Greenhouse gas emission intensities and economic efficiency in crop production: a systems analysis of 95 farms

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Abstract

To increase food production while mitigating climate change, cropping systems in the future will need to reduce greenhouse gas emission per unit of production. We conducted an analysis of 95 arable farms in Norway to calculate farm scale emissions of greenhouse gases, expressed both as CO_2eq per unit area, and CO_2eq per kg DM produced and to describe relationships between the farms' GHG intensities and their economic efficiencies (gross margin). The study included: 1) design of a farm scale model for net GHG emission from crop production systems; 2) establishing a consistent farm scale data set for the farms with required soil, weather, and farm operation data; 3) a stochastic simulation of the variation in the sources of GHG emissions intensities,and sensitivity analysis of selected parameters and equations on GHG emission intensities; and 4) describing relationships between GHG emission intensities and gross margins on farms. Among small seed and grain crops the variation in GHG emissions per kg DM was highest in oilseed (emission intensity at the 75th percentile level was 1.9 times higher than at the 25th percentile). For barley, oats, spring wheat, and winter wheat, emissions per kg DM at the 75th percentile levels were between 1.4 to 1.6 times higher than those at the 25th percentiles. Similar trends were observed for emissions per unit land area. Invariably soil N_2O emission was the largest source of GHG emissions, accounting for almost half of the emissions. The second largest source was the off farm manufacturing of inputs (~25%). Except for the oilseed crop, in which soil carbon (C) change contributed least, the on farm emissions due to fuel use contributed least to the total GHG intensities (~10%). The soil C change contributed most to the variability in GHG emission intensities among farms in all crops, and among the sensitivity elasticities the highest one was related to environmental impacts on soil C change. The high variation in GHG intensities evident in our study implies the potential for significant mitigation of GHG emissions. The GHG emissions per kg DM (intensity) decreased with increasing gross margin in grain and oilseed crops, suggesting that crop producers have economic incentives to reduce GHG emissions.

Keywords: farm scale; crop production; soil C; soil N_2O; stochastic simulation; profitability;

1. Introduction

Arable farms can have significant environmental impacts (e.g. Stoate et al., 2001), including the emission of air pollutants and greenhouse gases (Snyder et al., 2009). In total, agriculture emits about 5.1 and 6.1 Pg CO_2eq year^{-1}, accounting for 10 – 12% of global GHG emissions. These emissions are mainly in the form of methane (CH_4), mostly from animal production (3.3 Pg CO_2eq year^{-1}); nitrous oxide (N_2O), mostly from arable land (2.8 Pg CO_2eq year^{-1}); and carbon dioxide (CO_2) mostly from soil carbon changes and energy use (0.04 Pg CO_2eq year^{-1})(Smith et al., 2007a). There is a growing consensus that global GHG emissions will need to be substantially reduced to minimize risk of unpleasant climate change (e.g. Godfray et al., 2011). But these emission reductions must take place in a world where its population is expected to reach 8900 million by 2050 and with a food demand expected to rise by 70% (FAO, 2006). Thus, lowering of worlds GHG emission by reducing food and feed production is not an option.

Being a part of the international society, the Norwegian Parliament has made a compromise agreement on the target for national GHG emissions that will require Norway to reduce emissions by 15 to 17 Gg of CO_2eq by 2020 (30 % reduction from 1990). The agricultural sector is required to contribute 1.2 Gg of CO_2eq to this reduction, which is more than 20 % of the sector's current emission (Climate and Pollution Agency, 2010). The Ministry of Agriculture and Food (2009) states that a significant part of the agricultural contribution is to be achieved through reduced use of nitrogen (N) fertiliser in crop production. Other suggested measures are reduced tillage and use of catch crops. Although the population growth rate in Norway is smaller than the global one, a reduction in food and feed production may not be a preferred option. The nation's population is estimated to grow by about 20% by 2060 (Statistics Norway, 2010). Thus, reductions in GHG emissions must be found through practices that do not lower food and feed production.

Total GHG emissions from agriculture are influenced by management practices on the farm. Because of the myriad interactions, however, the effects of single changes, e.g. lower fertilisation rates or reduced tillage, on a farm's total GHG emission cannot be determined without a holistic analysis at the farm level (Janzen et al. 2006). This challenge has in many countries fostered the development of decision support tools such as simulation models or simpler calculators for estimation of GHG emission at farm level (e.g. Flessa et al., 2005; Shils et al., 2007; Berry et al., 2008). However, management decisions at the farm level are generally motivated by maximising profit, which involves improving efficiency and lowering costs, i.e. maximising the difference between output and input. In theory, farms with high outputs (yields) relative to input factors (fertilisers, pesticides, fuel etc.) are expected to have low GHG emission intensities, at least per kg DM yield. On an area basis this relationship may not be apparent, as high input farms may have a high profit and also a high GHG emission per ha.

To clarify these relationships, we analyzed 95 Norwegian farms with field crop production. Our objectives were: 1) to estimate the farm scale GHG emissions intensities by using adequate models encompassing the farms' natural resource bases and operational data, 2) to quantify the variation in GHG emissions among Norwegian crop production farms, and 3) to estimate the relationships between the farms' GHG intensities and their profits. The broader goal was to identify opportunities for mitigating GHG emissions from crop production farms, and provide insights pertinent to agricultural policy makers in fulfilling the goals of emission reduction as specified by the Climate and Pollution Agency (2010).

2. Materials and methods

This study has four main components: 1) design of a farm scale model for net GHG emission from crop production systems; 2) establishing a consistent farm scale dataset for 95 crop production farms with respect to soil, weather, and farm operation data, using 2008 data; 3) a stochastic probability analysis of the farm population's generalised distribution of the sources of GHG emissions intensities, and a sensitivity analysis of selected key parameters and equations on the GHG emissions intensities; and 4) describing relationships between GHG emissions intensities and gross margins on farms.

2.1. Model overview

We developed an empirical farm scale model of net GHG emission from crop production systems, with a yearly time-step, based on the Intergovernmental Panel on Climate Change methodology (IPCC 2006), including soil carbon (C) changes. The following GHG sources are considered: on-farm CO_2 emissions or removal (sequestration) due to soil C changes; on-farm N_2O emissions from soils; off-farm N_2O emissions from N leaching, run-off and volatilization (indirect N_2O emissions); CO_2 emissions from energy used on-farm; and off-farm CO_2 and N_2O emissions from inputs. All gas emissions were expressed as CO_2 eq to account for the global warming potential of the respective gases for a 100-year time horizon: kg CO_2 eq = N_2O kg × 298 + CO_2 kg × 1 (IPCC 2007). To report GHG intensities, emissions are expressed as kg CO_2 eq kg^{-1} DM yield and kg CO_2 eq ha^{-1}.

2.1.1. Soil carbon change

The estimates of soil carbon change are based upon the Introductory Carbon Balance Model (ICBM) of Andrén et al. (2004). The ICBM is a two-component model, comprising young (Y) and old (O) soil carbon, with decay constants of k_Y and k_O, respectively, and the following parameters: crop residue input (i), humification factor (h), and a combined index of external influences (r_e). The model, which has a time step of one year, requires initial values of Y and O, the latter amounting to 93 per cent of the total top soil C. Total C in residues of various crops were estimated by allometric functions of harvested crop yields (Andrén et al. 2004). For our model runs, $k_Y = 0.8$, $k_O = 0.007$ $year^{-1}$, and h = 0.13 dimensionless. The external influences on the decomposition rates (r_e) were combined in a farm specific multiplicative index describing the relative effects of soil moisture (r_w)

and soil temperature (r_T) indices (values from 0.0 to 1.0), and a cultivation factor (r_c). The indices and their product (r_e) were all estimated on a daily basis and averaged over the year. The constant r_c (dimensionless) = 0.9 for conventional tillage and 0.8 for reduced tillage. The proportions of arable land in cereal production, and of farms with arable crops only have been continuously increasing in Norway during the last 60 years (Statistics Norway, 2010). Over time, the rate of soil carbon loss gradually declines in a continuously arable crop system when following a mixed farming system (Riley and Bakkegard, 2006). Thus, we used the ICBM's estimate of soil carbon change in the 30th year of continuous arable cropping. For farm specific input variables, i and of r_e, data of the year 2008 were applied throughout the 30 year period.

2.1.2. Nitrous oxide (N_2O) emission

Estimates of N_2O emissions are based upon the IPCC (2006) emission factor of 0.01 of the total N input (Ntot), defined as the sum of nitrogen fertiliser applied, crop residual N, and mineralised nitrogen. The residue N is calculated as the sum of above ground and below ground residue N (Janzen et al., 2003). The mineralised N is derived from an assumed N:C ratio of soil organic matter of 0.1 (Little et al., 2009).

The N_2O emission is strongly affected by soil moisture and temperature conditions (Watts and Hanks, 1978). The functional relationships are often considered to be linear and together multiplicative (e.g. Li et al., 1992; Smith et al., 2007b). Functional relationships between soil moisture expressed as water filled pore space of top soil (% WFPS) as well as soil temperature at 30 cm depth (ts30 ^{o}C) were derived from Sozanska (1999, 2001). The model of Sozanska (2001) was not directly applicable to our approach, as it does not take into account the differences in crop residue N among the crops.

The model of Sozanska (2001) was run with an orthogonal data set of WFPS, ts30, and N fertilisation rates using the equation: $\ln(N_2O) = -2.7 + 0.60\ln(N) + 0.61\ln(WFPS) + 0.35ts30 - 0.99A$, where N_2O = N_2O emission (kg ha^{-1}y^{-1}), N = nitrogen input (kg ha^{-1}year^{-1}), and 'A' = land use type (A =

2 for tilled land). Linear regression equations were derived for the individual, relative effects of WFPS and ts30 on N_2O emission with unit values (1.00) for WFPS = 49.24 per cent and ts30 = 13.22 ^{o}C, based on the global N_2O experimental data set of Sozanska (1999). The equations were:

$$\mathrm{WFPS\_I} = 0.4573 + 0.01102 \times \mathrm{WFPS}$$

$$\mathrm{ts30\_I} = 0.5862 + 0.03130 \times \mathrm{ts30}$$

where WFPS_I and ts30_I are the relative effects of WFPS and ts30, respectively, on N_2O emission.

N_2O emission varies during the year with the highest fluxes often occurring after fertiliser application (e.g. Drury et al. 2006, Mosier et al. 2006). The seasonal (j) variation in N_2O emission was taken into account by dividing the year into four seasons, spring April-May, summer June-August, autumn September-November, and winter December-March with their respective values of Ntot_j, $\mathrm{WFPS\_I}_j$, and $\mathrm{ts30\_I}_j$. Thus, the global IPCC N_2O emission factor could be adjusted to the specific levels of the driving variables of the following equation:

$$\mathrm{N_2O}\,(\mathrm{kg\,ha^{-1}year^{-1}}) = \sum_{j=1}^{4} 0.01(\mathrm{Ntot}_j)(\mathrm{WFPS\_I}_j)(\mathrm{ts30\_I}_j)$$

This approach, although approximal, allows for a simple description of the seasonal interaction between the fertilisation rate and the current soil moisture and temperature conditions.

The emissions due to leaching and runoff were calculated according to Rochette et al. (2008). The leaching fraction of total N (applied in fertiliser, residues, mineralisation) was, according to Rochette et al. (2008), set to 0.3, and the emission factor for leaching and runoff was set to 0.0075 kg N_2O-N $(\mathrm{kgN})^{-1}$ (IPCC 2006). Emissions due to volatilisation were calculated using a volatilisation fraction of 0.1 and an emission factor of 0.01.

2.1.3. Energy use and manufacturing of purchased farm inputs

Direct emission from diesel fuel was set to 2.7 kg CO_2 eq per litre (Australian Government, 2006). Indirect emission factors for purchased inputs were: diesel fuel 0.3 kg CO_2 eq per litre (Australian Government, 2006), electric power 0.11 kg CO_2 eq per kWh (Nordic mean; Berglund et al., 2009), nitrogen-based compound fertilisers 4 kg CO_2 eq per kg N (DNV, 2010), and pesticides 0.069 kg CO_2 eq per MJ pesticide energy (Williams et al., 2006).

2.2. Data input

2.2.1. Farm operational data

Effects of management practices on farm-scale GHG emissions for 2008 were explored by combining the model with data from the Norwegian Farm Accountancy Survey (NILF 2009). This survey is a farm-level panel data set, collected by the Norwegian Agricultural Economics Institute. It includes agronomic and economic data annually collected from about 1,000 farms. The survey includes 95 crop farms, all without animals. Of these, 70 grew barley (*Hordeum vulgare*),, 63 oats (*Avena sativa*), 51 spring wheat (*Triticum aestivum*), 35 winter wheat (*Triticum aestivum*), 20 spring oilseed (*Brassica napus* var. o*leifera* and *Brassica rapa* var. *oleifera*), 9 potato (*Solanum tuberosum*), and 7 rye (*Secale cereale*). Data used included: yields, mineral fertilisers, pesticides, tillage (reduced or conventional), fuel and electricity, straw removal, and gross margin (table 1).

INSERT TABLE 1 HERE

The crop yields (kg ha^{-1}) of 2008 are specified in the Norwegian Farm Accountancy Survey (NILF 2009) for barley, oats, wheat, winter rye, spring oilseeds, and potatoes. The survey does not differentiate between spring and winter wheat areas and yields. For all farms, data for winter wheat area were accessible from the Norwegian Agricultural Authority, and we estimated the specific yields by assuming that the farms' winter wheat yields were 1.38 times the farms' spring wheat yields, based on the 2008 advisory performance trials weighted by the individual cultivars' market shares

(Åssveen et al. 2009). The farm specific cost of mineral fertiliser of 2008 is available from the accountancy survey (NILF 2009). The on-farm distribution of mineral fertiliser among the crops was based on relative factors related to the Norwegian recommendations of N levels and the typical fertiliser types of the crops: barley 1.0; oats 0.9; spring wheat 1.2; winter wheat 1.5; rye 1.3; oilseeds 1.2; potatoes 1.5. Based on these relative factors, the crop areas (ha) and the typical mineral fertiliser types and their prices, the farm specific levels of nitrogen-based compound fertilisers applied were estimated for the different crops. The farm specific cost of pesticides in 2008 was available from the accountancy survey (NILF 2009). The distribution of the on farm cost to different crops was calculated by use of relative weighting factors: barley 1.00; oats 0.51; spring wheat 1.05; winter wheat 1.71; rye 1.71; oilseeds 1.65; potatoes 4.99. This weighting was derived by using the most typical types and amounts (relative area sprayed) for each crop by: glyphosate, other herbicides, pesticides, insecticides, growth regulators (cereals), and desiccants (potatoes), their mean rate of application and their prices according to a survey conducted in 2008 (Aarstad et al. 2009). The MJ pesticide energy per crop was estimated according to Audsley et al. (2009). Farms receiving regional payments for acreage under reduced tillage are specified in the accountancy survey (NILF 2009). The distribution of a farm's area with reduced tillage among the crops was done as follows (based on agronomic experience): first priority was given to spring cereals, second to (spring) oilseeds, and third to (winter) rye and winter wheat. The farm costs of fuel and electricity (NILF 2009) were distributed to the crops according to their areas, and the energy and fuel use was calculated by dividing with the 2008 average consumer price of electricity (Statistics Norway 2010) and the 2008 average on-farm price of fuel (BFJ 2010), respectively. The amount of straw sold from the farm is specified in the accountancy survey (NILF 2009), and was apportioned to the crops according to their areas.

The gross margin was calculated as the gross income minus production costs for each of the crops. The on-farm gross incomes exclusive of governmental payments are specified for each of the crops except for spring and winter wheat (NILF 2009). For farms with both spring and winter wheat, the gross incomes were related to the proportion of the yields. The farms’ production costs were distributed to each of the crops in relation to the amounts of inputs used. In addition to the inputs of fertiliser and pesticides, the costs of seeds were distributed by using relative weighting factors: barley 1.0; oats 1.12; spring wheat 1.30; winter wheat 1.17; rye 1.25; oilseeds 0.34 according to NILF (2008). The cost of seed potatoes was specified (NILF 2009).

2.2.2. Natural resource base data and their processing

Soil survey records of the 95 farms, located in the southeastern and central parts of the country from 59 to 64 °N, were provided by The Norwegian Forest and Landscape Institute for homogenous soil type mapping units down to 0.4 ha; each with descriptions of top soil and subsoil layers such as: layer depth, texture of particles < 2 mm, content of organic matter, gravel, and bulk density. From these records soil moisture capacities were derived by pedotransfer functions of Riley (1996) for: saturation to field capacity (pF 0.0 to 2.0), readily plant available water (pF 2.0 to 3.0), and less available water (pF 3.0 to 4.2), for each of six soil layers with depths of: 15, 10, 10, 10, 10, and 10 cm, respectively, sequentially from soil surface down to a rooting depth of 65 cm. Top soil was defined as the two uppermost layers (25 cm). The parameters ‘U’ and ‘α’ of Ritchie’s (1972) soil moisture model were derived from soil texture according to Skjelvåg (1981). All these characteristics as well as soil carbon content of top soil (25 cm) at each soil type mapping units were averaged to farm level by weighting according to area of each mapping unit at the farm.

The 2008 daily weather data from the network of The Norwegian Meteorological Institute were interpolated to each farm’s geographic midpoint and altitude for: diurnal mean temperature, relative air humidity, wind speed, cloud cover, and precipitation (Tveito et al. 2005). Global radiation was calculated on the basis of extraterrestrial radiation, daily clear sky radiation, and reduction due to cloud cover. Daily estimates of potential evapotranspiration were calculated according to Penman (1956).

Soil moisture conditions were estimated for soil water evaporation and plant evapotranspiration separately (Ritchie, 1972); and a further expansion to include a soil moisture budget (Skjelvåg, 1981). The combined model calculated potential and actual evapotranspiration from plants on the basis of potential evapotranspiration, leaf area index (LAI), and the content of plant readily and less available moisture in the current root zone. Soil water filled up by precipitation to more than half the total pore volume above field capacity, was allowed to remain in this fraction above field capacity for a maximum of four days; and for two days only with filling up to half or less of the pore volume between saturation and field capacity.

The plant part of the soil moisture model was configured for 'Avle' spring wheat in the five southernmost counties and for 'Thule' spring barley in the four northern ones. Sowing date was determined by the soil moisture model, starting when the current seven day diurnal mean temperature passed 5°C for the first time after April 1, assuming soil moisture of the top soil at field capacity on this day; and choosing as sowing day the first time soil moisture content passed to less than 80 per cent of field capacity (Skjelvåg, 1986). Day of emergence was set to a temperature sum 100 d °C above 0 °C in both species. Separate functions, derived during crop modelling work (Bleken, 2001), were applied for the subsequent phases to heading and physiological (yellow) ripeness.

The LAI was set to 0.1 at day of emergence, allowed to increase exponentially to a typical value of 4.0 at heading; the level at which it remained until twenty days before yellow ripeness, after which it was reduced linearly with time to a typical value of 2.0 of a canopy with yellow stems and leaves. From day of yellow ripeness it was kept at 2.0 until the end of the year, assuming that stubble and straw remained on the field after harvesting. Interception of precipitation during this period was calculated according to Chang et al. (2010), in order to handle the separation of evaporation from soil and plant material. From January 1st to day of emergence LAI was kept at zero. Root depth was set to 5 cm at day of emergence, from which it was increased linearly with time to 65 cm at day of heading. After day of harvesting, assumed to occur fourteen days after day of yellow ripeness, soil moisture reduction was due only to soil evaporation from underneath the mulch of stubble and straw

From these data the daily values and annual means of $r_w \times r_T$ of ICBM were calculated. However, the model has been developed on field experiment data from the period 1956-1990 at Ultuna, Sweden, and $r_w \times r_T$ was normalised to 1.0 for this data set. Thus, the same procedures and software were applied with weather and soil records from the experimental field, with exception of extreme treatments such as fallow or addition of sawdust (Kirchmann and Gerzabeck, 1999). This yielded a 35 year mean of $r_w \times r_T$ at 0.066 with a range from 0.030 in 1959 to 0.105 in 1961. Given the normalisation of $r_w \times r_T$ to 1.0 for this data set, the calculated $r_w \times r_T$ values of the 95 individual farms in year 2008 were adjusted by dividing them by the 35 year mean of 0.066.

2.3. Stochastic simulations, sensitivity tests, and statistical analyses

Due to the sparse data set, irregularities in the distributions were smoothed, assuming that the population follows a smooth distribution (Hardaker and Lien 2005). Thus, the distributions and the expected values of the input on soil, weather, and farm operational data and their intercorrelations were estimated using a multivariate empirical array function (Richardson et al. 2000) (Table 1). The variation among farms in gross margin was from 46 to 59 % of the mean. The variation in the input yields and N input were lower, on average, by 31 and 38 % of the mean, respectively, whereas the variation in pesticide use and fuel was higher – on average 63 and 56 % of the mean, respectively. The SOC variation among the farms was on average 19 %, whereas the variation in $r_w \times r_T$ on average was 13 %. The distribution of each variable is assumed to be a linearly smoothed empirical distribution function. The sampling method used was Latin Hypercube and the number of iterations was 1000 – one iteration representing one draw in a sequence of the random variables. This approach accounts for stochastic dependency among input variables. On the basis of this analysis the probability distributions of key output variables were estimated. For the rye and potato, data were too limited for this procedure.

Linear relationships for each type of crop were established between GHG emission intensities per unit land area or unit produce and economic efficiency (gross margin of each crop) on farm scale. Further, the corresponding relationships to individual inputs were investigated.

A sensitivity analysis of the effect of errors on the GHG emissions intensities of key model parameters and variables was conducted using the SIMETAR software (Richardson et al. 2004). The selected key model parameters and variables perceived to be most important were: the IPCC (2006) N_2O emission factor, the amount of residue N, the amount of mineral fertiliser N, the yearly $r_w \times r_T$, the amount of residue C, the reduced tillage factor, and the year of continuous cropping. The chosen range to illustrate the direction and magnitude of influence of the key model parameters and variables was from 0.85 to 1.15 of their respective values. In steps of 0.05 of the key model parameters and variables, the sensitivity analysis calculated mean values of the GHG intensities based on 1000 iterations per step. We further calculated mean sensitivity elasticities expressed by the slope of a linear regression of relative values of key model parameters or variables and the relative GHG emission intensities.

3. Results

Based on data from 2008 the expected values of GHG intensities were: 2442 kg CO_2 eq ha^{-1} and 0.62 kg CO_2 eq kg^{-1} DM in barley, 2483 and 0.64 in oats, 2960 and 0.81 in spring wheat, 3505 and 0.70 in winter wheat, and 2551 and 1.28 in oilseed (Table 2). Invariably, soil N_2O emission contributed most to total GHG emissions, and was the largest source both on area and on kg DM basis, accounting for 45 to 49 % of the emissions (Fig. 3, and Fig. 4). The second largest source was the off farm manufacturing of inputs, accounting for 23 to 27 % of the emissions. Except for oilseed where soil C change contributed least, the on farm emissions due to fuel use contributed least to the total GHG intensities accounting for 10 to 14% of the emissions.

INSERT TABLE 2 HERE

There was a large variation in estimated GHG emissions intensities among farms (Fig. 1, Fig. 2). Among the small seed and grain crops the variation in GHG emission per unit land area was somewhat larger in oilseed with 1.5 times higher emission at the 75th percentile level than at the 25th percentile, a difference of 910 kg CO_2 eq ha^{-1} (Fig. 1A). In barley, oats, spring wheat, and winter wheat, the 75th percentile levels were between 1.3 to 1.4 times higher than those at the 25th percentiles; the differences were 830, 740, 860, and 870 kg CO_2 eq ha^{-1}, respectively. The difference between the 25th and the 75th percentile levels was estimated to be 950 kg CO_2 eq ha^{-1} in rye, and the estimated 1520 kg CO_2 eq ha^{-1} in potatoes was much greater than the corresponding differences in oilseed and grains (Fig. 2A).

INSERT FIG. 1 HERE

The variation among farms in GHG emissions per kg DM was relatively larger than that per unit land area. The mean level as well as the variation among farms in GHG emission from oilseed exceeded those from the grain crops (Fig. 1B); the difference between the 25th to 75th percentile levels was 0.85 kg CO_2 eq kg^{-1} DM, close to twice that at the lower level. In barley, oats, spring wheat, and winter wheat, the 75th percentile levels were between 1.4 to 1.6 times higher than those at the 25th percentile levels, amounting to differences of 0.31, 0.27, 0.39, and 0.25 kg CO_2 eq kg^{-1} DM, respectively. It is notable that the estimated distributions in Fig. 1B have longer upper than lower tails for the GHG emissions per kg DM; this means that the variation is greater among farms above the expected GHG emission levels than among the farms below the respective median levels. In crops with the limited dataset, the differences in rye and potatoes were estimated to 0.25 and 0.41 kg CO_2 eq kg^{-1} DM, respectively (Fig. 2B).

INSERT FIG. 2 HERE

Looking at the differences between the 10th and 90th percentile levels, the soil C change contributed most to the variability in GHG emission intensities among farms in all crops except for winter wheat on CO_2 eq kg^{-1} DM basis where soil N_2O emissions distribution was similar to that of soil C change (Fig. 3). The variation in soil C change among farms was highest in oilseed; its probability of soil C sequestration being close to 30 %. In barley, the probability of soil C sequestration among farms was estimated to be 20 %, whereas in the rest of the crops the probabilities of soil C sequestration were smaller than 10%. Variation in soil N_2O emission per ha was highest for farms in winter wheat and spring wheat, and variation in emission per kg DM was highest in oilseed (Fig. 3).

INSERT FIG. 3 HERE

The GHG emissions per kg DM decreased with increasing gross margin (NOK per ha^{-1}) in grain and oilseed crops (Fig. 4). This relationship was, however, not as clear in winter wheat as it was in most other crops; for potatoes, based on few observations, there seemed to an increase in emissions with increasing gross margin. A decreasing GHG emission per hectare with increasing gross margin was less pronounced than on the kg DM basis. None of the crops showed an increasing trend, but the relationships were very weak for winter wheat, oats, and potato. The farms with lower GHG emissions per kg DM yield also had lower GHG emissions per area unit; the coefficients of determination were 0.57 in barley, 0.31 in oats, 0.56 in spring wheat, 0.38 in winter wheat, and 0.74

in oilseed. A high N fertiliser efficiency expressed as yield per N fertiliser unit, along with high residue C, is the key to this relationship. The strongest correlations were found between GHG emission per kg DM produce and yield level, and between GHG emission per ha and N fertilisation rate.

INSERT FIG. 4 HERE

Among the sensitivity elasticities the highest one was related to environmental impacts on soil C change. Reliable estimates of the farms' $r_w \times r_T$ are thus very crucial for the assessment of the GHG emissions intensities (Table 3). The model output was also highly sensitive to the estimates of crop C residues. The factor accounting for the effect of reduced tillage is its fractional occurrence in each crop. Thus, its elasticity was low in winter wheat and higher in the spring sown crops. The sensitivity elasticities of the IPCC (2006) based factor were all about 0.3, and similarly the elasticities of the effect of manufacturing fertiliser were about 0.25; this means that an error of ±15% in the IPCC (2006) factor will cause an error of about ±4.5 % in the estimates of GHG intensities, and an error of ±15% in the factor for the effect of manufacturing N fertiliser will cause an error of about ±3.75%. The sensitivity elasticities of the year from start of continuous arable cropping were low. An error of ±15%, or ±5 year from the base case year of 30, will cause an error of ±0.6% in the estimates of the GHG emissions intensities.

INSERT TABLE 3 HERE

4. Discussion

The decrease in estimated GHG emission intensities with increase in gross margin, especially on per kg DM basis but also on per area basis, suggests that crop producers have economic incentives to reduce the emission intensities (Fig. 4). However, increasing the input of N fertiliser poses a risk of higher GHG emissions intensities. As reported by Archer and Halvorson (2010) the per-area-unit profitability stabilised near the economic optimum N fertiliser rate whereas the GHG emissions further increased. Further, the timeliness costs (e.g. de Toro et al. 2005) contribute to the variation in GHG emissions (risk). This is a time-related penalty decreasing the gross margin in crop production that arises when an operation is performed at a non-optimal time or with non-optimal capacity of the equipment, thus affecting the quality and or quantity of the crop. Also occurrences of pests and diseases, and unfavourable weather conditions during farm operations will contribute to weaker relationships between the GHG emissions intensities and gross margin when determined for real farms than for hypothetical farms.

Comparisons of our estimates of GHG emissions intensities with estimates reported by others may be tenuous as different assumptions and model boundaries influence the estimates. However, Dyer et al. (2010), using a similar concept in Canada, found comparable emissions per kg DM for oilseed and small grains, but values 50 percent lower for potatoes. Emissions per unit of land were less than half for oilseed and small grains, but comparable for potatoes; lower yields and lower N fertiliser rates under Canadian conditions may explain this difference. The estimates of Dyer et al. (2010) did not include soil C change. For the grain crops the soil C loss accounted for 15 to 21 % of the total emissions on area basis (Table 2). The expected values estimated were similar to the value found by Persson and Kirchman (1994) for the N fertilised treatments and the figures reported by Uhlen (1973) and Christensen (1990), whilst Riley and Bakkegaard (2006) have reported figures of C loss several orders of magnitude higher. The latter was outside the estimated distribution range for

2008 (Fig. 3), a year of unusually high grain yields (Åssveen et al., 2009) and high crop residues and thus lower C net losses.

At a tactical level (e.g. Bonesmo et al., 2010), mitigation options assume the existence of a significant variation within the cropping system. Thus, clarifying this variation is more important than estimating the exact average level. Our results (Fig 3) demonstrate options for measures. As the use of N fertiliser contributes the most to the total, both from soil N_2O emission and the fertiliser manufacturing, optimisation of N fertiliser use is crucial. The economically optimal N fertiliser rate differs between fields and is also highly variable within fields (Sharf et al., 2005), indicating a need to manage N fertiliser differently for different fields. However, at farms with higher levels of N fertilisation, close to N optimum and above, the risk of high emissions will increase; the probability curve will extend into the range of high emissions due to the likelihood of occurrence of uncontrollable events. Other GHG mitigation measures include the use of reduced tillage regimes. In our study more than half of the spring cereal area was managed by reduced tillage (Table 1). In the model the effect of reduced tillage is accounted for by the cultivation factor r_c, and the model is sensitive to changes in that factor (Table 3). However, grouping the farms according to the frequency of reduced tillage gave no significant effect of the tillage system on GHG emissions. The intercorrelations with the N fertiliser rate, pesticide use, and yields outweighed the direct effect of reduced tillage through slower decomposition of soil organic matter. In our model, the reduced tillage did not affect the N_2O flux from soil, in accordance with findings for spring barley in Irish arable soils (Abdalla et al., 2010). An interesting observation is the apparent possibility of C sequestration under oilseeds, perhaps because of effects on residue input (Fig 3). Thus, the inclusion of oilseed crop in crop rotation on farms without manure could aim to maintain the soil C level. The positive effect on subsequent crop production of including oilseed crop in rotation systems is well documented (Brandt et al., 1995; Heenan, 1995; Anderson et al., 1999; Engström and Lindén, 2009). Agronomic measures at the tactical level are perhaps the most difficult mitigation practices to assess; reducing N fertilisation, the use of reduced tillage, catch crops, and crop rotation impact yields and crop residues. Thus, whole-farm analysis by the use of farm level decision support tools is helpful (e.g. Beauchemin et al., 2010). However, the risk of GHG emissions has to be included; the fact that the GHG emissions increase even if the yield does not respond to the input factors (due to the occurrence of uncontrollable events) has to be considered.

As demonstrated in this paper, whole-farm systems analysis is a useful tool for assessing mitigation options and risks. Whole farm models of GHG emissions intensities, integrating the effects of the natural resource base and farm management, like the one presented in this paper could also be a good base for national inventories using an up-scaling methodology (e.g. Dalgaard et al., 2006). Farm scale based inventories would ensure that the effect of mitigation measures would be incorporated into the national inventories.

5. Conclusion

The model was able to reflect the variation in GHG emissions intensities among farms on the basis of robust and reliable farm scale data for natural resource base and farm management. Our results showed a decrease in estimated GHG emission intensities with increase in gross margin, especially on a per kg DM basis but also on a per area basis, suggesting that crop producers have economic incentives to reduce the emissions. However, risk is involved and has to be considered when evaluating the mitigation options at a tactical level. Our paper demonstrates that whole-farm analysis by the use of farm scale models is helpful to evaluate mitigation practises and the risk involved.

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Tables and figures:

Table 1 Expected values and 0.1 and 0.9 quantiles for the GHG model input data and Gross Margin as calculated by a multivariate empirical distribution procedure on the basis of a consistent farm scale data set of 95 crop production farms[a]. For rye and potatoes only mean values are given.

	Barley, n=70		Oats, n=63		Spring wheat, n=51		Winter wheat, n=35		Oilseed, n=20		Rye, n=7	Potatoes, n=9
	Expected value	Quantile [0.1, 0.9]	Expected value	Quantile [0.1, 0.9]	Expected value	Quantile [0.1, 0.9]	Expected value	Quantile [0.1, 0.9]	Expected value	Quantile [0.1, 0.9]	Mean	Mean
Yield, kg DM ha^{-1}	3922	[2662, 4993]	3895	[2507, 4971]	3651	[2583, 5039]	5039	[3108, 5911]	2000	[1268, 2458]	5646	5278
N fertiliser, kg ha^{-1}	130	[79, 171]	120	[61, 152]	152	[102, 232]	193	[127, 257]	143	[57, 175]	168	137
Pesticide, NOK ha^{-1}	490	[35, 750]	260	[0, 374]	650	[114, 890]	1000	[240, 1250]	870	[165, 1220]	914	3082
Reduced tillage, ratio	0.7	[0.0, 1.0]	0.7	[0.0, 1.0]	0.5	[0.0, 1.0]	0.0	[0.0, 1.0]	0.0	[0.0, 1.0]	0.3	0.0
Fuel, l ha^{-1}	105	[61, 197]	113	[62, 187]	123	[59, 186]	134	[63, 200]	135	[63, 220]	125	162
Electricity, kWh ha^{-1}	401	[99, 830]	305	[94, 698]	403	[110, 805]	305	[121, 792]	390	[143, 1225]	429	441
Straw removal, ratio	0.0	[0.0, 0.0]	0.0	[0.0, 0.0]	0.0	[0.0, 0.0]	0.0	[0.0, 0.0]	0.0	[0.0, 0.0]	0.0	0.0
ts30 winter, °C	0.8	[-0.1, 1.7]	0.9	[0.4, 1.9]	1.0	[0.2, 1.9]	1.3	[0.6, 2.3]	1.1	[0.6, 2.3]	1.4	1.0
ts30 spring, °C	8.0	[6.3, 8.8]	8.1	[6.9, 9.0]	8.1	[7.3, 8.9]	8.4	[7.7, 9.3]	8.1	[7.3, 9.3]	8.4	8.1
ts30 summer, °C	15.5	[14.1, 16.3]	15.7	[14.7, 16.5]	15.8	[15.3, 16.5]	15.8	[15.3, 16.8]	15.7	[15.1, 16.8]	15.9	15.8
ts30 fall, °C	6.3	[5.5, 7.5]	6.5	[6.0, 7.9]	6.7	[6.0, 8.0]	6.8	[6.1, 8.7]	6.6	[6.1, 8.7]	7.1	6.8
WFPS winter, %	79	[68, 84]	80	[75, 84]	80	[73, 84]	80	[76, 84]	81	[76, 85]	80	75
WFPS spring, %	68	[59, 74]	69	[62, 74]	68	[62, 73]	71	[63, 74]	70	[63, 75]	68	63
WFPS summer, %	64	[54, 70]	66	[56, 71]	64	[54, 70]	66	[58, 71]	67	[57, 72]	65	56
WFPS fall, %	79	[66, 83]	80	[72, 84]	80	[71, 83]	81	[75, 84]	81	[74, 84]	80	74
r_w x r_T yearly, dim.less	1.48	[1.30, 1.71]	1.54	[1.35, 1.81]	1.54	[1.38, 1.77]	1.59	[1.47, 1.86]	1.56	[1.37, 1.86]	1.66	1.49
SOC, Mg ha^{-1}	69.5	[48.5, 82.0]	72.0	[55.4, 84.2]	73.0	[48.6, 86.0]	76.0	[64.0, 85.0]	76.0	[65.0, 84.5]	73.0	67.2
Gross Margin, NOK ha^{-1}	6145	[3580, 9740]	5310	[2312, 8132]	5336	[2779, 7695]	8667	[4032, 12923]	5910	[2715, 9735]	6633	44546

[a]NOK = Norwegian kroner, ts30 = soil temperature at 30 cm depth, WFPS = water filled pore space, r_w and r_T = the relative effects of soil moisture and soil temperature on the soil C decomposition rates, SOC = soil organic carbon.

Table 2. Expected values of four sources of GHG emissions as kg CO_2eq ha^{-1} and CO_2eq kg^{-1} DM for five small grain crops as estimated by stochastic simulations with an empirical multivariate model based on a consistent farm scale data set for 95 crop production farms with respect to soil, weather, and farm operation of year 2008.

	kg CO_2eq ha^{-1}					kg CO_2eq kg^{-1}DM				
	Barley	Oats	Spring wheat	Winter wheat	Oilseed	Barely	Oats	Spring wheat	Winter wheat	Oilseed
Soil C change	420	483	605	532	288	0.11	0.12	0.17	0.11	0.14
Fuel use	283	305	331	361	365	0.07	0.08	0.09	0.07	0.18
Manufaturing, off farm	613	566	707	883	682	0.16	0.15	0.19	0.18	0.34
Soil N_2O	1125	1129	1316	1730	1221	0.29	0.29	0.36	0.34	0.61
Total	2441	2483	2959	3506	2556	0.63	0.64	0.81	0.7	1.27

Table 3 Mean sensitivity elasticities for the GHG emissions intensities (kg CO_2 eq ha^{-1}, kg CO_2 eq kg^{-1} DM) as based on 1000 iterations by a stochastic simulation model. The chosen range of the key model parameters and variables was from 0.85 to 1.15 of their respective values. Sensitivity elasticities are expressed by the slope of a linear regression of relative values of key model parameters or variables and the relative GHG emission intensities.

	Barley	Oats	Spring Wheat	Winther Wheat	Oilseed
IPCC N_2O factor	0.305	0.297	0.308	0.336	0.326
Residue N	0.116	0.13	0.097	0.109	0.113
Manufact. fertiliser	0.229	0.207	0.233	0.251	0.256
r_w x r_T yearly[a]	0.662	0.702	0.586	0.567	0.809
Residue C	-0.536	-0.549	-0.449	-0.469	-0.764
Reduced tillage factor	0.366	0.378	0.306	0.082	0.274
Year of cont. crop	-0.042	-0.053	-0.05	-0.039	-0.021

[a] r_w and r_T are the relative effects of soil moisture and soil temperature on the soil C decomposition rates.

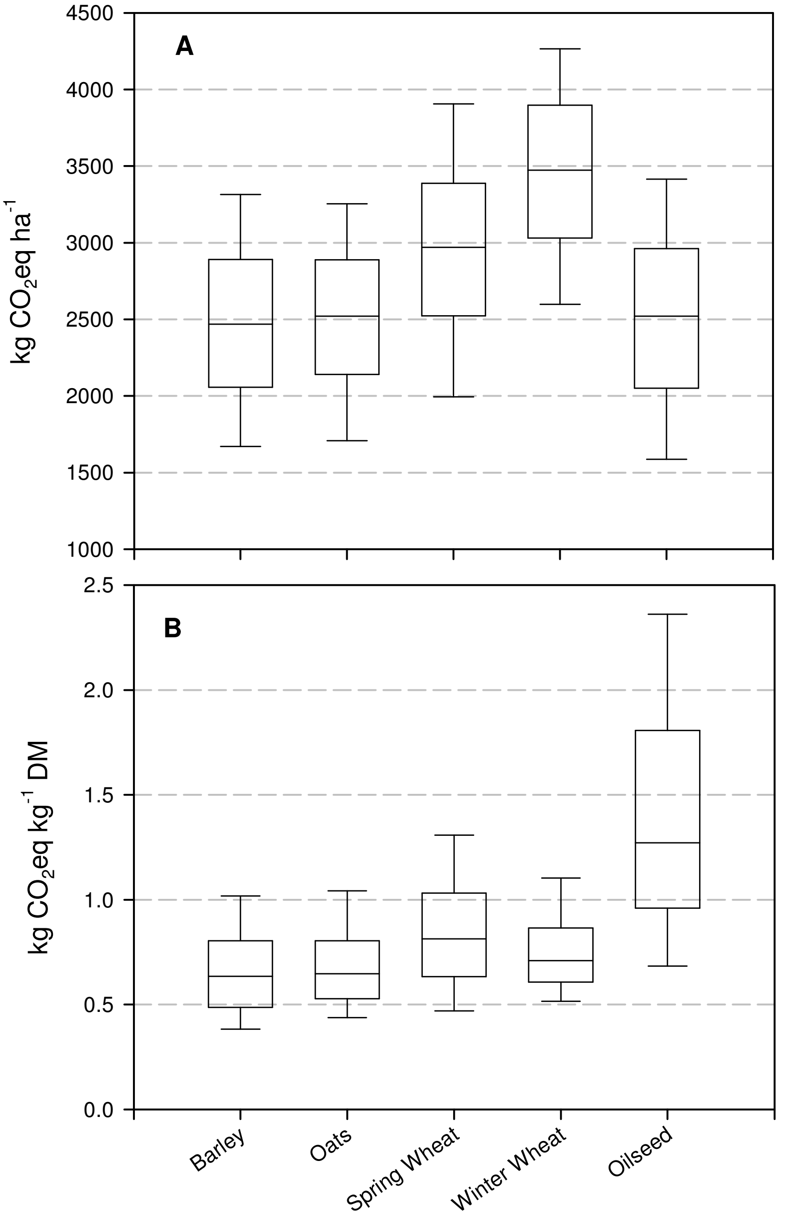

Fig. 1. Median (−), 25th and 75th percentiles (box), and 10th and 90th percentiles (т) of GHG emission intensities as kg CO_2eq ha^{-1} (A) and CO_2eq kg^{-1} DM (B) for five small seed and grain crops, grown as estimated by stochastic simulation using a multivariate empirical model on the basis of a consistent farm scale data set of 95 crop production farms with respect to soil, weather, and farm operation of year 2008.

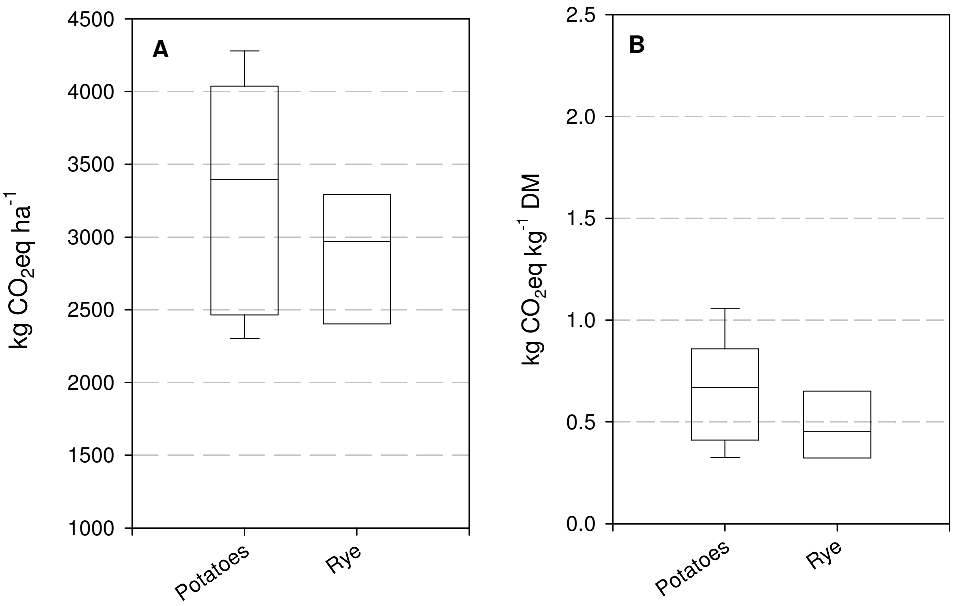

Fig. 2. Median (−), 25th and 75th percentiles (box), and 10th and 90th percentiles (т) of GHG emission intensities as kg CO_2eq ha^{-1} (A) and CO_2eq kg^{-1} DM (B) for potatoes and rye as estimated by nine and six runs, respectively, of a consistent farm scale data set with respect to soil, weather, and farm operation of year 2008 with deterministic models for potatoes and rye, respectively.

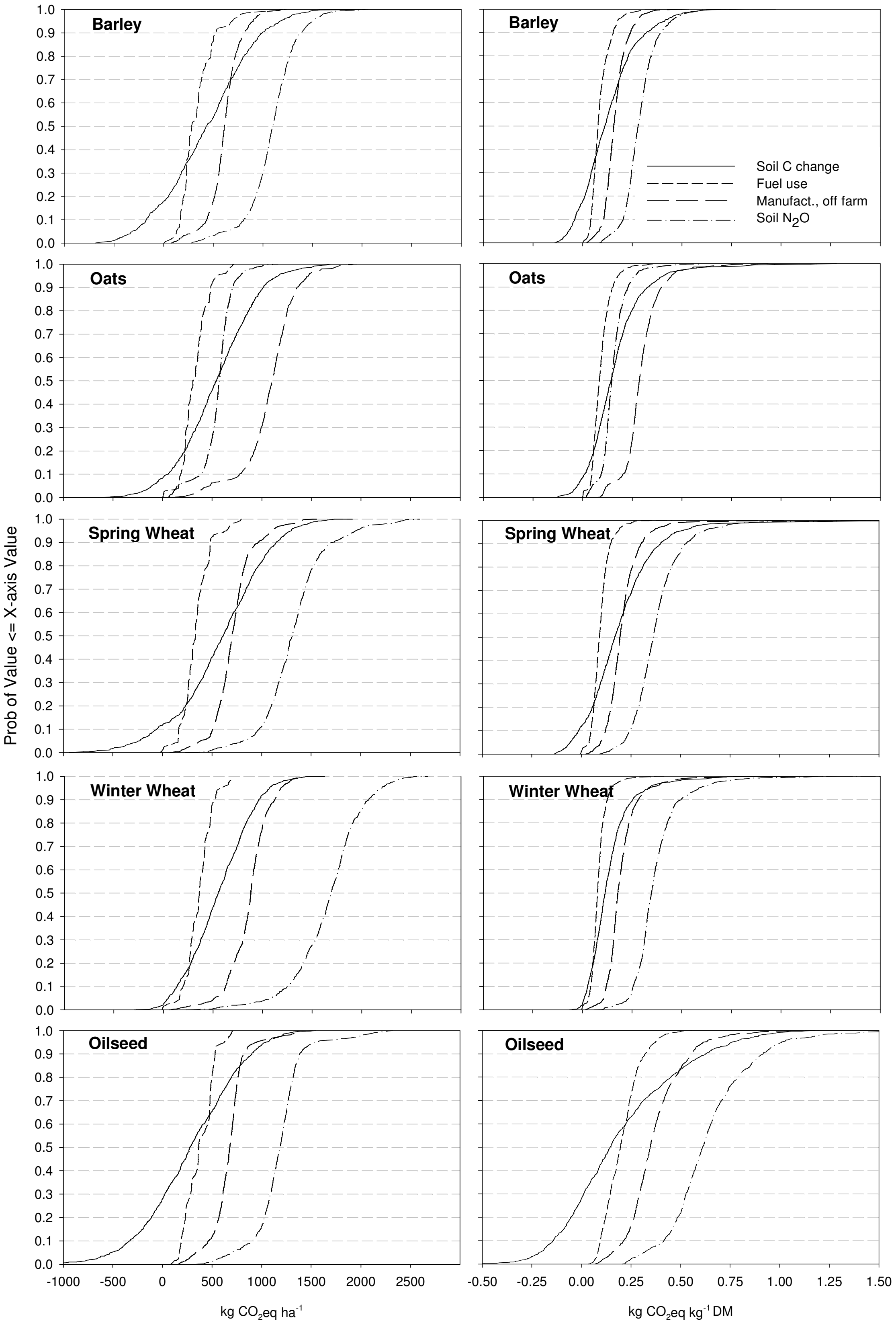
Barley
Oats
Spring Wheat
Winter Wheat
Oilseed
Prob of Value <= X-axis Value
Soil C change
Fuel use
Manufact., off farm
Soil N_2O
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-1000
-500
0
500
1000
1500
2000
2500
-0.50
-0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
kg CO_2eq ha^{-1}
kg CO_2eq kg^{-1} DM

Fig. 3. Cumulative distribution functions of four sources of GHG emissions as kg CO_2eq ha^{-1} and CO_2eq kg^{-1} DM for five small grain crops as estimated by stochastic simulations with an empirical multivariate model based on a consistent farm scale data set for 95 crop production farms with respect to soil, weather, and farm operation of year 2008. Values less than 0 indicate removal from atmosphere (i.e., soil C gain).

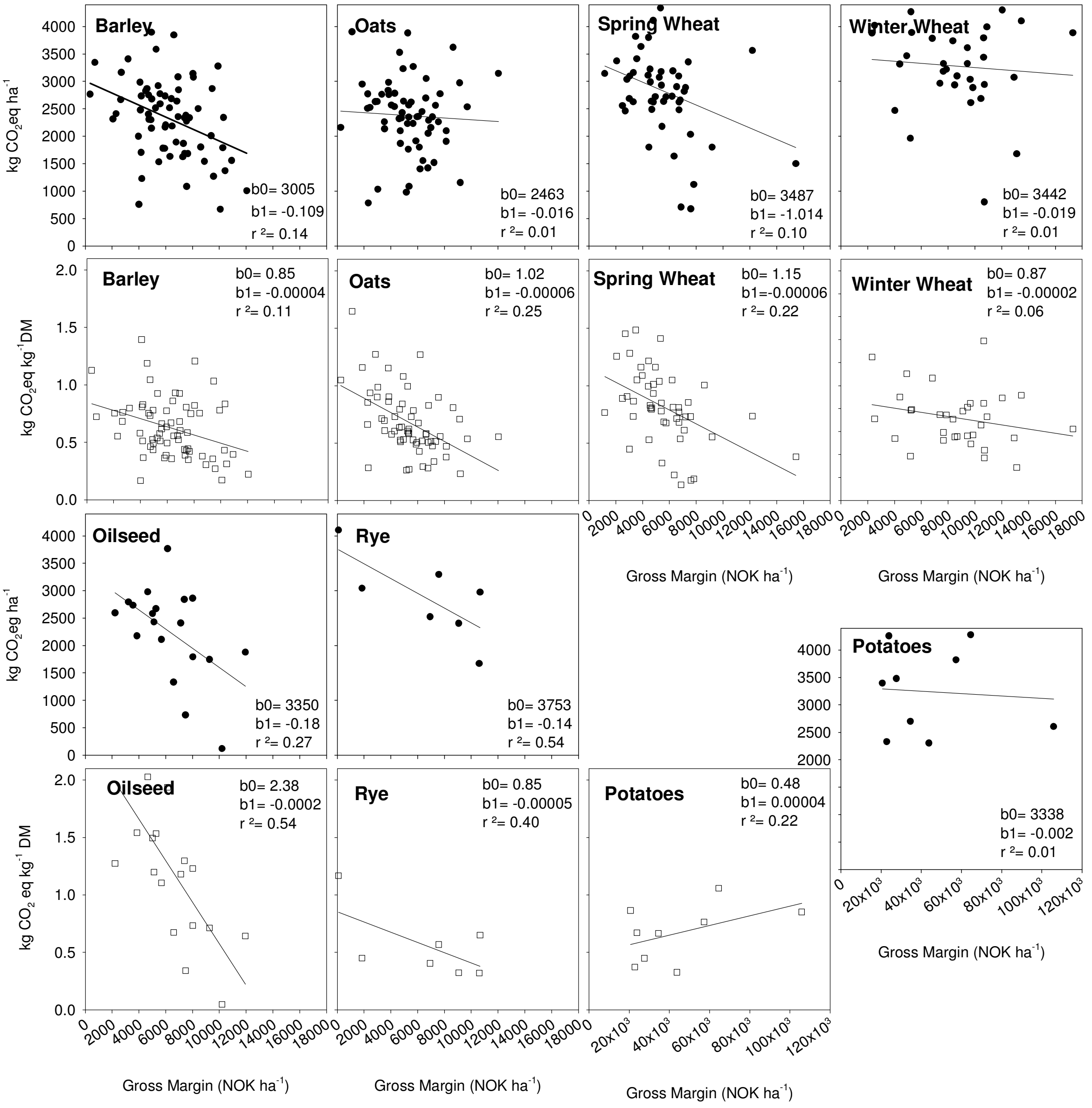

Fig. 4. Relationships between estimated GHG emission intensities as kg CO_2eq ha^{-1} (closed circles) and CO_2eq kg^{-1} DM (open squares) and economic efficiency as the gross margin (NOK ha^{-1}) for seven crops at 95 farms; b0, b1, and r^2 are intercept, regression coefficient, and coefficient of determination, respectively, for a linear regression between gross margin and GHG emission intensities.