Title: Intra- and inter-year variability of agricultural carbon footprints – A case study on field-grown tomatoes

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Abstract

The performance of agricultural systems and their environmental impacts can vary considerably within a single crop supply chain, due to differences in farming practices, soil properties, and yearly climatic conditions. In this paper, we characterised the variability of carbon footprints of open-field tomato production by analysing a comprehensive farm dataset gathered over 4 years. We also assessed the importance of the different drivers of variability as compared to model uncertainties. The primary data used in this study were collected from 189 farms from the Extremadura region in Spain and Portugal over a period of four years, from 2012 to 2015. We modelled the carbon footprint of these farms using the Cool Farm Tool model developed by Hillier et al. (2011) and conducted statistical analysis on the results to understand the relative importance of inter-year and intra-year variability. We performed sensitivity analysis to understand how sensitive the results were to variability in the farmers' input parameters and to the uncertainty in model parameters. This was done by varying all factors one-at-a-time, and then by running a Monte Carlo simulation where all uncertainties were propagated simultaneously. Results clearly show significant inter-year and intra-year variability in carbon footprints of tomato production within the study region. We observed approximately 20% variation for each annual carbon footprint (intra-year variability), resulting in an overall 28% coefficient of variation in the aggregated footprint across the different years. The carbon footprint of the whole tomato supply, calculated with the 4-year dataset, showed a weighted geometric mean of 51 kg CO_2-eq/t and a weighted GSD of 1.32, meaning a 95% confidence interval of 29 to 89 kg CO_2-eq/t. Results also show that small farms were characterised by a larger variability than larger ones. This highlights the need to weight farm results by production volumes if the objective is to obtain a carbon footprint for the total production in a given region. The carbon footprint was found to be mainly sensitive to variability in farm practices, notably extent of pump irrigation and choice and amount of fertiliser used, with model uncertainties influencing the results to a relatively smaller extent. Further work is needed to extend these findings to other crops, regions and impact categories.

Keywords

Carbon footprint; Uncertainty; Variability; Reporting; Agriculture; Tomato

1 Introduction

In the context of growing consumer awareness of sustainability issues, corporate sustainability activities and reporting have expanded to cover full supply chains including agricultural production. Many companies have implemented sustainable sourcing initiatives to promote sustainable farming practices in their own or supplier operations. While these strategies were primarily focused on management practices, they are starting to drive the collection of farm data to generate the evidence of environmental performance and reductions in environmental impacts. For example, Unilever has developed a Sustainable Agriculture Code (SAC)[1], which defines sustainable farming practices using 11 social, economic and environmental indicators (Unilever website). Compliance with the SAC is achieved through self-assessment and verification against the code, or compliance with an external certification scheme with similar requirements. In terms of the former, suppliers are requested to collect and submit farm data annually, in order to demonstrate sustainable farming practices and continuous improvement. This includes an estimation of the life-cycle greenhouse gas (GHG) emissions from their agricultural production using a recommended GHG calculator: the Cool Farm Tool (CFT, Hillier et al., 2011). Other companies also use the Cool Farm Tool (Cool Farm Tool website) or other similar tools (e.g. Diaterre, Farm Carbon Calculator, CALM, CCalc, or PalmGHG; see Colomb et al. 2012 and Whittaker et al. 2013 for reviews of such GHG calculators) to assess the GHG emissions of agricultural production and raw material supply.

However, estimating GHG emissions of agricultural practices and evidencing progress over time presents challenges that are not encountered when assessing impacts from industrial processes and energy systems. The carbon footprint of agricultural production can vary significantly between farms and from year to year and many authors, such as Sala et al. (2017), have stressed the need for more local assessments of crop production. This is because agricultural systems are, by nature, highly variable: weather conditions fluctuate; soil and topographic conditions vary from location to location and; genetic material and farming practices are influenced by factors such as local knowledge, socio-economic status of the farmer and local legislation. Therefore, the analysis and interpretation of farm data collected through sustainable agriculture initiatives and certification schemes are challenging, particularly if the objective is to benchmark performance and evidence improvement over time. For this, a better understanding of inherent variability and uncertainties in calculated emissions is required.

[1] Abbreviations used in the article: CFT: Cool Farm Tool; CRM: Crop residue management; GM: Geometric mean; GSD: Geometric standard deviation; SAC: Sustainable Agriculture Code.

A number of studies have started evidencing the variability of environmental impacts associated with specific crop productions. Gerber et al. (2010) quantified the GHG emissions associated with global dairy production and showed significant variability between regions and between production systems. Ntinas et al. (2017) showed how the carbon footprint of tomato production differs between various cultivation systems, based on data collected over several months in two fields and five greenhouses located in Greece and Germany. Pishgar-Komleh et al. (2017) analysed the variability of the GHG emissions from open-field tomato production using data collected in 204 farms in two regions of Iran. They obtained a carbon footprint ranging between 0.1 and 0.4 kg CO_2-eq per kg tomato and showed that the performance in one region was systematically better than in the other one due to a combination of the use of modern irrigation system, less fertiliser use and better yields.

Even though multi-year base periods are recommended (World Resources Institute, 2014), many studies of agricultural production are based on data collected over periods shorter than a year as monitoring farm practices over several years can be very resource intensive. Inter-year variability is however of high relevance when assessing open-field agricultural production. Röös et al. (2010) quantified the uncertainty of potato production in a region of Sweden and obtained a carbon footprint of 0.10–0.16 kg CO_2-eq per kilogram of potatoes with 95% certainty for an arbitrary year and field, which was reduced by 19% when the temporal variation was locked to a specific year. Fedele et al. (2014) compared the performance of conventional and organic production of barley and soybean in an Italian region and confirmed the importance of considering annual variations. Boone et al. (2016) analysed factors of variability in production systems of maize and showed that year-to-year weather variation resulted in large differences in the environmental footprint. Even though more insights are gained on variability of the environmental impacts between production systems, none of these previous studies systematically addressed the separate influence of intra-year variability (differences between farms within one year due to e.g. soil conditions or farm practices) and inter-year variability (due to year-to-year weather variations).

In this study we made use of a large dataset collected at the farm level over a four-year period by the tomato processor Agraz (part of Conesa Group), supplying Unilever with tomato products in accordance with Unilever's SAC. A total of 189 quality-checked datasets from farms located in the Extremadura region across Spain and Portugal were analysed. The objectives of this study were to:

1. Characterise the intra- and inter-year variability in the carbon footprint of tomato production in the study region,

2. Employ sensitivity and uncertainty analysis methods to systematically assess how parameter variability and model uncertainties respectively influence variability in the carbon footprint,
3. Elaborate on the implications of our findings in terms of best practice for farm data collection and carbon footprinting of crop production.

2 Materials and Methods

2.1 Farm data collection

Data were collected over 4 years by Agraz from open-field tomato cultivating farms located in the Extremadura region across Spain and Portugal. All farms under contract with Agraz are operated according to the SAC guidelines for farming practices. In total, 189 datasets were collected: 31 in 2012, 42 in 2013, 60 in 2014, and 56 in 2015. Each year, the reporting farms were selected randomly from within Agraz's farmer base, as required by the SAC. Small and large farms were included with production areas varying from 0.3 to 231 ha and annual production from 24 to 19,500 tonnes per year (Figure 1).

Farm-specific variables were collected, reviewed and input in the CFT, an Excel-based tool developed by Hillier et al. (2011), including factors such as the types and amounts of fertiliser used, the amount of diesel used, and the production yield. Before running the carbon footprint calculations in the CFT, we run a second check to ensure the results did not have gross mistakes e.g. in reporting units, and spotted if some data points were wrong e.g. with regards to fertiliser reporting. Table 1 shows the full list of variables collected and the ranges of values observed in the farms sampled over the four years and distributions are presented for selected variables in Figure S1 of the Supplementary Information (SI).

2.2 Carbon footprint assessment

The carbon footprints of the 189 sampled farms were estimated by using the CFT model (Hillier et al., 2011). This tool was recently rated as the best carbon accounting tool for arable crops by Whittaker et al. (2013) due to its user-friendliness, transparency and comprehensiveness. The CFT takes an attributional life cycle assessment (LCA) approach, estimating the carbon footprint of a crop based on the following parameters: (i) farm conditions, i.e. location, climate, soil parameters (soil moisture, drainage, pH, soil organic matter); (ii) material and energy inputs to farming, i.e. fertiliser and pesticide types and amounts and energy used on farm and; (iii) efficiency of the farm, i.e. area harvested and volume of fresh tomato produced.

The system boundary for this study was the farm gate (Figure 2) and included the preparation of land, transplanting of the seedlings in the field, growing the plants, fertiliser and pesticide application, irrigation, harvesting, and management of crop residues. Nursery operations were excluded as these are a minor contributor to the carbon footprint of the crop. The production of capital goods was excluded (Hillier et al., 2011), as well as the impacts from land use change as this happened more than 20 years ago (BSI PAS 2050, 2011). Primary data from the farms (Table 1) were paired with secondary data taken from the CFT (Hillier et al., 2011), including inventories for production of fertilisers and pesticides, production of energy carriers, i.e. electricity and diesel, and emission factors for estimating field emissions and diesel burning (Table 2). All equations and related parameters are provided in SI.

2.3 Statistical methods for characterising the variability in carbon footprints

An arithmetic mean is the simplest way of describing central tendencies, but it can be influenced by outliers or skewed data. Geometric characteristics are better suited for skewed distributions such as the ones observed for most parameters in this dataset. LCA practitioners often use lognormal distributions for intermediate and elementary flows (Weidema et al., 2013) which are associated with geometric mean and standard deviation. Here we decided to present both arithmetic and geometric characteristics of the dataset as readers may be more familiar with the arithmetic metrics. Equations 1-4 show the arithmetic mean (μ) and standard deviation (σ) of a set of n numbers $\{x_i\}_{i=1}^{n}$, as well as the geometric mean (GM) and standard deviation (GSD). Note that 95% confidence intervals were defined for normal distributions as [μ - 2*σ - μ + 2*σ], and for lognormal distributions as [GM / GSD^2 – GM*GSD^2].

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (1)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n-1}} \qquad (2)$$

$$GM = \exp\left(\frac{\sum_{i=1}^{n} \ln(x_i)}{n}\right) \qquad (3)$$

$$GSD = \exp\left(\sqrt{\frac{\sum_{i=1}^{n}(\ln(\frac{x_i}{GM}))^2}{n-1}}\right) \qquad (4)$$

As observed in Figure 1, the size of the farms sampled varied significantly. To account for this, volume-weighted means and standard deviations were used. Equations 5-8 specify how they were calculated, $\{w_i\}_{i=1}^{n}$ being the production volumes associated with the carbon footprints $\{x_i\}_{i=1}^{n}$.

$$\mu_w = \frac{\sum_{i=1}^{n} x_i * w_i}{n} \qquad (5)$$

$$\sigma_w = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu_w)^2}{\frac{n-1}{n} * \sum_{i=1}^{n} w_i}} \qquad (6)$$

$$GM_w = \exp\left(\frac{\sum_{i=1}^{n} w_i * \ln(x_i)}{\sum_{i=1}^{n} w_i}\right) \qquad (7)$$

$$GSD_w = \exp\left(\sqrt{\frac{\sum_{i=1}^{n} w_i * (\ln(\frac{x_i}{GM_w}))^2}{\frac{n-1}{n} * \sum_{i=1}^{n} w_i}}\right) \qquad (8)$$

Distribution fitting was performed with the @RISK software (PALISADE website) which provides the Akaike information criterion for any chosen distribution type.

2.4 Methods for sensitivity and uncertainty analyses

Sensitivity analysis was performed to understand the sensitivity of the GHG emissions to the variability in the different input parameters (for both farmer's inputs and model parameters). A one-factor-at-a-time technique was used:

1. GHG emissions per tonne were first calculated for an "average farm" defined with median values for all parameters,
2. Then GHG emissions per tonne were calculated using extreme (minimal and maximal) values for each parameter, one at a time: the values used were actual minimal and maximal values observed in the 189 farm datasets for all farmer input variables, and minimal and maximal values found in literature for model uncertainties.

Tables 1 and 2 present the values used for all parameters in the sensitivity analysis. To simplify calculations, the use of fertilisers was limited to one fertiliser type: "Compound NPK", and represented solely by the total amount of nitrogen input (kg N per ha) and the content of nitrogen within the fertiliser (%). The amount of fertiliser input (kg fertiliser per ha) was then back-calculated. This was deemed reasonable since the "Compound NPK" fertiliser type represented 91% of all fertiliser use over all 189 farms, the remaining 9% being compound NK, ammonium nitrate or in some rare occasions potassium sulphate, calcium nitrate, calcium ammonium nitrate, poultry layer manure, super phosphate or sheep farmyard manure. In addition, the carbon emission factor of compound NPK lies within the medium range of the emission factors of other fertilisers.

We used mostly the information found in Hillier et al. (2011) to set minimal and maximal values for all model parameters (See last column of Table 2). The CFT uses the model by Bouwman et al. (2002) for estimating emissions of N_2O, NO and NH_3. Bouwman et al. (2002) specifies that the 95% confidence interval for N_2O estimates is [-40%; +70%], which we used, but they could not assess the uncertainty around the estimations of NO and NH_3 due to a lack of data. We arbitrarily assumed the same 95% confidence interval for NO and NH_3 as for N_2O, and added for them the uncertainty in the conversion to N_2O as given by IPCC (2006). We employed the same approach for the leaching-related emissions.

Subsequently, uncertainties in all variables were propagated jointly using a Monte Carlo sampling. Parameters' distributions were selected to fit best to the reality: lognormal distribution for most continuous parameters (fitted to observed data) and discrete probabilities for the discrete parameters such as soil moisture. Tables 1 and 2 present all assumptions used for primary and secondary data respectively. Three sets of 10,000 simulations were run: first, only the variability in farmer's inputs were propagated (primary data from Table 1), then only model uncertainties (secondary data from Table 2), and finally all uncertainties and variability together.

3 Results and discussion

3.1 Variability in the carbon footprints of the sampled farms

The carbon footprint of the whole tomato supply, calculated with the 4-year dataset, showed a weighted geometric mean of 51 kg CO_2-eq/t and a weighted GSD of 1.32, meaning a 95% confidence interval of 29 to 89 kg CO_2-eq/t. These results were expressed with geometric characteristics since the carbon footprint results were slightly skewed as confirmed by distribution fitting performed with the @RISK software (PALISADE website). Arithmetic means were found systematically higher than geometric ones due to the positive skewness of the dataset (See Table 3). The results were weighted by production volumes because, as can be observed from the 189 farm results presented on Figure 3, minimum and maximum results were usually found for smaller rather than larger farms. Weighting farm results by the associated production volumes therefore significantly decreased standard deviations as confirmed in Table 3. When weighting by production volumes larger farms have more weight in the resulting carbon footprint, providing a more accurate estimate for the tomato supply than when all farm results were weighted equally regardless of their size. On the other hand, unweighted results can be useful if one wants an overview of farming practices regardless of the size of the farms, e.g. to demonstrate change of farming practices within a region or to know the performance of individual farms. The volume-weighted estimate is therefore more relevant to buyers and users of tomatoes whereas the non-weighted one is more useful to contractors and growers.

Our results of 51 kg CO_2-eq per t tomato are comparable with the results obtained by Karakaya & Ozilgen (2011) and Ntinas et al. (2017) for open-field production of industrial tomatoes in Turkey (67 kg CO_2-eq per t tomato[2]) and Greece (72 kg CO_2-eq per t tomato) respectively. However, they lie in the lower range of the data generally found in literature for tomato production. The review by Clune et al. (2017) reported a range of 80 to 1000 kg CO_2-eq per t tomato with a mean of 460 kg CO_2-eq per t tomato, based on 19 LCA studies. Differences in production systems and system boundaries can partly explain the variation. For example, Jones et al. (2012) obtained a carbon footprint of 190-270 kg CO_2-eq per t tomato for open-field tomato production in Florida. The higher results can be attributed to factors such as a higher nitrogen input per hectare, the use of plastic mulch and inclusion of post-farm gate transportation. Pishgar-Komleh et al. (2017) also reported values of 100-400 kg CO_2-eq per t tomato for 204 Iranian open-field tomato farms and these were driven by high energy consumption for pump irrigation and biogenic carbon emissions linked to recent land use change. In comparison the farms

[2] All results are presented in kg CO_2-eq per t tomato for the purpose of comparability.

reported this paper are all well-established farms with no land use change in the last 30 years, and operating under sustainable agricultural farming practices and with less energy required for irrigation than in the Iranian case.

3.1.1 Contribution analysis

GHG emissions originated mostly from fertiliser production (45% on average), on-farm energy consumption (30%) and direct N_2O field emissions (11%), while background N_2O emissions, pesticides production and use, and crop residues management contributed relatively less to total GHG emissions, 4%, 3% and 7% respectively. Figure 4 shows the GHG emissions of all processes aggregated in six groups: background N_2O emissions (background), direct field N_2O emissions (field), fertiliser production (fertiliser) which includes production processes of the different types of fertilisers used by the farms, pesticide production and use (agrochemicals), on-farm energy consumption (energy) which includes both diesel consumption for agricultural machinery and diesel and electricity consumed for running the irrigation pumps, and crop residue management (CRM). The greatest contributors to the carbon footprint (fertiliser production and on-farm energy use) also showed the largest variability. For fertilisers, this was mostly explained by the differences in the quantity of nitrogen applied on land and by the different types of fertiliser used by individual farms. The choice of fertiliser combination to use each year is made by the farmer to optimise yields and the use of the CFT highlights the wider GHG implications of such management decisions. For energy-related emissions, the differences were due to the different irrigation systems used by farmers, i.e. conventional vs. drip irrigation, powered by either diesel or electric motors, depending on the farm. Conventional irrigation systems were found to be more energy intensive than drip irrigations systems that circulate and use less water, irrespective if the farms used diesel or electric pumps. This contribution analysis highlighted the key activities for GHG management in tomato production in this region, indicating that efforts should be focused on optimising the choice and use of fertilisers and the efficiency of the irrigation system. The large contribution of energy (for irrigation) and fertiliser uses was highlighted as well by Pishgar-Komleh et al. (2017) and Ntinas et al. (2017).

3.1.2 Inter-year variability of GHG emissions from tomato production

Results presented in Figure 3 clearly show that both the intra-year and inter-year variabilities are significant when assessing the carbon footprint of tomato production within a single region. The level of variability observed in this study is particularly interesting since all farmers in our sample worked with the same supplier (Agraz) and complied with the same set of best management practices, as laid out in the SAC.

Figure 3 shows that the 2014 production had the lowest GHG emissions as opposed to the 2013 dataset which showed the highest impacts. This was confirmed by the weighted geometric means presented in Table 3, where the largest difference was observed between the 2013 and 2014 datasets (49% difference). The 2013 results could be explained by bad weather conditions that year that resulted in lower yields and higher use of fertilisers. We ran a statistical analysis using both an ANOVA on the full dataset and two-sample t-tests, which we considered valid even if t-tests assume normal distributions and the dataset was slightly skewed. The statistical analysis confirmed that, despite the intra-year variability, all annual datasets were significantly different with a significance level of 0.90, and therefore it evidenced the importance of the year effect for this dataset.

In addition, the spread of GHG emissions per tonne of tomato produced varied depending on the year: it was, for example, much larger for the 2013 dataset than for the 2014 dataset. This was confirmed by the standard deviations presented in Table 2, where the coefficients of variations varied between 22% and 33%, and pointed to the influence of weather conditions as a major driver for production and GHG performance.

The results show that, for this dataset, intra-year and inter-year variability had an equivalent importance. Indeed, the coefficient of variation between the four yearly weighted arithmetic means was 20%, a similar magnitude to the coefficients of variation (weighted arithmetic) calculated within each year, which were between 19 and 24%. The full dataset, which combined intra-year and inter-year variability, had a coefficient of variation equal to 28% (weighted).

3.2 Sensitivity and uncertainty analyses

The variability of carbon footprints observed in Figure 3 is due to many factors. Although some of the explanations were revealed by the contribution analysis or by the observation of the 189 single GHG results presented in Figure S1, no simple correlation could be drawn between the variability in just one or a few of those parameters and the variability in the total carbon footprints. It is interesting to note in particular from Figure S1 that the farms' carbon footprints per tonne were not correlated with their sizes.

The objectives of the sensitivity analysis were to quantify the importance of each individual parameter (both primary and secondary data) in determining the farm's GHG emissions and to verify if the variability observed in the primary data is a bigger contribution to the variability in total carbon footprint than the uncertainty in the model parameters.

Figure 5 presents the total GHG emissions per tonne of tomato produced, when individually varying the values considered for each parameter, using the minimal and maximal values presented in Tables 1 and 2. We distinguished between parameters collected at farm level for which minimal and maximal reported values were used (underlined in Figure 5, input parameter variability from Table 1), and model parameters for which we used literature estimates of uncertainty and variability (from Table 2). The results indicated that the variability of total GHG emissions per tonne of tomato produced was very sensitive to variations in the production yield, in line with what other studies showed, e.g. Röös et al. (2010). For example, a 70% reduction in the production yield induced a threefold increase of the GHG emissions per tonne of tomato. In general, GHG emissions were found to be mainly sensitive to variability in farm practices (underlined in Figure 5), in particular to the ones related to fertiliser and diesel uses (confirming the variability observed in Figure 4). A 269% increase in nitrogen input on the field (kg N per ha) implied a 205% increase in the GHG emissions of the tomato production. The influence of model uncertainties on the GHG results was found to be relatively lower. Only the carbon emission factor from fertiliser production was found to be of importance due to the high contribution of fertiliser use to the impact. The use of the highest value for fertiliser production (2.5 kg CO_2-eq per kg fertiliser) lead to a 70% higher GHG emission result than when using the default (0.96 kg CO_2-eq per kg fertiliser).

The combined effects of all sources of uncertainties and parameter variability were analysed by running three Monte Carlo simulations, each with 10,000 random samples. Results presented in Figure 6 show that the distribution obtained by propagating only variability in farmers' input parameters was more spread (standard deviation of 20 kg CO_2-eq/t) than the one with only model uncertainties implemented (st. dev. of 11 kg CO_2-eq/t). This confirms that the impact of the variability in the farmers' input parameter was more important than the impact of model uncertainties in this case study, as also observed in Figure 5. This result is important and highlights the fact that efforts should be focused on collecting sufficient amounts of farm data when building crop production datasets or databases, and that model uncertainties are relatively less important. The distribution obtained by propagating all uncertainties was (as expected) the most spread (standard deviation of 27 kg CO_2-eq/t) because it was the result of the joint propagation of variability in farmer's input variables and of model uncertainties. Overall, the non-weighted coefficient of variation increased from 36% when only farmer-specific variabilities were implemented, to 49% when model uncertainties were considered as well. Note that these coefficients of variation are different from the ones reported in Section 3.1, as here they are a result of the

Monte Carlo simulation using a distribution for each individual parameter, while the coefficients of variation presented in Table 3 reflected the actual variation between the farms' individually reported GHG emissions.

3.3 Implications for data requirements and carbon footprinting

The study has shown that the variability of the parameter values collected at the farm level was critical when assessing the carbon footprint of tomato production within one region. It is therefore crucial to collect enough data over several years in order to represent correctly the diversity of practices within a crop supply chain. It was then reasonable to consider what a representative sample should include, i.e. how many farms should be considered, and how many years' worth of data are required. Even though we presented here a specific case study, general conclusions could be drawn from this analysis for the amount of data required for getting a robust estimate of the carbon footprint of an agricultural product.

To assess how much data would be required to account for intra-year variability, we performed bootstrapping of the GHG emission results within each year. This consisted of randomly selecting one farm at a time and evaluating at each step the weighted geometric mean of all selected farms. Repeated application of this technique allowed us to establish the number of farms after which the collection of additional farm data did not affect the final result much, because of the inherent variability.

Figure 7 shows the results we obtained for 100 random samplings of farms from the 2014 dataset. For example, if we consider the dark line, we can see that the mean GHG emissions of the two first farms are around 38 kg CO_2-eq/t and that the five next randomly picked farms have higher GHG emissions making the weighted geometric mean increase to 46 kg CO_2-eq/t, before decreasing again. The 100 random farm samples presented in Figure 7 show that in all cases, once 30 farms had been sampled from the 2014 dataset, the weighted GM stayed within the zone of natural variability. The same approach was applied to the three other annual datasets. The results, presented in SI, confirm that the weighted geometric mean remained stable with sampling of 25-30 farms. Note that in this study we used verified and cleaned data and that in the presence of measurement or reporting errors the minimum amount of data required might have been higher.

Regarding inter-year variability, Table 3 showed that the mean obtained with 1 year of data was 9% to 27% different from the one obtained with the 4-years' worth of data. This difference between single-year results meant that if we had sampled farms only in one year (e.g. 2013), the carbon footprint would not have been representative of the average performance of tomato production in this region. The statistical test performed on the dataset confirmed this result. The limited number of years covered in this study (four) did not allow us to reach a conclusion about the minimum amount of years required to account for inter-year variability, but certainly, an average of several years appears more appropriate than a 1-year average.

4 Conclusions

This analysis of a comprehensive dataset of farm data provides insights into the variability of GHG emissions of crop production between farms and between years and can help in the context of interpretation and use of data. First, we showed that, in our dataset, small farms were characterised by a higher variability than larger ones, while not showing systematically higher carbon footprint per tonne than larger farms as opposed to results presented by Pishgar-Komleh et al. (2017). This confirms the need to weight farm results by production volume if the objective is to obtain a carbon footprint for total production in a given region.

Second, we quantified separately the intra-year and inter-year variabilities for our dataset. They were found of similar importance (approximately 20% variation when considering volume-weighted carbon footprints) and resulted in an overall volume-weighted variability of 28% (or a GSD of 1.32). We showed that variability in on-farm data in different years was more significant than model uncertainties in our case study; however, LCA studies in the literature have generally put greater emphasis on addressing model uncertainties, probably due to difficulties in obtaining large primary data sets. Our study suggests the need for collection and reporting of crop carbon footprints based on a minimum of 30 farms for the region of concern and on several years' worth of data, particularly as climate change effects become more prevalent and extreme events such as draughts or torrential rain become norm rather than the exception. In the case of regions of larger sizes or of a supply base, the minimum amount of farms required may differ and further work is needed to extend these findings to such cases. This confirms the need for datasets to be representative of local conditions as argued by Sala et al. (2017) and reinforces the relevance of initiatives such as the Cool Farm Alliance, Roundtable on Sustainable Palm Oil (RSPO) or the Sustainable Agriculture Initiative (SAI) platform, which are providing mechanisms for standardising and mainstreaming farm data collection for the assessment of environmental performance and improvement opportunities. In fact, other certifications schemes could usefully follow suit and initiatives such as Agrimetrics (Agrimetrics website) may also promote collection and sharing of large agricultural data sets in the future, as well as providing quantitative analytics. This suggests the need for an evolved approach to ensure that life cycle inventories in commonly-used LCA databases keep pace and reflect these developments.

The variability between farms was found to be similar to that observed by Pishgar-Komleh et al. (2017). However, the carbon footprints of the farms were generally lower than reported studies and this may be explained by the fact that the farms are well established, they operate according to the same guidelines for sustainable farming practices and their energy and fertiliser uses are in the lower ranges. This study is the first to present an analysis of the intra- and inter-year variability of GHG emissions from tomato production and to demonstrate the influence of yearly weather conditions. The need to optimise yields through N fertiliser input and energy use for irrigation is consistent with the single year findings of Jones et al. (2012) and Pishgar-Komleh et al. (2017).

This study confirms the need for data collection over several years for more robust environmental footprint assessment of crop production, as recommended by World Resources Institute (2014). Further work is required to extend this study to more crops and regions to validate our findings. For instance, different types of crops may be affected differently by the annual variation in weather conditions. Longer assessments would also be needed in order to help determine the optimum temporal extent of datasets required for carbon footprinting. In summary, our work highlights the fact that carbon footprints cannot be reduced to single numbers, in particular in the case of agricultural production, and variability needs to be better accounted for in life cycle assessments.

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Tables

Table 1. Data collected in the 189 farms under study and used in the GHG calculations (min and max values were used in the sensitivity analysis, distributions were used in the Monte Carlo simulation)

Parameter name	**Unit**	**Median**	**Min**	**Max**	**Distribution used in Monte Carlo simulation ***
Nitrogen input	kg N / ha	188	66.1	505.7	Lognormal (5.19, 0.334)
Content of nitrogen in fertiliser	%	10.4	4.8	20.4	Lognormal (2.35, 0.311)
Yield	t / ha	86.1	29.3	148.5	Lognormal (4.44, 0.249)
Pesticides applications	-	7	3	34	Lognormal (2.01, 0.45)
Electricity use	kWh / ha	225.5	0.0	2743.0	0 with 158/189 probability, else Uniform (46, 2743)
Diesel use	L / ha	420	29.2	998.2	Lognormal (6.02, 0.438)
Soil organic matter	%	1.3	0.26	3.44	Lognormal (0.161, 0.54)
Soil texture		Medium (128/189)	Fine (47/189)	Coarse (14/189)	Discrete
Soil moisture		Moist (149/189)	Dry (40/189)		Discrete
Drainage		Good (111/189)	Poor (78/189)		Discrete
Soil pH **		Mid-low** (105/189)	Low** (6/189)	High** (4/189)	Discrete
Country		Spain (151/189)	Portugal (38/189)		Discrete

*: The characteristics shown for lognormal distributions are the mean and standard deviations of the associated normal distribution as required for the MATLAB function “logrnd”

**: The data on soil pH is divided into four categories: low (pH≤5.5), mid-low (5.5<pH≤7.3), mid-high (7.3<pH≤8.5), high (pH>8.5)

Table 2. Secondary data used in the GHG calculations (min and max values were used in the sensitivity analysis, distributions were used in the Monte Carlo simulation)

Parameter name	Unit	Median	Min	Max	Distribution used in Monte Carlo simulation	Source for min, max and distribution used
GHG emissions from fertiliser production	kg CO_2-eq / kg fertiliser	0.96	0.19	2.50	Triangular (0.19, 0.96, 2.50)	Extreme values found in Hillier et al. (2011)
GHG emissions from pesticides production	kg CO_2-eq / fert. applic.	20.50	14.70	28.10	Triangular (14.7, 20.5, 28.1)	Extreme values found in Audsley and Alber (1997)
Content of N in residues	%	0.015	0.01	0.03	Triangular (0.01, 0.015, 0.03)	Estimated based on variability observed for other crops (Hillier et al. 2011)
Tonnes residues per ha *	t / ha	3.227	1.00	8.00	Triangular (1, 3.227, 8)	
GHG emissions from electricity grid in Spain	kg CO_2 – eq / MJ	0.083	0.04	0.12	Triangular (0.04, 0.083, 0.12)	Assumed 50% higher and 50% lower values
GHG emissions from electricity grid in Portugal	kg CO_2– eq / MJ	0.102	0.05	0.15	Triangular (0.05, 0.102, 0.15)	
GHG emissions from diesel production	kg CO_2-eq / L	2.68	2.00	3.11	Triangular (2, 2.68, 3.11)	Hillier et al. (2011)
N_2O direct emissions	% of N input	100	60	170	Triangular (60, 100, 170)	95% confidence interval of model by Bouwman et al. (2002)
N_2O emissions due to NO emissions	% of N input	1	0.12 (0.2*0.6)	8.5 (5*1.7)	Triangular (0.12, 1, 8.5)	Same uncertainty assumed as for N_2O emissions adding the uncertainty of conversion to N_2O according to IPCC (2006)
N_2O emissions due to NH_3 volatilisation	% of N input	1	0.12 (0.2*0.6)	8.5 (5*1.7)	Triangular (0.12, 1, 8.5)	
N_2O emissions due to NO_3^- leaching (moist soil conditions)	% of N input	1	0.03 (0.05*0.6)	4.25 (2.5*1.7)	Triangular (0.03, 1, 4.25)	

*: In the Cool farm tool the amount of residues produced can be specified by the farmer instead of using the default value of 3.22 t/ha. However, none of the farmers reported a specific amount so we used the default value.

Table 3. Arithmetic and geometric means and standard deviations for the 4 yearly datasets as well as for the total 4-year dataset. Data presented as unweighted and weighted with production volumes (in kg CO_2-eq per t tomato).

			2012	2013	2014	2015	Total
Arithmetic	Non-weighted	Arithmetic mean (μ)	57.4	65.1	42.7	47.4	51.5
		Arithmetic standard deviation (σ)	19.4	21.7	9.5	13.9	18.0
		Coefficient of variation (σ/μ)	34%	33%	22%	29%	35%
	Weighted	Weighted arithmetic mean (μ_w)	62.6	65.6	44.1	47.3	52.9
		Weighted arithmetic standard deviation (σ_w)	15.0	12.9	8.4	10.9	14.7
		Coefficient of variation (σ_w/μ_w)	24%	20%	19%	23%	28%
Geometric	Non-weighted	Geometric mean (GM)	54.7	61.6	41.6	45.4	48.7
		Geometric standard deviation (GSD)	1.37	1.41	1.25	1.34	1.39
	Weighted	Weighted geometric mean (GM_w)	60.6	64.4	43.4	46.1	50.9
		Weighted geometric standard deviation (GSD_w)	1.31	1.22	1.21	1.27	1.32

Figures

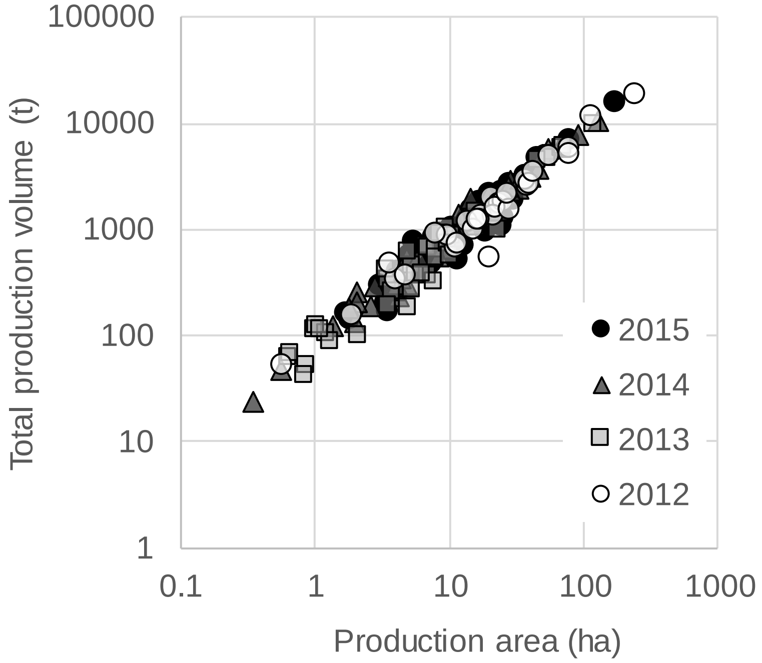

Figure 1. Production area and total weight of harvested tomatoes of the 189 farms analysed

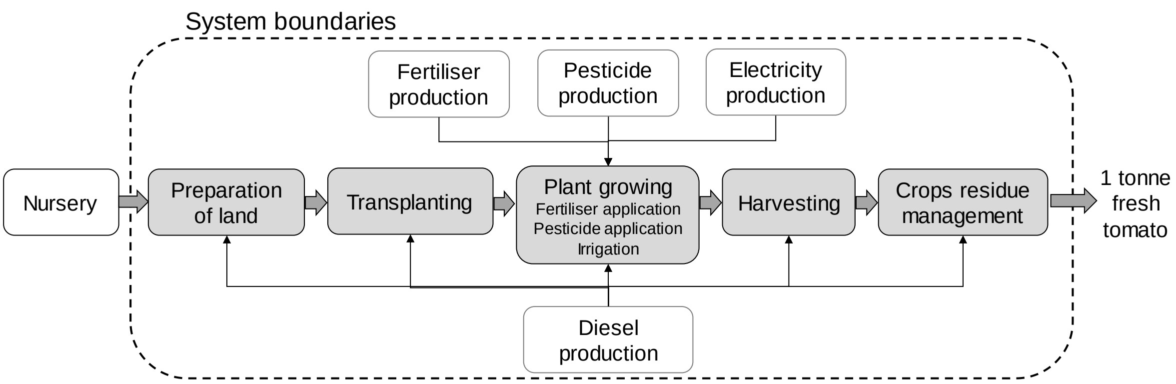

Figure 2. System boundaries for producing open field tomatoes. Grey background indicates processes modelled with primary data, white background indicates secondary data.

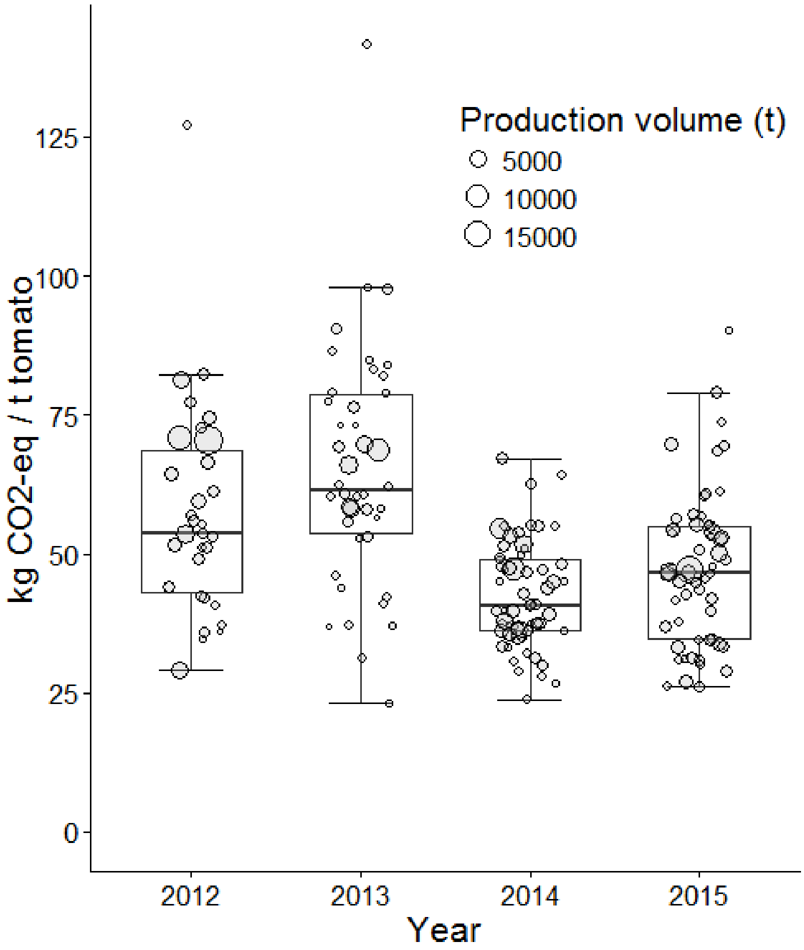

Figure 3. GHG emissions from tomato production calculated with the 189 farm datasets (bubble sizes show production volumes in tonnes) and resulting box plots showing quartiles, median and outliers for each dataset. A data point was considered an outlier when it is further away from the 1st or 3rd quartiles by more than 1.5 times the inter-quartile range (IQR).

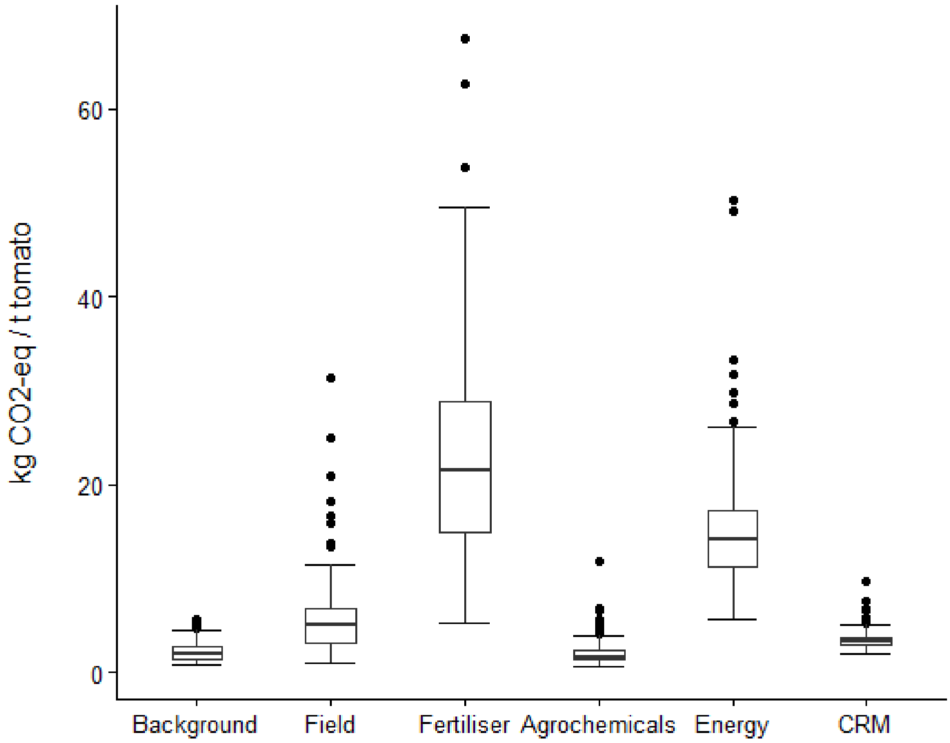

Figure 4. GHG emissions calculated for each group of processes for the 189 farms: background N_2O emissions, direct field N_2O emissions, fertiliser production, pesticides production, on-farm energy consumption, crop residue management (CRM). Box plots show minimum, 1st quartile, median, 3rd quartile and maximum. A data point was considered an outlier when it was further away from the 1st or 3rd quartiles by more than 1.5 times the IQR.

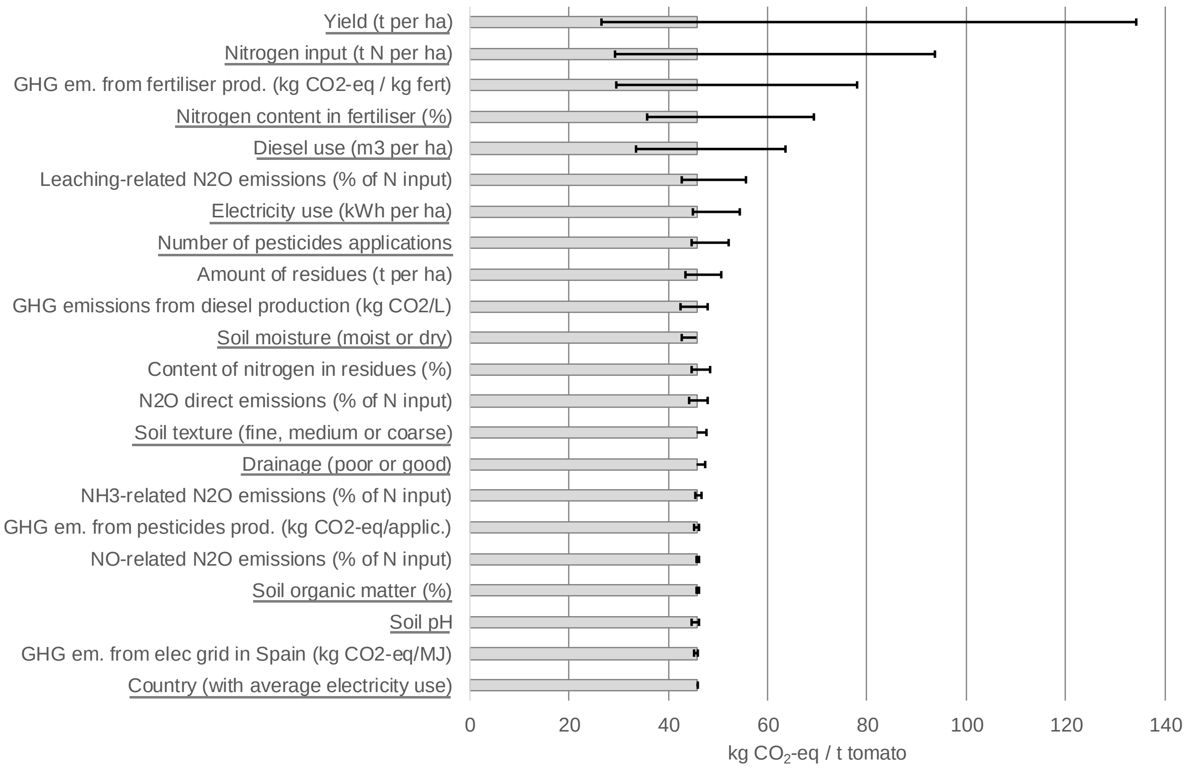

Figure 5. Total GHG emissions obtained using median values for all parameters, with error bars showing the minimal and maximal GHG emissions obtained when testing minimal and maximal values for each parameter one at a time. Farmer-input data are underlined. Input parameter variabilities are presented in Tables 1 and 2.

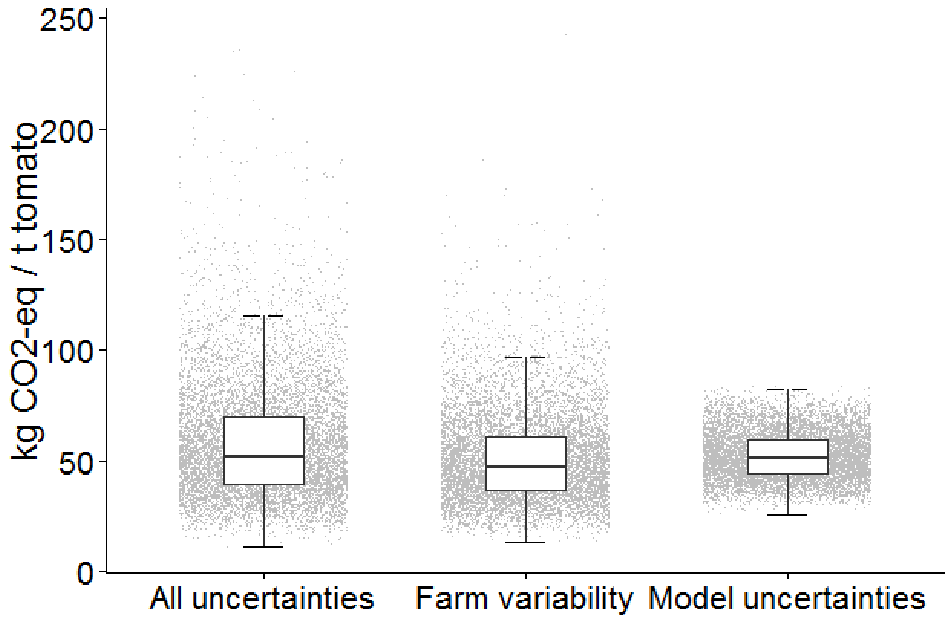

Figure 6. Results of the Monte Carlo simulations (10,000 runs each) for the carbon footprint of tomato production when implementing solely farm input variability, solely model uncertainties, or both. Box plots show median, quartiles and minimal and maximal (or 1.5*IQR away from the 1[st] or 3[rd] quartiles in the presence of outliers).

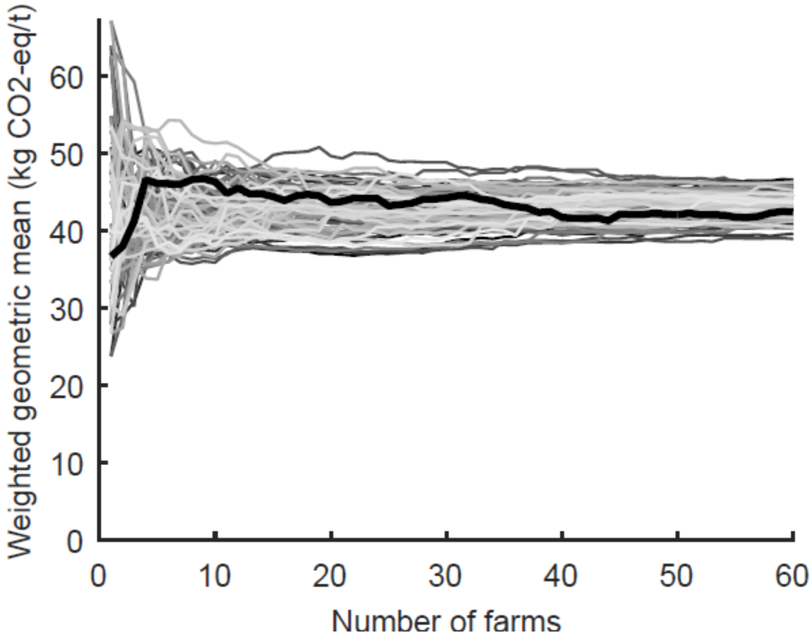

Figure 7. Weighted geometric mean of the carbon footprint of tomato production obtained with 100 different random samplings of 2014 farm data (bootstrapping). The dark bold line shows one specific sampling described in the text.