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New approach to calculate agri-environmental indicators using greenhouse gas emissions in Switzerland as an example

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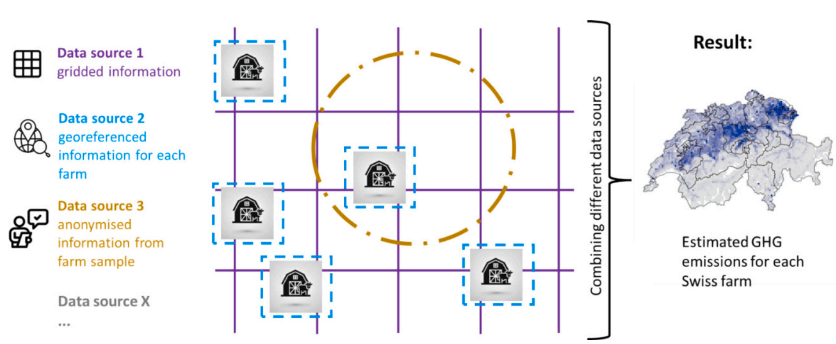
HIGHLIGHTS

- New approach for agri-environmental monitoring (here: GHG emissions) is presented.
- Approach relies on an extensive farm-level data compilation.
- Farm-based GHG emissions can easily be aggregated to larger scales.
- Two regional emission hotspots were identified, linked to high animal densities.
- The Swiss agricultural subsidy system could be optimised to reduce emissions.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Agri-environmental monitoring programmes provide policy makers and society with important information on the state of the environment and the achievement of agricultural policy objectives. In this study, we present the new Swiss agri-environmental monitoring programme MAUS (German: "Monitoring des Agrar-Umweltsystem Schweiz") using the indicator of greenhouse gas emissions (GHG) as an example.
OBJECTIVE: The main objective of this study was to determine GHG emissions for different regions and production systems in Switzerland, thereby demonstrating the feasibility, strengths, and weaknesses of the new monitoring approach MAUS. Furthermore, we aimed to identify the most effective levers for achieving greatest reduction in emissions.
METHODS: The new monitoring programme approach maximises the use of existing data. To achieve this, it is necessary to compile and link existing data from different sources. An approximate indicator value is calculated for each Swiss farm, and these values are then aggregated to larger scales. To identify the strongest levers for emission reductions, a sensitivity analysis was carried out with three very different case study farms.
RESULTS AND CONCLUSIONS: GHG emissions varied spatially across Switzerland, with two hotspot regions of around 7–8 t CO_{2eq}/(ha•yr). Regression analysis on all Swiss farms showed that GHG emissions were mainly driven by (ruminant) livestock density. In the sensitivity analysis conducted on the exemplary farms, livestock density was also by far the most influential variable to change emissions. Additional factors driving GHG

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emissions were – depending on the farm type – feeding intensity and applied commercial fertiliser/liming amount. Other variables, e.g. related to the barn system, had only minor effects on total GHG emissions.
MAUS reduces the administrative burden for farmers to deliver data compared to the old monitoring framework, while simultaneously providing flexibility in aggregating the results and a simple framework to integrate additional data sources. However, MAUS requires substantial scientific effort for collating and processing data from multiple organisations and is limited regarding retrospective calculations, thus impeding comparison with previous agri-environmental indicator calculations.
SIGNIFICANCE: This study provides decision makers with essential evidence to drive legislation forward by highlighting the regions and key levers where GHG emission reductions can be most effectively achieved. Part of the current agricultural subsidies that aim at reducing GHG emissions are allocated on a per livestock unit basis. Thereby, these subsidies might counteract the reduction in livestock numbers and thus the desired reduction in greenhouse gas emissions.

1. Introduction

While being essential for food production, many current agricultural practices have a detrimental effect on the environment, with consequences including groundwater pollution, global warming, and soil deterioration (FAO, 2017; Mbow et al., 2020). In Switzerland, legislation and financial incentives have been implemented to promote environmentally sustainable agricultural practices. Nevertheless, the environmental goals defined for the agricultural sector have so far not been achieved (FOEN and FOAG, 2016).

Switzerland's Federal Office of Agriculture (FOAG) runs an agri-environmental monitoring programme that evaluates the impact of agriculture on the environment over time. The results provide a basis for assessing progress towards policy goals and supporting decision-making. The programme utilises data about agricultural structures and practices, such as livestock numbers and mineral fertiliser use. These data are used to calculate indicators, such as greenhouse gas (GHG) emissions or pesticide risks, which reflect the expected environmental impacts. The agri-environmental monitoring consists of 1) national indicators, such as the Swiss GHG inventory (FOEN, 2024a), calculated with national statistics, and 2) indicators at regional and farming/production system levels, which rely on farm-level data. We use the term 'production system' when distinguishing between methods of production (e.g. non-organic versus organic farming), and the term 'farming system' when distinguishing between the focus of production (e.g. arable versus livestock). The agri-environmental monitoring programme is complemented by direct environmental observation programmes, e.g. soil and biodiversity measurements (e.g. Gubler et al., 2018; Meier et al., 2021).

Between 2009 and 2022, the indicators at regional and farming/production system levels in Switzerland were based on the Swiss Agri-Environmental Data Network (SAEDN), which collected detailed management data from about 300 farms (Gilgen et al., 2023). These data enabled the calculation of indicators for three altitudinal zones (valley, hill, mountain) and four farm types (arable-focused, animal-focused, mixed, special crops). While the approach provided valuable insights at farm level, the limited sample size restricted its usefulness for monitoring purposes; certain regions (e.g. southern Switzerland) and farming systems (e.g. specialised crops) were hardly represented in the sample, meaning that no reliable statements were possible for these (Gilgen et al., 2023). To improve coverage and spatial resolution, SAEDN has now been replaced by MAUS (German: Monitoring des Agrar-Umweltsystems Schweiz). MAUS retains most of the indicators and targets of SAEDN, but its data collection and calculation methods differ substantially (Fig. 1). Instead of relying on self-reported, detailed management data from a small farm sample, MAUS combines various existing – though in some cases less detailed – datasets to approximately calculate the indicators for all Swiss farms, before being aggregated at regional or farming/production system level.

For many years, few European countries other than Switzerland have implemented agri-environmental monitoring programmes that cover farming systems and regions. One notable exception is the Netherlands,

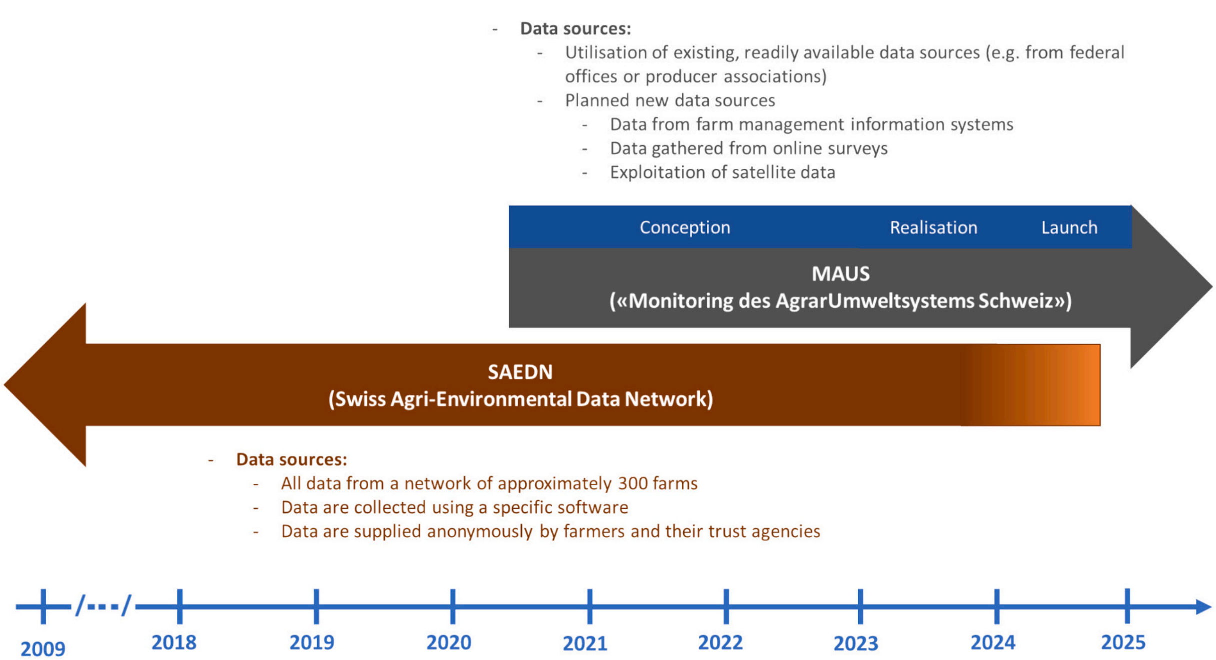

Fig. 1. Overview of the previous (SAEDN) and the new (MAUS) agri-environmental monitoring system of Switzerland.

where environmentally relevant data has long been collected within the Farm Accountancy Data Network to calculate indicators such as energy consumption and nutrient balances (Boone and Dolman, 2010; Vrolijk et al., 2016). Recently, the European Union decided to adopt a similar approach by expanding the Farm Accountancy Data Network into a Farm Sustainability Network. This initiative involves collecting economic, environmental, and social data from the same sample of farms to enable the calculation of sustainability indicators. In contrast, the new MAUS is independent from the Swiss Farm Accountancy Data Network.

In this study, the new MAUS concept is illustrated using the GHG emission indicator as an example. GHG emissions are responsible for global warming, which will, among other consequences, threaten future agricultural production and lead to the loss of biodiversity (Abbass et al., 2022; IPCC, 2022). In 2022, the agricultural sector contributed 14% to the Swiss national GHG emissions (FOEN, 2024a). The share would be somewhat higher if additional emission sources from energy use, land use, and land use change were attributed to the agricultural sector as well. According to the 'Climate Strategy for Agriculture and Nutrition 2050' (FOAG et al., 2023), Swiss GHG emissions from agriculture are to be reduced by at least 40% by 2050 (reference year 1990).

The main objective of this study was thus to calculate GHG emissions for different regions (Section 3.1) and farming/production systems (Section 3.2) in Switzerland using the new MAUS approach. A second objective was to identify which levers are most effective in reducing GHG emissions on three very different farms by using a sensitivity analysis approach (Section 3.3).

These results are important for the direction of national political measures (e.g. direct payments) to reduce GHG emissions, but they also help to tailor cantonal policy to regional environmental issues; Swiss cantons are the member states of the Swiss Confederation, having their own governments, constitutions, and certain autonomous powers within the federal system. Furthermore, our results show which variables require a solid data basis to obtain robust results for different farms.

In the material and methods part, we describe the concept of the new monitoring programme MAUS (Section 2.1), the system boundary and reference value of the study (Section 2.2), the model used for the GHG calculations (Section 2.3), the input data compiled (Section 2.4), the statistical approach to examine regional differences in GHG emissions (Section 2.5), and the three case study farms (Section 2.6). In the discussion, we compare our results with other approaches for GHG emission assessments (Section 4.1), address uncertainties and limitations of the results (Section 4.2), describe the strengths and weaknesses of the new monitoring concept (Section 4.3), and point towards the need for action in agricultural policy (Section 4.4).

2. Material and methods

2.1. Concept of the new monitoring programme MAUS

The guiding principle of MAUS is to make optimal use of already existing data. These are compiled in such a way that the required model inputs (e.g. number of animals, stable system) are available for every Swiss farm. The individual farm indicator values are then aggregated on various geographical and structural scales ('bottom-up approach').

The existing data sources compiled for and used in MAUS differed in sample size and in spatial and temporal resolutions (Section 2.4; Supplementary Table S1). Some data sources were available for each farm and included a specific farm identifier, allowing to link corresponding information directly at the farm level. Other data sources only covered subsamples of farms, often in anonymised form. In such cases, we derived reference values from the respective sample and applied them to all farms. For example, yield data of a few thousand farms were used to derive reference values for different crops, regions, and production systems (non-organic/organic).

Existing datasets provided a solid basis for some indicators, notably GHG emissions described in this study, but were insufficient for others, such as pesticide risk. To address these gaps, targeted new data collections (online surveys of ~1000–2000 farms, georeferenced farm management data from ~200–500 farms, and satellite-based observations) have recently started and will be gradually integrated into MAUS in the coming years (Fig. 1).

The GHG emission calculations from this study were carried out for the year 2021, the earliest year with a complete compiled dataset. For data that are only collected every few years, we used the most recent year available at the time (Supplementary Table S1). The calculations will be repeated annually to provide time series from 2021 onwards. Most of the data sources are available on an annual basis (Supplementary Table S1), which facilitates their integration in MAUS. We also use yearly values for data with high interannual variability (e.g. harvest yields) and consider this when interpreting the time series. Once sufficient years of results are available, moving averages (e.g. over 3 years) can be used to smooth out strong temporal variability. Single data sources are only updated every few years (Supplementary Table S1). If these relate to land use or management (i.e., data from HAFL and FSO), we will use linear interpolation between years as soon as new data become available (the results presented here for 2021 do not yet include any temporal interpolations). Data from sources that are no longer maintained (i.e. SAEDN) will be replaced in future by our own targeted surveys.

MAUS only considers (all-year) farms that fulfil the farm definition of the Federal Statistical Office (FSO, 2016): 1 ha of utilised agricultural area or 0.3 ha of special crops or 0.1 ha in protected cultivation or 8 suckler pigs or 80 fattening pigs or 300 poultry. This definition covers farms that altogether encompass >99% of Switzerland's total agricultural production (FSO, 2016).

2.2. System boundary and reference value

Our GHG emission model (Section 2.3) follows the IPCC system boundaries of the agricultural sector (Eggleston et al., 2006). Emissions are calculated on farm level excluding pre-chain (upstream) and post-farmgate (downstream) processes of food production, such as mineral fertiliser production and food processing. Furthermore, emissions from energy use as well as CO_2 sources and sinks from soils are not considered in our calculations as these are attributed to different sectors. Note that neglecting these sources limits cross-study comparison (see Section 4.2.2).

We calculated GHG emissions in tonnes of CO_{2eq} per area. In Switzerland, part of the cattle is moving to higher alpine pastures during summer ("summering pasture"). Therefore, Switzerland distinguishes between all-year farms and summering pasture farms. While all-year farms have a clearly defined, farm specific utilised agricultural area (UAA), the summering pasture area is to a certain degree unknown and cannot easily be attributed to individual summering pasture farms (information is only available on the cantonal level). One reason for this is that many of the summering pastures are used as common grazing land. The Swiss summering pasture area is approximately half as large as the Swiss UAA. In the following, we refer to the sum of UAA and summering pasture area as total agricultural area (TAA). For the most accurate spatial representation, we allocated emissions from animals and manure management to the actual locations where they occur – partly to all-year farms and partly to summering pasture farms. When reporting emissions per unit area at the farm level, however, we only consider all-year farms with clearly defined UAA.

We converted CH_4 and N_2O emissions to CO_{2eq} using GWP100 factors of 28 and 265, respectively (Buendia et al., 2019).

2.3. GHG emission model

We used the Swiss Ammonia and Greenhouse Gas Emission version 1.0 (SAGE1.0) model to calculate GHG emissions (Fig. 2). The agricultural GHGs considered are methane (CH_4), nitrous oxide (N_2O), and

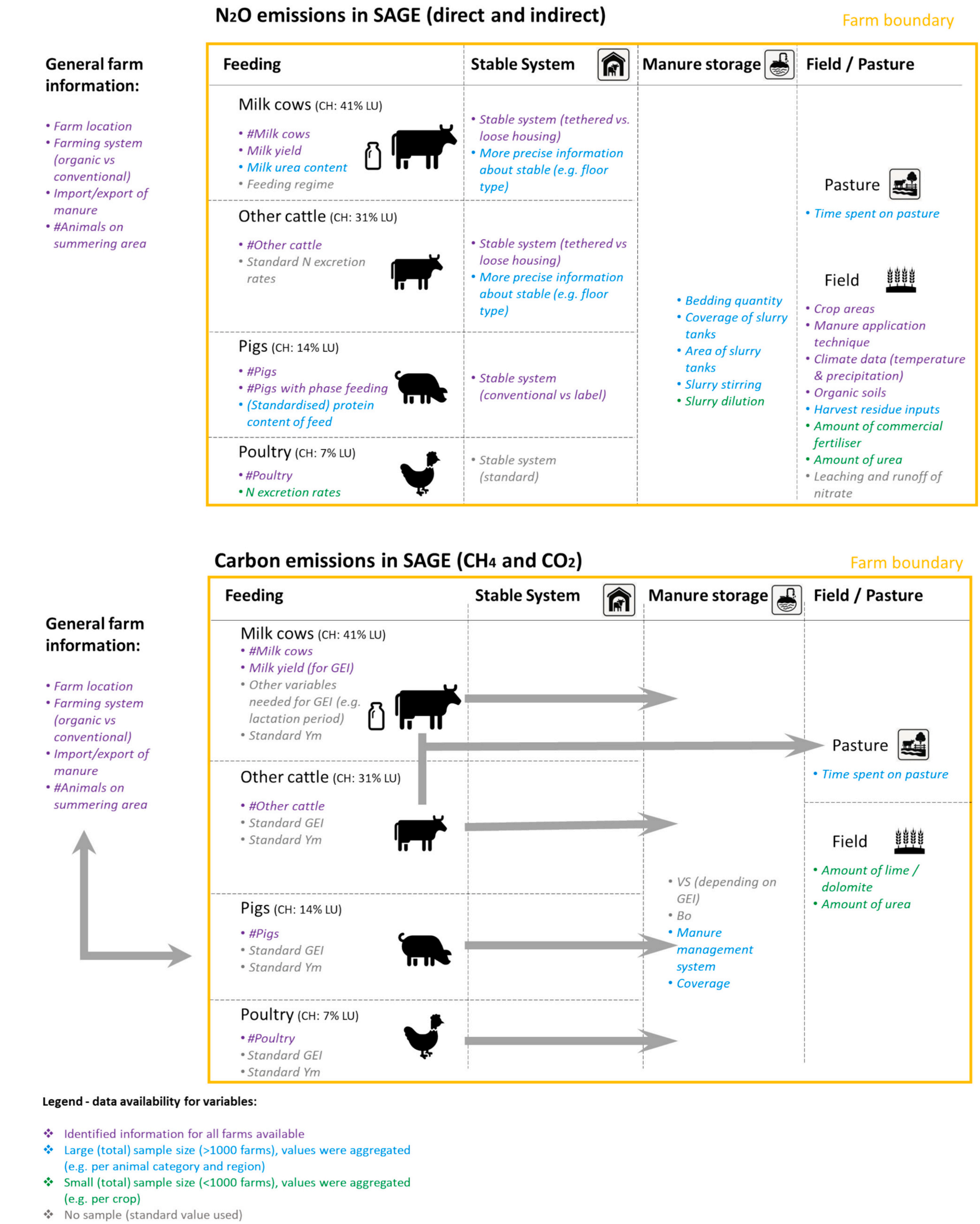

Fig. 2. Illustration of the SAGE1.0 model framework used to calculate farm-specific ammonia and greenhouse gas emissions. The upper part of the figure illustrates the calculation of N_2O emissions, the lower part the calculation of CH_4 and CO_2. For the sake of simplicity, only the most important animal categories in Switzerland are shown (the national shares are shown in brackets). The information needed for the calculation is in italics. The colour indicates the (total) sample size used to derive the information (more details in Supplementary Material, Section A1). GEI stands for gross energy intake, Ym for methane conversion factor, VS for volatile solids, and Bo for maximum methane producing capacity (see text for more details).

carbon dioxide (CO_2). Since parts of ammonia (NH_3) and nitrate are converted to N_2O in the environment (so-called indirect N_2O emissions), SAGE1.0 also calculates these precursor emissions. The calculation generally follows the methodology of the national NH_3 and GHG emission inventories (FOEN, 2024a; Kupper et al., 2022). This was done deliberately to be consistent with the approaches in the national inventories. In contrast to the tool for calculating national GHG emissions, SAGE1.0 can be applied at the individual farm level. The following emission sources according to the IPCC guidelines are considered (Buendia et al., 2019; Eggleston et al., 2006):

- 3A Enteric fermentation: CH_4
- 3B Manure management: CH_4, N_2O
- 3D Agricultural soils: N_2O
- 3G Liming: CO_2
- 3H Urea Application: CO_2

Rice cultivation, prescribed burning of savannahs, and field burning of agricultural residues are non-existent or negligible in Switzerland and were thus not considered. In contrast to the national GHG inventory, we did not consider N_2O emissions of nitrogen mineralisation/immobilisation associated with loss/gain of soil organic matter as no reliable, spatially explicit data for soil organic carbon changes are available. Model results indicate that average carbon balances of mineral soils are close to zero in Switzerland (FOEN, 2024b), therefore this neglection is assumed to have no influence on total GHG emissions.

In the following, we describe in more detail how the different GHG emissions are calculated in SAGE1.0.

2.3.1. Methane emissions

Methane emissions from enteric fermentation of livestock depend on the animals' gross energy intake (GEI) and the animal category-specific methane conversion rate (Ym). Gross energy intake is estimated from energy requirements, which vary with performance (e.g. live weight, milk yield). For most animal categories, standard performance values are assumed. For dairy cows, GEI is derived as a function of milk-related variables, such as milk yield and lactation period.

Methane emissions from manure storage depend on volatile solids (VS), the maximum methane-producing capacity (Bo), and the manure management systems (pasture, solid manure, slurry, deep litter systems, poultry manure systems). VS is a function of GEI. For slurry storage, the calculation also accounts for whether the facilities are covered. For further details about the calculation of methane emissions see FOEN, 2024a.

2.3.2. Nitrous oxide

The calculation of N_2O and NH_3 (precursor of N_2O) emissions mainly follows the approach of the AGRAMMON model (Kupper et al., 2010; Kupper et al., 2022). AGRAMMON simulates the nitrogen flow from the animals' excrements to the field, either through manure management and application or grazing ("manure cascade"). Emissions therefore occur on pasture, in stable (including exercise yard), during manure storage, and during manure application. In addition to these animal-driven emissions, emissions of commercial fertiliser (i.e. mineral fertilisers, recycling fertilisers, and commercial organic fertilisers such as feather meal) applications are also considered.

We implemented the following modifications in the ammonia emission pathways to the (current) AGRAMMON model:

- Nitrogen excretion rates: As in AGRAMMON, nitrogen excretions of milk cows can be corrected by the milk yield. In the SAGE1.0 model, it is additionally possible to adjust the nitrogen excretions based on information about milk urea content and breed (Braun et al., 2021) instead of milk yield.
- Slurry storage: More recent NH_3 emission factors for cattle (0.08 g NH_3 m^{-2} h^{-1}) and pig (0.24 g NH_3 m^{-2} h^{-1}) slurry stored in tanks by Kupper et al. (2020) are considered.
- Slurry application: We used the semi-empirical ALFAM2 model (Hafner et al., 2018) version 3.17 to calculate emissions from slurry applications, which results in lower emissions than AGRAMMON. ALFAM2 calculates cumulative NH_3 emissions over a defined period of time as a function of slurry (e.g. application rate, slurry type), management (e.g. application method), and meteorological variables (e.g. air temperature). We calculated the cumulative NH_3 emissions in the 72 h following slurry application. As detailed information on the slurry application time is missing, we used average values from March to November for the meteorological variables (temperature, precipitation, wind speed). The spatial variability in climate conditions caused by the different locations of the farms is thus considered.

Compared to AGRAMMON, SAGE1.0 is extended with two additional N_2O emission sources: a) N_2O emissions from crop residues and b) N_2O emissions from cultivated organic soils. Crop residue emissions are calculated with the same methodology as in the national GHG inventory (FOEN, 2024a) and thus depend on harvest yield. N_2O emissions from cultivated organic soils were calculated with a new georeferenced map of organic soils (new version of Wüst-Galley et al., 2015) and the emission factors from the national inventory (FOEN, 2024a).

The calculation of nitrate (precursor of N_2O) is very simplified: it is assumed that a fixed proportion of the total nitrogen input into agricultural soils is lost through leaching and that a fixed part of this is released into the atmosphere as N_2O.

2.3.3. Carbon dioxide emissions

For CO_2, emissions from the application of lime, dolomite, and urea are considered. Since these emissions are small compared to the other sources, IPCC default emission factors are used.

2.4. Input data

Multiple data sets with different sample sizes were used for the calculation (Fig. 2). Table 1 provides an overview of the most important data sources, while a fully comprehensive description of all data sources used can be found in Supplementary Table S1 (in Section A.1). In the following, a synthesis of these sources is presented.

The core of our calculations are the farm specific data from the FOAG and the Swiss cantons on the farm's location, the UAA and TAA, the georeferenced crops grown, the number of animals, and milk placed on the market. Farm-specific subsidies paid by the FOAG were used for some of

Table 1
Overview of the most important data sources used in this study to calculate GHG emissions. A more comprehensive and detailed table can be found in the Supplementary Material (Table S1).

Most important data sources	Key variables
Federal Office of Agriculture	Structural farm data (e.g. livestock numbers), manure and recycling fertiliser exchanges, and information on direct payments (e.g. organic yes/no) for all Swiss farms
Cantons	Georeferenced data of agricultural area and different crops for all Swiss farms
Agricultural associations	Harvest data (anonymised) and milk yield/urea content for part of the Swiss farms
School of Agricultural, Forest and Food Sciences / HAFL	Aggregated survey results for feeding and grazing, stable systems, and fertiliser storage and application
Agroscope	Additional farm management data (e.g. nitrogen mineral fertiliser applications, slurry dilution) of ~300 farms and harvest data of ~1700 farms (both anonymised)

the calculations, namely: production system payments to identify organic farms, animal welfare payments to identify animal-friendly stables and animals with (presumably) above-average grazing days, and resource efficiency payments to determine the number of phase-fed pigs. In addition, we used the FOAG data on all transports of manure and recycling fertilisers, the documentation of which is mandatory in Switzerland.

Another important information source was the management survey in the context of the national ammonia inventory, which is carried out every five years by the School of Agricultural, Forest and Food Sciences (HAFL) and the Federal Statistical Office on behalf of the Federal Office for the Environment (Kupper et al., 2022). The survey is filled in by 2000–3000 farms and collects information about feeding and grazing, stable systems, and fertiliser storage and application. Farm specific data were not available, but only weighted average values for different regions, altitudinal zones, and production systems. Therefore, reference values were derived from the HAFL dataset and applied to all farms in the corresponding category (see Supplementary Table 1): Depending on the variable, we chose either one national value, three altitudinal-specific values (valley, hill, and mountain), or two values for different production systems (non-organic, organic).

Breeding associations provided farm specific information about the breeds, the milk yield, and the milk urea content of their farms, covering ~48% of Swiss dairy cows. These data were linked to the respective farms using the identifiers from the animal traffic database. Furthermore, we gathered farm and crop-specific harvest data from various organisations (e.g. Swiss farm accountancy data network, several agricultural associations, statistical service of the Swiss Farmers' Union). All compiled harvest data were anonymised, but providing information about the municipality, which allowed us to create distinct regional yield maps for conventional and organic farming. Grassland yields (and its residues), which are difficult to estimate, were determined indirectly via the need for roughage consumption per farm (see Supplementary Section B for more details).

The SAEDN dataset – although it will not be continued – was still used to derive reference values for individual variables. In particular, we used it to estimate the amount of mineral and commercial organic fertilisers (e.g. feather meal) per farm. For this purpose, we derived crop-specific average nitrogen application rates from the SAEDN dataset while distinguishing between production systems (non-organic and organic). An exception are mineral fertiliser application rates for special crops, which were derived from Principles of Agricultural Crop Fertilisation in Switzerland (see Baumgartner et al., 2024 for explanations). The resulting rates were applied evenly to the geo-referenced crop areas, with mineral fertiliser rates assigned to non-organic farms exclusively. In the future, the data currently derived from SAEDN will be replaced by new data sources (see Section 4.3).

Further data sources of lesser importance for the calculation comprise the Swiss land use statistic (FSO, 2021), a sample of import-export balances of pig/poultry farms from the Canton of St. Gallen (not published), and meteorological data of MeteoSwiss (2024).

In some cases, alternative data sources were found for the same variable (e.g. number of pigs fed in phases). We performed separate calculations using these different data inputs to assess the impact on GHG emissions (Supplementary Material, Section A.2).

2.5. *Statistical analysis for regional differences*

To better understand regional differences in GHG emissions across all Swiss farms (Section 3.1), we performed LASSO (Least Absolute Shrinkage and Selection Operator) regression analysis. LASSO adds a penalty to the absolute values of regression coefficients, which shrinks some coefficients to zero and thus effectively removes irrelevant predictors from the model. The categorical predictor variable "Swiss canton" was dummy-coded and then grouped when using the R package *gglasso* (Yang and Zou, 2015). The regularisation parameter lambda was derived by minimising cross-validation error. We scaled the predictors to compare their influence on the response variable (GHG emissions per ha-$_{UAA}$). Only all-year farms with at least 1 ha of UAA were included in this regression analysis because the response variable and several predictors were divided by the UAA, resulting in extreme or even infinite values otherwise. The following predictor variables were analysed: farm size (UAA), proportion of (open) arable land on UAA, organic farming (yes/no), nitrogen mineral fertiliser amount per UAA, livestock density, proportion of ruminants in livestock population, air temperature, wind speed, precipitation, clay content, soil organic carbon content, and Swiss canton.

2.6. *Case study farms and sensitivity analysis approach*

To identify different levers for reducing agricultural GHG emissions, we selected three case study farms. The diversity of farms in Switzerland is high. Many farms, especially in mountainous areas, have almost exclusively permanent grassland and ruminants (Fig. 3b), with dairy cows being the most common. However, there are also (among others) arable farms and specialised crop farms without animals, livestock farms focusing on monogastric animals instead of ruminants, and mixed farms both keeping livestock and cultivating open arable land (i.e. arable land without ley). Our aim was to select farms for the sensitivity analysis that differ as much as possible in terms of production, GHG emissions, and mitigation potential. We also wanted these three farms to cover the most important crop types (grassland > arable land > specialised crops) and animal categories (cattle > pigs > poultry) in Switzerland (Gilgen et al., 2023). Accordingly, we chose a dairy farm, a mixed pig/poultry farm, and an arable farm without livestock (Fig. 3a; Table 2). The farms are located in different Swiss regions and all larger than the average Swiss farm size of 21 ha, thus making an above-average contribution to production.

For these farms, input variables related to the structure and management of the farms – which can be influenced by farmers and agricultural policy – were varied. The chosen variables can either be influenced directly by farmers (e.g. pasture hours per day) or indirectly (e.g. milk yield as a proxy for feeding intensity). This sensitivity analysis approach allows to identify the levers for reducing emissions across farm types.

For each of the three farms, we conducted 10,000 simulations, where the input variables were randomly sampled within predefined ranges described in Supplementary Section C (Monte-Carlo approach). To derive these ranges, several datasets were used (see Supplementary Tables S2-S4 in Section C). The ranges were chosen to cover broad conditions but are still considered plausible for the represented Swiss farm types. Thus – although the selected farms themselves are not "representative" – the ranges selected per variable (e.g. for livestock density or pasture days) are representative of the respective farm type.

In a next step, we performed for each farm a linear regression analysis on the 10,000 simulations, with the varied variables as predictors and the calculated GHG emissions (in CO_{2eq}/(ha-$_{UAA}$•yr)) as response. For categorical predictor variables, their corresponding emission/correction factors from SAGE were used. The predictors were scaled to compare their influence on the response variable. We applied the function *lm()* of the R package *stats* for the linear regression. The linearity assumption was confirmed by expert knowledge, visual inspection of predictor-response relationships, and very high R^2 (>0.95) of the three linear regressions. Note that high R^2 are realistic in this set-up, as SAGE is a deterministic model and we have only varied variables that we subsequently included in the regression models as predictors. The high R^2 are unproblematic in this case (no over-fitting), as we are not attempting to find a suitable prediction model, but to identify the variables with the strongest influence on the three case-study farms.

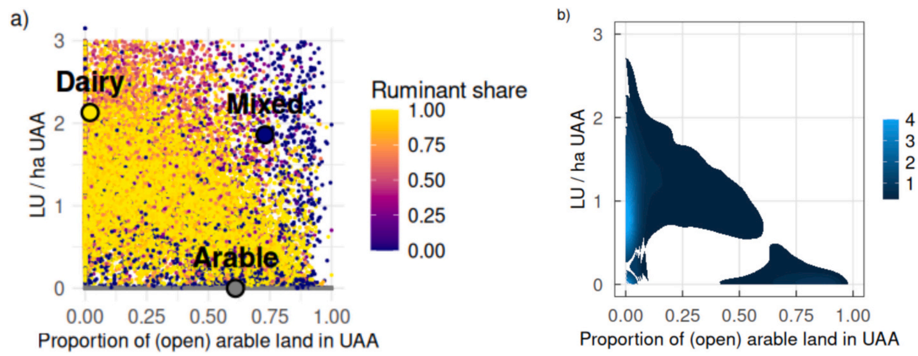

Fig. 3. a) Overview of all Swiss (all-year) farms with the proportion of (open) arable land (i.e. arable land excluding ley) in utilised agricultural area (UAA) on the x-axis and the livestock unit density on the y-axis. Each point represents a farm, with the colour indicating the LU proportion of ruminants (cattle, sheep, and goats) in the total livestock population. The three farms selected for the sensitivity analysis are highlighted. Values higher than 3 LU / ha UAA are not shown. Note that livestock unit density was one of the variables varied within the sensitivity analysis, ranging between 0.78 and 1.96 LU / ha UAA for the dairy farm and between 0.83 and 6.48 LU / ha UAA for the mixed pig/poultry farm. b) Density plot to highlight where most farms are located in panel a).

Table 2
Overview of the case study farms used for the sensitivity simulations. "KT" stands for Swiss canton, "masl" for metres above sea level, and "LU" for livestock unit (LU conversion factors according to Swiss Confederation, 2024).

Farm type	Location	Farm area (ha UAA)	Animals	Cropping system
Arable	Valley, Canton Vaud (VD), 500 m asl	75	0	46 ha open arable land (incl. vegetables) 16 ha grassland 10 ha fruits 7 ha vegetables 2 ha vineyards
Mixed pig/ poultry	Hill, Canton Schaffhausen (SH), 650 m asl	51	73 LU poultry 16 LU pigs 6 LU cattle	37 ha open arable land 15 ha grassland
Dairy	Hill, Canton Fribourg (FR), 820 m asl	104	222 LU cattle	102 ha grassland 2 ha open arable land

3. Results

3.1. Differences between regions

The average agricultural GHG emissions of Switzerland per UAA amounted to 5.2 t CO_{2eq}/(ha-$_{UAA}$•yr). The spatial pattern of emissions showed two large hotspots, one in central Switzerland (predominantly located within canton of Lucerne) and one in north-eastern Switzerland (mainly canton of Thurgau and northern part of canton St. Gallen; Fig. 4a). Emissions were 7.9 t CO_{2eq}/(ha-$_{UAA}$•yr) in the canton of Lucerne and 6.8 t CO_{2eq}/(ha-$_{UAA}$•yr) in the canton of Thurgau. Both regions are characterised by above-average animal densities, namely 2.2 LU/(ha-$_{UAA}$•yr) and 1.7 LU/(ha-$_{UAA}$•yr) for Lucerne and Thurgau, respectively, compared to the Swiss average value of 1.2 LU/(ha-$_{UAA}$•yr).

Emissions were significantly below average in the mountain regions and on the southern side of the Alps (Fig. 4a). The average emissions across the cantons of Valais, Ticino, and Grisons (i.e. the three large cantons in the South) amounted to 2.5 t CO_{2eq}/(ha-$_{UAA}$•yr), which is about half the Swiss average. The average livestock density across these three cantons was 0.77 LU/(ha-$_{UAA}$•yr). These three cantons also have a lot of summering pastures with low emissions per area (Fig. 4b), as summering pastures are in general used extensively and only contribute 6% of total agricultural GHG emissions.

To gain a better understanding of regional differences, we conducted

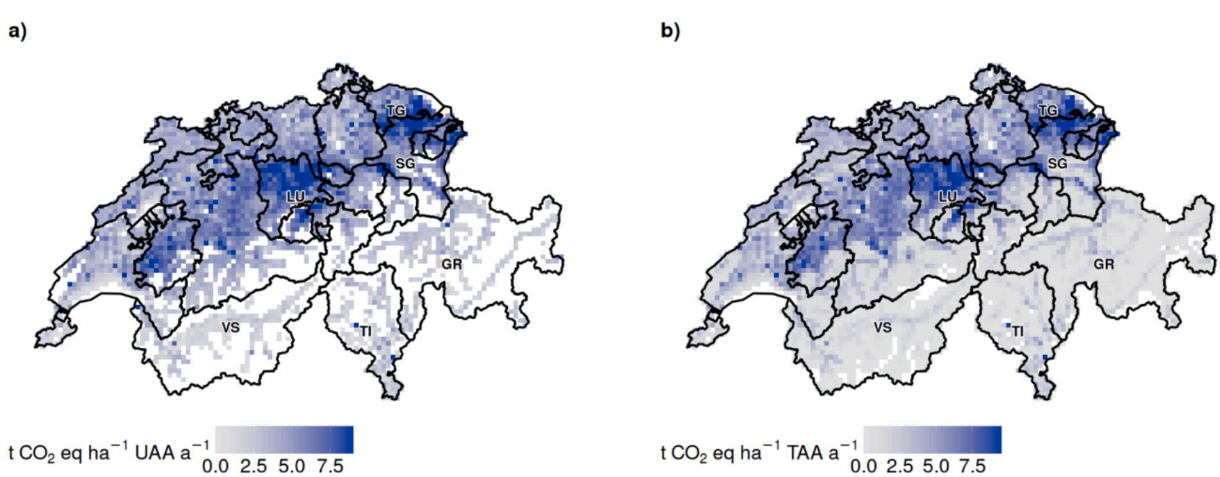

Fig. 4. Spatially resolved agricultural greenhouse gas emissions in Switzerland a) per utilised agricultural area (UAA) and b) per total agricultural area (TAA; including summering pastures) for the year 2021. Cantonal and national borders are shown in black. TG = Thurgau, SG = St. Gallen, LU = Lucerne, GR = Grisons, VS = Valais, and TI = Ticino.

a LASSO regression analysis (see Section 2.5). We examined structural and management variables (e.g. farm size, livestock density), pedoclimatic factors (e.g. clay content, air temperature), and the Swiss cantons as a proxy for regional agricultural policy as predictor variables. Livestock density was by far the most important factor for GHG emissions (coefficient = 3.17), followed by the ruminant share (1.43; Table 3). From the pedo-climatic factors, soil organic carbon content (−0.46) and air temperature (0.28) had the highest impact on GHG emissions, while others were (close to) zero. It should be noted that the high CO_2 emissions from drained organic soils were not taken into account in this study, as they lie outside the system boundary; otherwise, a higher soil organic carbon content would likely lead to higher GHG emissions. The predictor Swiss canton also had a significant influence on GHG emissions. The canton of Lucerne (LU) had the greatest emission-increasing effect (0.39), while the canton of Valais (VS) has the greatest emission-reducing effect (−0.30). This indicates that different regional policies influence GHG emissions.

3.2. Differences between farming/production systems

The major influence of animal density on GHG emissions became again evident when the farms were categorised according to their livestock density (Fig. 5b). While farms with an animal population of <0.5 LU/(ha-$_{UAA}$•yr) had an (area-weighted) average value of 1.4 t CO_{2eq}/(ha-$_{UAA}$•yr), the mean for farms with >2 LU/(ha-$_{UAA}$•yr) was 11 t CO_{2eq}/(ha-$_{UAA}$•yr).

Table 3
Results of the LASSO regression analysis, which was performed to determine the most influenceable predictors on regional GHG emissions (t CO_{2eq}/ha UAA; UAA stands for utilised agricultural area). The magnitude of each coefficient indicates how strongly the predictor influences the response variable. Positive values indicate that a higher predictor value leads to higher emissions; the opposite is true for negative values. Insignificant predictors receive a value of 0.

Predictor variable	Coefficient	
Farm size (UAA)	0.26	
Proportion of (open) arable land on UAA	−0.35	
Organic farming	−0.37	
Nitrogen mineral fertiliser amount per UAA	0.12	
Livestock density	3.17	
Proportion of ruminants in livestock population	1.43	
Air temperature	0.28	
Wind speed	−0.05	
Precipitation	0.00	
Clay content	−0.05	
Soil organic carbon content	−0.46	
Swiss cantons	AG	−0.08
	AI	0.07
	AR	0.04
	BE	0.09
	BL	−0.13
	BS	−0.02
	FR	0.03
	GE	−0.11
	GL	−0.02
	GR	−0.14
	JU	−0.15
	LU	0.39
	NE	−0.09
	NW	0.07
	OW	0.16
	SG	0.20
	SH	0.05
	SO	−0.07
	SZ	0.07
	TG	0.12
	TI	−0.18
	UR	−0.02
	VD	−0.27
	VS	−0.30
	ZG	0.07
	ZH	−0.08

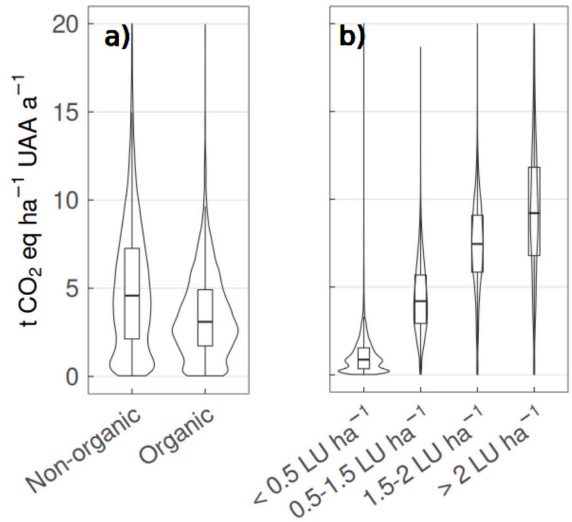

Fig. 5. Farm-specific greenhouse gas emissions per utilised agricultural area (UAA) categorised by a) production system and b) animal density for the year 2021, shown as violin plots with included boxplots.

Approximately 15% of the Swiss farms in 2021 were organic. We examined differences between non-organic and organic farms using two-sided Mann-Whitney *U* tests. With an (area-weighted) average value of 3.5 t CO_{2eq}/(ha-$_{UAA}$•yr), organic farms had (statistically) significantly lower emissions than non-organic farms with 5.5 t CO_{2eq}/(ha-$_{UAA}$•yr) (see also Fig. 5a), which was mainly due to the significantly lower average animal density of organic farms (0.94 LU/(ha-$_{UAA}$•yr) versus 1.3 LU/(ha-$_{UAA}$•yr)). The significantly lower animal density on organic farms was attributable not only to the fact that there were proportionally more organic farms in (extensive) mountain areas but was found in all altitudinal zones. Organic farms are by regulation limited in the use of concentrate feeds, which automatically restricts animal densities. To a smaller extent, the renunciation of mineral fertiliser application (Section 2.4) also contributed to the lower emissions on organic farms. Organic farms achieve the avoidance of mineral fertilisers, among other things, through a significantly higher proportion of legumes on their open arable land (9.2% versus 2.1%). These two factors – lower animal densities and avoidance of mineral fertilisers – outweigh the significantly higher LU proportion of ruminants on organic farms compared to non-organic farms (86% versus 74%) and the higher nitrogen excretion rates per animal for pigs and fattened chicken (Supplementary Table S1), which would lead to higher GHG emissions.

3.3. Sensitivity analysis on case study farms

The sensitivity analysis revealed that GHG emissions and their drivers varied strongly by farm type: the three selected case study farms showed large differences in emissions with 56 t CO_{2eq} for the arable farm, 133 t CO_{2eq} for the mixed pig/poultry farm, and 1364 t CO_{2eq} for the dairy farm. With respect to the farms' agricultural areas, the values were 0.75 t CO_{2eq}/(ha-$_{UAA}$•yr), 2.6 t CO_{2eq}/(ha-$_{UAA}$•yr), and 13 t CO_{2eq}/(ha-$_{UAA}$•yr), respectively.

To determine the most important levers for reducing emissions on these case study farms, we conducted Monte-Carlo simulations combined with linear regression (see Section 2.6). In the following, we will use the regression coefficients as a measure of the strength that each input variable had on GHG emissions in the sensitivity analysis. All regression coefficients and *p*-values can be found in Supplementary Tables S2-S4.

The only variables from the sensitivity analysis that influenced GHG emissions of the arable crop farm were the amount of commercial nitrogen fertiliser and lime (Supplementary Table S2), since this farm has no animals and does not use any organic fertiliser. Other variables such as crop residue management are currently not considered in SAGE. The amount of commercial nitrogen fertiliser had a considerably stronger influence on the result (0.121) than the amount of lime 0.043; Fig. 6a).

Livestock numbers had by far the strongest influence on the mixed pig/poultry farm (1.728; Supplementary Table S3, Fig. 6b). Commercial nitrogen fertiliser (0.105) and lime amendments (0.067) follow as the next most important variables. Regression coefficients related to pig feeding amounted to absolute values of around 0.03. It should be noted that this case study farm had a considerably higher share of poultry (77%) than pigs (17%; Table 2) and animal category shares were fixed in the simulations. On a mixed farm with predominantly pigs, the relative influence of pig feeding would be larger. Individual variables related to slurry management (application technique, cover type, and fraction applied in summer) had coefficients around 0.02–0.03. All other variables – including those related to the barn – had a smaller influence (< 0.015; Supplementary Table S3).

Animal numbers also had the largest effect on the dairy farm (0.707; Supplementary Table S4, Fig. 6c). The regression coefficient is smaller than for the mixed pig/poultry farm (1.728), because the livestock density of dairy farms has a smaller range than that of mixed pig/poultry farms (Supplementary Tables S3-S4). This is plausible, as dairy cows mainly eat grass, which is usually produced on the own farm, thereby limiting the number of animals per area. Milk yield, which is closely linked to feeding intensity, had the second largest influence (0.222). Slurry application technique and pasture time had absolute coefficients of around 0.02, while all other variables had an influence <0.015 (Supplementary Table S4).

4. Discussion

4.1. Comparison with other emission calculations

We compared our results with the emissions for the year 2021 of the national GHG inventory (FOAG, 2023a; FOEN, 2024a, 2024b). The calculation method and the system boundaries between the national inventory and our approach were very similar. However, there were differences in the data sources used and in individual equations and emission factors (see Section 2.3 for details).

Our calculated GHG emissions for Switzerland (5.68 Mt. CO_{2eq}) were slightly lower than the 5.90 Mt. CO_{2eq} reported in the national inventory. A closer look revealed that the largest absolute differences occurred for indirect N_2O emissions from volatilisation and N_2O emissions from commercial fertilisers (Fig. 7). The 138 kt CO_{2eq} (−26%) lower emissions from volatilisation (indirect N_2O) are caused by the lower NH_3 precursor emissions. These lower precursor emissions are mainly due to updated emission factors during slurry storage and the use of the model ALFAM2 (Hafner et al., 2018) for the calculation of NH_3 slurry application emissions (Section 2.3). It is likely that the emission factors in the national inventories will also be updated in the future. The 50 kt CO_{2eq} (−21%) lower emissions from commercial fertilisers in our calculations can be explained by the different data sources, as the SAEDN dataset used in our calculation results in 27% less mineral fertiliser nitrogen than the data used for the national inventory. In contrast, N_2O emissions from organic soils were higher in our calculations, a discrepancy attributable to an updated map of organic soils, which has not been used in the national inventory in 2021.

Overall, our results are consistent with the values from the national inventory on GHG emissions. The occurring differences, particularly for precursor NH_3, can be plausibly explained, mainly by more up-to-date emission factors used in our calculations.

On behalf of the Federal Office for the Environment, a spatial breakdown of the national GHG emissions using a top-down approach is performed every few years following the methods described in Heldstab

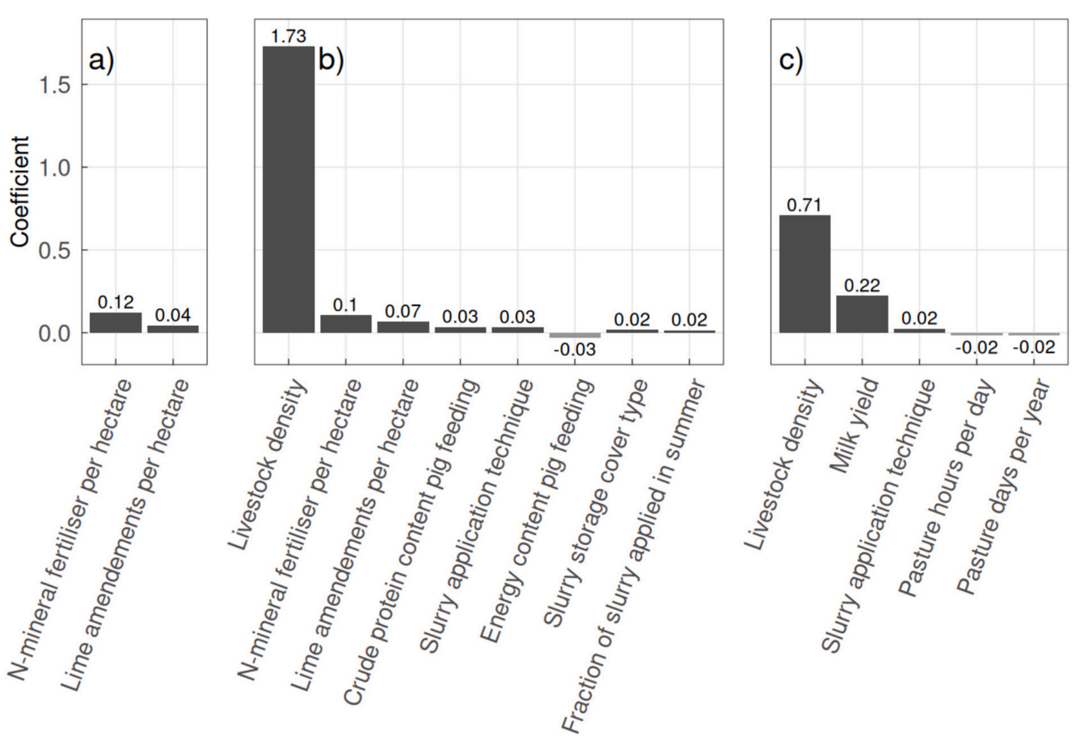

Fig. 6. Results of the sensitivity analysis for the three case study farms: a) arable farm, b) mixed pig/poultry farm, and c) dairy farm. Individual bars show regression coefficients, indicating how much the respective variables influence GHG emissions per ha. Effects assumed to decrease the emissions with increasing variable size (i.e. negative coefficients) are shown in light grey.

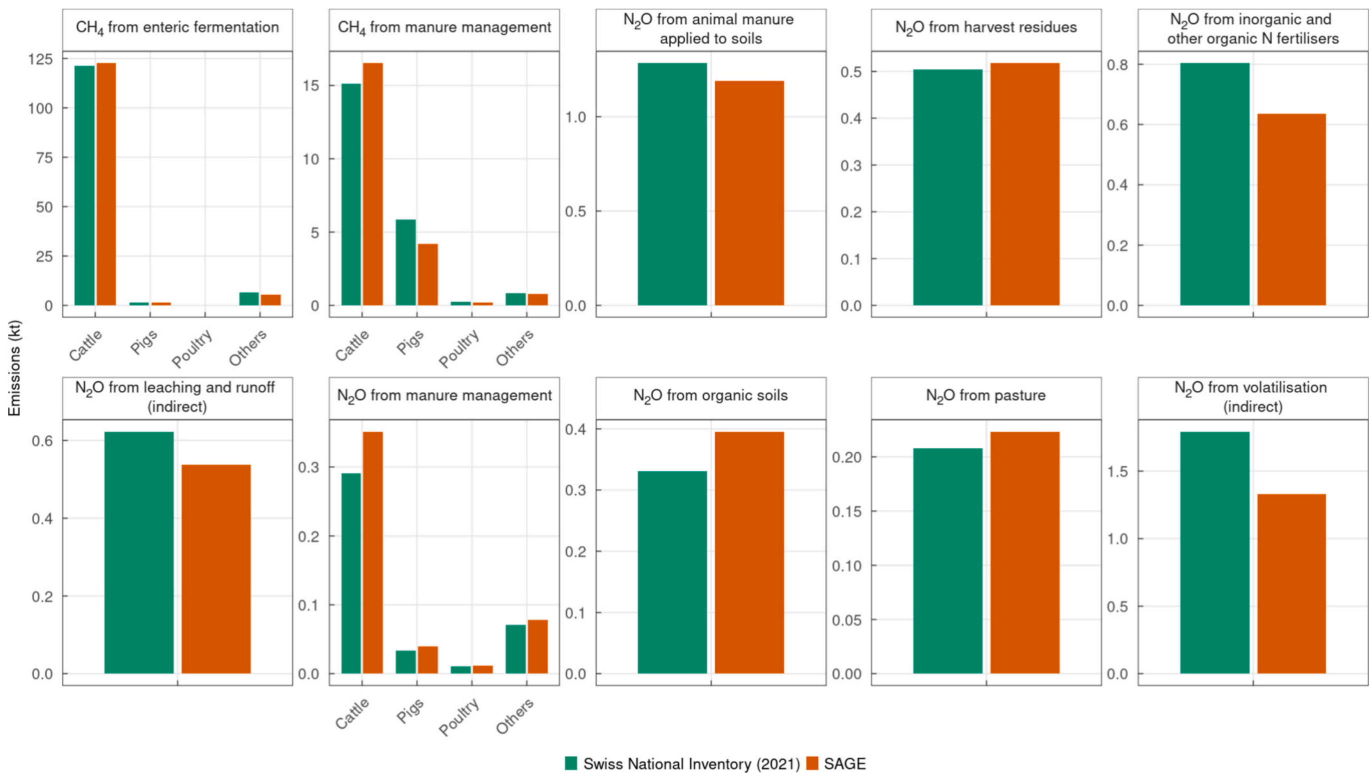

Fig. 7. Comparison between the most important GHG emissions sources from the national inventory (green) and our MAUS emissions calculated with SAGE1.0 (orange). Emissions are given in kt of the respective gas. Year of calculation: 2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

et al. (2021). This is called Switzerland's GHG balance cadastre. For the cadastre of 2021, the N_2O and CH_4 emissions were distributed in proportion to the NH_3 emissions of Rihm and Künzle (2023). These spatially resolved NH_3 emissions of Rihm and Künzle (2023) were calculated using geo-referenced information on animals, areas, and manure exchanges as well as categorised emission factors.

The spatial pattern between our MAUS GHG emissions (Fig. 8a) and the cadastre emissions (Fig. 8b) was similar, showing the same hotspots. We created an additional figure (Fig. 8c) to make differences in regional distribution more visible. Since we were primarily interested in the difference in spatial distribution – the difference in absolute emissions was already discussed when comparing to the national inventory – we chose the following approach: first, we calculated for each 3 × 3 km grid cell what proportion of the national emissions occur in it (e.g. 0.02% of

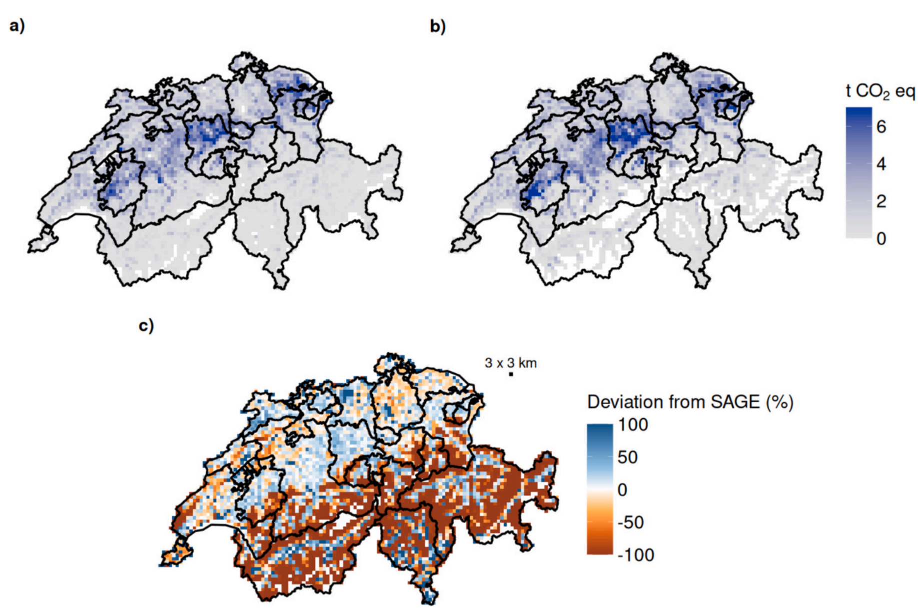

Fig. 8. Agricultural greenhouse gas emissions in t CO_{2eq} per 3 × 3 km grid cell from a) this study (MAUS approach using GHG model SAGE1.0) and b) Switzerland's GHG balance cadastre (Heldstab et al., 2021). In c), we show the relative difference in the spatial distribution between the cadastre and our calculations. The limits are set at −100 and 100%. Year of calculation: 2021. National and cantonal borders are shown in black.

national emissions for a specific grid cell). In the next step, we compared how these proportions differ between the cadastre and our MAUS approach. The 3 km grid resolution was chosen to show sufficiently detailed representation without appearing noisy.

The cadastre exhibited lower GHG emissions in the mountain regions than our approach. This is particularly the case because the cadastre does not consider summering pastures. Relative differences between the cadastre and our calculations also occurred in other Swiss regions, which can mainly be explained by the different data sources. We considered more individual farm data (e.g. milk yield, housing system, organic farming, differences in arable crops) than the cadastre.

Although both approaches yield similar spatial distributions, the MAUS approach offers a wider range of applications. For example, our approach can also be used to compare production systems (Section 3.2) or to model the effect of mitigation measures on a region-specific basis. Furthermore, we will repeat our calculations annually to analyse developments over time at the regional scale in the future.

4.2. Uncertainties and limitations of the calculated GHG emissions

4.2.1. Input data

Data availability varied for the different input variables (Table S1), and some input variables occurred in more than one dataset. Variables with more than one data source include the number of fattening pigs fed in phases, nutrient excretions of milk cows, animal category mapping, time of animals spent on pastures, and mineral fertiliser applications. We calculated the influence of this input data uncertainty using different simulations (Supplementary Material, Section A.2). While there were in some cases substantial differences for individual farms, the results were very similar when aggregated to a higher level (e.g. municipality). At the national level, the different data sources only resulted in emission differences between 0.08 and 1.7%. Our results are therefore not strongly influenced by the choice of data source. More details can be found in the Supplementary Material (Section A.2).

4.2.2. System boundary and reference value

The system boundary and reference value chosen for this study allow for a direct comparison with the GHG emissions from the national inventory. However, not all GHG sources, agricultural measures, and research questions can be depicted with it. Therefore, an extension of the SAGE model would be beneficial. As an example, the system boundary could be extended to voluntarily incorporate emissions from on-farm energy consumption and pre-chain emissions. In Switzerland, these amount to approximately 0.6 and 0.9 Mt. CO_{2eq} at the national level (FOAG, 2023b), i.e. together ~20% of total (standard + energy + pre-chain) GHG emissions. Considering these emissions would mean that farms with high energy consumption (e.g. for heating greenhouses) or high use of mineral fertilisers and concentrated feed – the main drivers of pre-chain emissions in Switzerland – would perform somewhat worse. The case study farms we analysed in the sensitivity analysis all used significant amounts of mineral fertiliser and/or concentrated feed, so higher emissions are to be expected in all cases. In contrast, extensive systems such as suckler cow or organic farms would probably be less affected by a change in system boundaries.

Extending the system boundaries and options for reference values would also have the advantage of making our results directly comparable with other scientific studies: sensitivity analyses in the area of GHG emissions are often carried out with a life cycle assessment (LCA; Abbas et al., 2022; Clavreul et al., 2017; Groen et al., 2016; Wolf et al., 2017), i.e. these studies take into account the pre-chain emissions in contrast to our current approach. To achieve this goal, we aim at extending the SAGE model and including additional data in the future.

4.3. Strengths and weaknesses of the new monitoring concept MAUS

In the following, we describe the strengths and weaknesses of MAUS. A comparison between the old monitoring system SAEDN and the new system MAUS is provided in Table 4.

The MAUS approach of linking as much existing data as possible means that less new data are collected specifically for the monitoring process, thus reducing the administrative burden on farms participating in the monitoring programme. This aspect is of particular importance in Switzerland, where farmers' administrative burden is a much-discussed topic (El Benni et al., 2024; Mack et al., 2021). Furthermore, multiple entries of the same data by farmers increase the potential for sources of error.

In cases where multiple data sources are available for a given variable, the MAUS approach allows to explore results using different sets of input data (Supplementary Section A.2). This contributes to a more robust overall assessment than that achievable with individual existing data sources, which may be biased when raised in different contexts.

However, the utilisation of existing data sources also has disadvantages for monitoring analysis. Firstly, the effort required for the continuous collation, linking, and processing of different data sources is considerable. Secondly, changes in survey methods or scope by the responsible organisations may compromise the consistency of the data series over time.

The new approach in MAUS approximates emissions for each Swiss farm and aggregates them with a bottom-up approach. By combining the data at the individual farm level, it takes very little effort to provide results on nearly any desired level (e.g. region, farming system). The farm level approach allows to create spatially explicit maps (Fig. 4), a great tool for communication as they are easier for policy makers to understand than complex scientific figures. Currently, some input variables were not available for every farm, which is why reference values (e.g. per crop or region) were used instead. Thus, results may be quite accurate at a regional level, but variability between farms can only be resolved to a limited degree. One of the affected input variables is mineral fertiliser application, for which fixed application rates per crop (for non-organic farms) are currently assumed (Section 2.4). As this input variable is relevant for many agri-environmental indicators of MAUS (e.g. nitrogen balance, GHG emissions, biodiversity), we intend to use own surveys in the future to improve its accuracy. In a first step, a regression model will be applied to data derived from an online survey.

Table 4
Comparison between the old monitoring system SAEDN and the new agri-environmental monitoring system MAUS. Statements refer to all agri-environmental indicators.

SAEDN (old monitoring system)	MAUS (new monitoring system)
Data sources and collection	
One data source: detailed data from a network of 300 farms (anonymous data)	Several data sources: - Use of existing data: data from the government, associations, etc. - Own data collections to fill gaps (will be implemented in the future)
- High workload for the 300 farms involved in data collection	+ Less effort for farms in data collection, as existing data is used as much as possible
- Satellite data could not be included in the calculation of indicators (location of 300 farms unknown)	+ Satellite data will be included in the calculation of indicators in the future
Calculation of agri-environmental indicators (e.g. *GHG emissions)*	
+ Relatively little effort required to process data and calculate indicators	- Considerable effort required to process and link the various data sources
- Calculation of indicators only for the 300 farms of the farm network	+ Calculation of indicators for all Swiss farms
- Regional evaluations of indicators only possible at valley, hill and mountain level	+ High spatial resolution of the calculated indicators
+ Well resolved variability between individual farms (for the 300 farms)	- Variability between individual farms cannot be fully reflected

This will enable us to estimate each farm's mineral fertiliser application (response variable) based on known information for each farm (predictor variables; e.g., number of animals, share of arable land, manure exchanges, region). In a next step, this estimate can then be further refined by future data collected from farm management information systems.

Retrospective calculations in MAUS are not planned, as several input data used for the calculation are not available for years prior to 2021. However, it will be possible to qualitatively compare the results with the time series of the old monitoring (SAEDN), for which there will be an overlap of two years (2021 and 2022).

Since the MAUS calculations are farm-specific and georeferenced, future data sources can be easily integrated into the monitoring concept. For example, satellite data can be spatially intersected or data from farm management information systems can be directly assigned to the respective farm. The spatially resolved calculations also make it possible to estimate the impact of agricultural policy measures in different regions or on different farming systems.

4.4. Need for action in agricultural policy

4.4.1. Alignment between farm subsidies and GHG emissions

Swiss farms receive substantial financial contributions from the federal government that are tied to specific requirements. Several of these farm subsidies are directly or indirectly related to GHG emissions. For example, there are subsidies for nitrogen-reduced phase feeding for pigs, which should decrease nitrogen excretion rates and thus N_2O emissions. Another example are animal-welfare subsidies for grazing, which has the additional effect of reducing GHG emissions per area (Section 3.3). Based on our previous analysis (Section 3.2, Section 3.3, Supplementary Section A.2), we qualitatively estimated the impact of different subsidies on GHG emissions (Supplementary Section D). We found that some governmental contributions (e.g. nitrogen-reduced phase feeding for pigs) could in principle be positive for the reduction of GHG emissions. However, the fact that many contributions are paid out per livestock unit – thereby subsidising animal husbandry – represents a potential trade-off. In order to sufficiently reduce GHG emissions from Swiss agriculture to reach the agri-environmental goal, it is necessary that Switzerland's livestock population declines (Bretscher et al., 2018). Some regions of Switzerland are hardly suitable for agricultural use except for roughage consumers, but in other regions, much arable land is currently used for the production of concentrated feed. The results of MAUS can help to determine in which regions livestock numbers should be adjusted. Targeted reductions in livestock numbers could be supported by restructuring per-livestock payments. The following examples outline possible approaches, although their effectiveness and feasibility would need to be further investigated: 1) lowering the subsidy weight based on the livestock number, 2) setting an upper limit on livestock numbers for payments, 3) paying all ruminant-related payments per grassland area instead of per LU, or 4) banning subsidies for feed production on arable land. Such payments would ideally be structured in a way that extensive livestock farms in mountainous areas, which already have low average income (Hoop et al., 2025), would not have to give up production.

In this regard, it should however be noted that a change in the farm subsidy system alone is insufficient to reach Switzerland's GHG emission goals. The current livestock numbers in Switzerland are also a result of the fact that specialising in animal products (meat from fattening, eggs) is lucrative due to market conditions. In 2024, farms specialising in these animal products earned an average income of CHF 92,500 per family worker (Hoop et al., 2025). This amount is the highest of all farm types and considerably higher than the average Swiss farm income of CHF 59,100 per family worker (Hoop et al., 2025). Next to farm subsidies, other levers are therefore also needed to enable farms to restructure their production. Considering the agricultural and food system as a whole, changes in consumption behaviour of the Swiss population could alter market conditions. A more plant-based consumption and reduction in food loss would not only offer advantages for GHG emission reduction, but also for aspects such as other environmental improvements, a healthier diet, and a greater food self-sufficiency (von Ow et al., 2020). As outlined in the 'Climate Strategy for Agriculture and Nutrition 2050', the Swiss government has indicated its intention to pursue this approach (FOAG et al., 2023). When making this transition, it is important to consider that major changes in production take a long time for farmers to implement, as they require retraining and changes to infrastructure.

4.4.2. Communication of monitoring results

The lower N_2O emissions in our calculations compared to the national inventory were primarily because we used more recent NH_3 emission factors (Section 4.1). These newer NH_3 emission factors are not related to changes in agricultural practices, but to new scientific findings (e.g. through better measurement methods). It has been known for some time that the national emission factors for e.g. slurry application are too high (Häni et al., 2016; Sintermann et al., 2011). There are probably two main reasons why older emission factors are retained for the national NH_3 calculations. First, it might be feared that communication to the public will be impeded if the figures suddenly change with the use of new emission factors, and that this reduces confidence in the reliability of the results. Second, the environmental target of ammonia emissions is formulated in absolute numbers (25′000 kt TAN). Updating the emission factors would bring Switzerland much closer to this target without actually reducing the harmful environmental impact of ammonia emissions.

While these reasons are understandable, there are also arguments in favour of changing emission factors. Emission factors or global warming potentials are continuously being updated by new scientific knowledge. It is good scientific practice to incorporate new research findings regularly into scientific models. When calculating time series, it is important to ensure that new emission factors can also be applied retrospectively to avoid artificial shifts. If communicated correctly, this approach should increase credibility. In extreme cases, changes in emission factors can lead to a shift in the focus of political measures. If, for example, it turns out that an emission source is more important than previously expected, policy makers must take appropriate measures.

In this context, care should be taken when defining emission targets in absolute numbers as in the case of Swiss ammonia emissions. This applies in particular when various processes (e.g. atmospheric transport, deposition) take place between the emissions and the environmental impact (e.g. exceeding critical nitrogen loads in sensitive ecosystems), which have to be modelled. Otherwise, as described above, there is a risk that the update of an emission factor will achieve the absolute emission target without the environmental problem (e.g. exceeding critical loads) having been solved. Defining such targets in relative terms, e.g. a 30% reduction, might be more appropriate.

5. Conclusions and outlook

This study demonstrates that the new Swiss agri-environmental monitoring programme MAUS enables spatially explicit and farm-level calculations of agri-environmental indicators across Switzerland, illustrated here with the example of GHG emissions. The results reveal clear GHG emission hotspots, mainly in regions with high livestock density, and confirm that livestock numbers are the dominant driver of agricultural emissions. Additional factors – such as feeding intensity or commercial fertiliser amount – also influence emissions, but less strongly and differently across farm types.

MAUS thereby provides policy makers with a solid evidence base to identify regions and levers where mitigation efforts are likely to be most effective. A qualitative assessment of the current subsidy schemes suggests that they may not be sufficiently aligned with climate objectives, as some of them provide incentives for livestock numbers. We propose that adjustments towards area-based or performance-based payments could help reduce GHG emissions more efficiently, while social and economic implications on farmers need to be considered.

Our calculations represent a valuable complement to the national GHG inventory and could be used, for example, to simulate the effects of policy measures on different production systems or to monitor climate strategies at the cantonal level. Many Swiss cantons already have, or are currently developing, climate strategies for agriculture (e.g. Fussen et al., 2021). Moreover, the same bottom-up approach will be applied to other agri-environmental indicators in MAUS (e.g. erosion risk), enabling comparisons across multiple indicators in the future.

For the GHG indicator, MAUS already builds on a comprehensive set of existing data sources, which enables robust national estimates with high spatial resolution. For other indicators, however, further data integration will be needed before comparably reliable results can be achieved. Future development of MAUS will therefore focus on closing these gaps, while maintaining transparency and continuity of the time series. A combination of satellite observations, data from farm management information systems, data from online surveys, and potentially more available administrative data will be used to achieve this.

At the methodological level, GHG calculations will be continuously refined in light of new scientific evidence, for example through more accurate consideration of harvest residues. In the medium term, it is also planned to expand the system boundaries of the GHG model to optionally include additional emission sources (e.g. diesel, organic soils, prechain emissions). This would allow a broader range of agricultural measures to be assessed and provide more detailed guidance for agricultural policy.

Although developed for Swiss conditions, MAUS illustrates how existing national data streams can be combined into a coherent monitoring framework. As such, it may serve as a case study for other countries considering similar approaches, while remaining tailored to national policy contexts.

In conclusion, MAUS represents an important step towards evidence-based agricultural policy in Switzerland. Its modular and extensible design ensures that the system can evolve with new data, methods, and policy needs.

CRediT authorship contribution statement

Anina Gilgen: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Formal analysis, Conceptualization. **Jérôme Schneuwly:** Writing – review & editing, Visualization, Software, Formal analysis, Data curation. **Cyrill Zosso:** Writing – review & editing, Validation, Conceptualization. **Lutz Merbold:** Writing – review & editing, Conceptualization. **Daniel Bretscher:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used deepl (https://www.deepl.com/) and chatgpt (https://chatgpt.com/) in order to translate single words from German to English and to improve the language of a few sentences. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2026.104887.

Data availability

The authors do not have permission to share data.

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