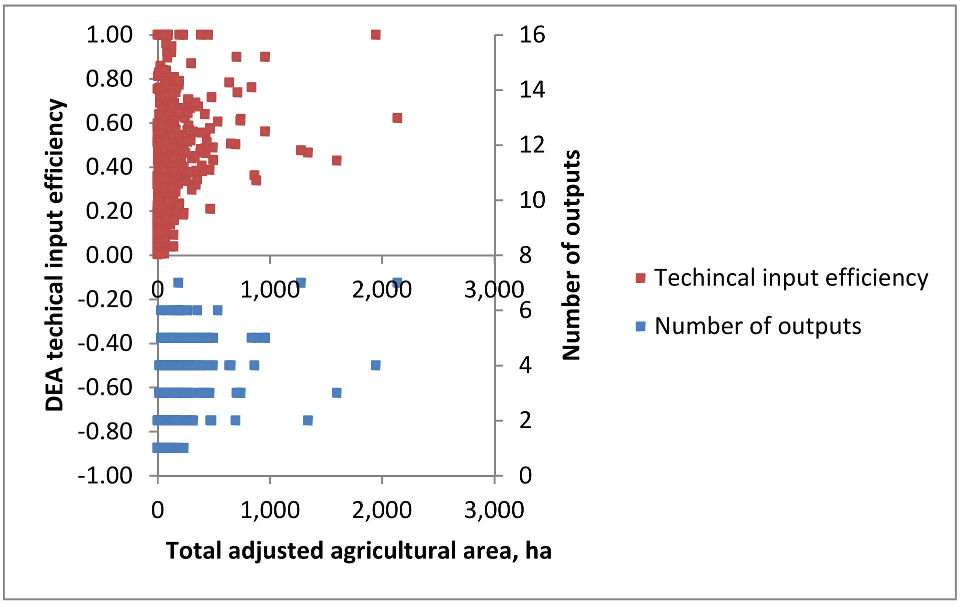


Figure 76 Scatter plots of the relationship between farm size and the number of different output stream produced and the technical input efficiency scores

Table 67 Correlation analysis of farm area, number of output streams, and technical input efficiency showing mild positive correlations.

	Total adjusted agricultural area, ha	*Number of outputs*	*Technical input efficiency*
Total adjusted agricultural area, ha	1		
Number of outputs	0.46	1	
Technical input efficiency	0.27	0.36	1

Concluding discussion on DEA

Data Envelopment Analysis has successfully discriminated relatively efficient from inefficient DMUs or farms. It has thus identified a set of relevant candidate benchmark farms and triggered a set of searching questions to account for the discrepancies between the inefficient farms and their peers. It is clear that the identification of unusual farms is a major outcome of the analysis. It maybe that the necessary simplifications of the number and measure of outputs, the approximations involved, or chance play a genuine role in making a DMU appear inefficient. It must also be remembered that farms are multi-functional in more ways than can be readily measured.

Various formulations of the DEA, criteria chosen and excluded outliers have been explored, whilst these changes affect some details in the results there is broad pattern of the efficient peers being common across formulations suggesting a degree of robustness.

Typically the DMUs or farms are dominated by a small group of efficient peers some distance away, the histograms often have two peeks one where the majority of the industry is and a smaller one set of efficient peers that are on the Pareto frontier. This may suggest that outliers play too big a role in the data, but that at least is a question that the DEA has revealed.

We have looked at farm size, region, type, and organic status as possible explanatory variables for the observed DEA scores. Some interesting effects due to farm type and organic status are suggested. However, these remain statistically elusive due to the limited amount of data available relative to the heterogeneity of the farms.

8. Future data collection

This subject will be considered in greater depth in a forthcoming project to enhance the UK GHG inventory (FFG0913) and this study can feed into that activity. The collection of data and subsequent empirical analysis always generates questions about data quality and provoking the wish that other questions had been asked and wondering if all questions were properly understood by the farmers and data collectors. It must be emphasised that we believe most data were recorded reliably.

Clarity of units

In the case of lime, it was apparent that some confusion had arisen about the data and whether the units should be t or kg. Such matters need to have robust method for sense-checking. It is also likely that some records of fertiliser use were erroneously recorded, e.g. the weight of a product rather than the component of interest (NPK). It may be more reliable to record actual product purchases by brand name, given that these are receipted items and a simple database can be created for all approved fertilisers sold in the UK that can contain environmental information, such as embedded energy and GHG emissions. Such an approach clearly needs to be tested by farmers and recorders.

Physical units

On some farms, the outputs were recorded only as cash values rather than physical ones. This particularly applied to horticulture, with its huge array of possible outputs from tomatoes to bedding plants. It would greatly help such analyses to have all major outputs recorded as physical units. For horticulture, we recognise that this is not easy, although it should be reasonably straightforward for food crops at least. On livestock farms that have live animals as inputs and outputs, we had to make best estimates of liveweights from some sparse data. It may not be feasible to expect all farmers to record liveweights at sale and purchase, but there must be cases where such data are known and could be provided. There is also the opportunity to relate deadweight values back to the farm of origin now that there are lifetime tagging systems in operation for some types of stock. Some farmers will also have contracts to produce, for example, broilers or lambs to a particular specification and this would be known and recorded, possible both as liveweight and deadweight. Future recording to involve a systematic screening of recorded data to eliminate spurious values and highlight inconsistencies. Examples could be animal production without feed, or excessively high fertiliser application rates.

Contracting

This is evidently a growing feature of contemporary farming. It caused some difficulty in analysing the data and must be a major source of uncertainty. There is a gulf of knowledge between actual farm records for fuel use and what a contractor may have used. A limited range of questions were asked and varied in the accuracy with which fuel use could be estimated. One question that was omitted was whether fuel used by contractors was taken from the farm tank or provided by the contractors. We took the view that they would usually provide their own. Activities like spraying per ha can be estimated reasonably accurately, but others like ploughing per hour depend much more on the field conditions as well as speed of the operation. The most open ended were ones like manure management operations per hour, which could include a gang of any number with any amount of equipment. Future questions should be more targeted, but there is also a need to get good activity data from contractors themselves. There are at least two aspects to this: one is to get fuel records for the specific farm being scrutinised from the specific contractor. The other is to engage with contactors more widely to get better generic data, e.g. through the National Association of Agricultural Contractors.

Overheads and non-farming enterprises

It is very likely that most energy gets used in actual farming activities. There were, however, some uses of fuels that seemed surprisingly high. These included electricity on LFA grazing farms and road diesel or petrol on most sorts of farms. Some of this could be accounted for by the farm office or possibly other activities that are not directly concerned with agricultural commodity production. Greater insight into energy use needs some of these features to be better understood and quantified. Sub-metering of electricity is one simple technical approach to obtain better quality data.

9. Concluding discussion

This analysis has delivered an invaluable baseline estimate of actual energy use and GHG emissions on contemporary commercial farms in England. Differences between some farm types are apparent, but not surprising. The effects of scale were limited to poultry and horticulture. Part of the uncertainty associated with the estimates of mean energy use and GHG emissions comes from the mixture of enterprises on farms within robust farm types. Cereals farms may grow other crops or support a variety of animal enterprises.

The use of two allocation methods delivered very useful results and allowed the energy use and GHG emissions associated with particular commodities to be quantified. These results were in broad agreement with those derived by LCA. It was also evident in these analyses that there was much scatter in the environmental performance of farms. It must be acknowledged that the methods are not perfect: the ideal would be to perform an in-depth analysis of each farm with many questions being asked of farmers to help explain results. The estimates for some animal outputs are inevitably less certain than most crops. Liveweight production is relatively hard to quantify with the data available, e.g. animal weights were not known, but estimated from prices, the diversity of purchases, sales and breeding is considerable and opportunism seems to play a large role in some enterprises. So, the uncertainty of the functional unit as a unit of liveweight is substantial. This is clearly in contrast to milk and eggs, which are simply recorded as such.

This scatter, together with that in economic performance, must underlie the somewhat disappointing relationships between farm financial performance and energy use or GHG emissions. The mere existence of these ranges shows that there is scope for improvement in both financial and environmental performance and that there is no apparent barrier for both to be achievable in harmony. The significant, although weak, negative slope for milk production and energy accords with reports from consultancies of increased profitability and environmental performance in dairying. DEA has shown considerable potential as a tool for analysing farm performance, although having a larger sample would have been helpful. At least, it is a powerful tool for rapidly identifying outliers, but the technique clearly has the power to go far beyond this.

There may be many reasons for the variations, such as soil texture, rainfall, topography, farmer type, degree of capitalisation, livestock breeds, machinery age or use the of contractors. It must also be remembered that this analysis is a snapshot of one farming year. Between years, there may be yield and price variation as well as capital investments etc. More detail is needed to understand why the variation occurs and data from more years are needed to track changes.

In some cases, the allocation of energy use was slightly problematic in that high allocations of, say, electricity or a heating fuel were made on some farms in farm types where little electricity use might be expected for the farm operations themselves, e.g. LFA grazing. This suggests that energy used in the office could be distorting what is used for the actual farm activities. Nonetheless, this type of energy use is part of an overall farm activity, but not one that is usually included in LCA studies.

One area in which there was not enough data to make a substantial analysis was of organic production. This was because of the very limited data available, with small numbers of farms of different types and relatively high diversity of outputs. There is no fundamental reason why the analysis can not be applied to organic systems; it just needs more data.

The recording of energy related data on farms is essential for the future, as it should enable improvements to be made. The improved UK agricultural GHG inventory will depend on high quality activity data as well as improved and more specific emission factors. The experience gained in this study will be invaluable in identifying what level of detail of data is needed. Future data requirements include a better understanding of contractor work rates and fuel use per unit area and per unit time, fertiliser and pesticide use by brand name, enhancing the quality of the physical inputs and outputs of farms, especially animal liveweights and horticultural produce being recorded by weight rather than by value. Future recording to involve a systematic screening of recorded data to eliminate spurious values and highlight inconsistencies. Examples could be animal production without feed or excessively high fertiliser application rates. A larger sample of organic farms is also needed to allow a conclusive analysis to be made.

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