The following full text is a publisher's version.

For additional information about this publication click this link.
http://hdl.handle.net/2066/182765

Please be advised that this information was generated on 2018-11-21 and may be subject to change.
Variability of Greenhouse Gas Footprints of Field Tomatoes Grown for Processing: Interyear and Intercountry Assessment

Wan Yee Lam,*† Rosalie van Zelm,† Ana Benítez-López,† Michal Kulak,‡ Sarah Sim,‡ J. M. Henry King,‡ and Mark A. J. Huijbregts†

†Department of Environmental Science, Institute for Water and Wetland Research, Radboud University, P.O. Box 9010, 6500 GL Nijmegen, The Netherlands
‡Unilever Safety and Environmental Assurance Centre, Unilever R&D, Colworth Science Park, Sharnbrook, Bedfordshire MK44 1LQ, United Kingdom

ABSTRACT: Our study provides an integrated analysis of the variability of greenhouse gas (GHG) footprints of field-grown tomatoes for processing. The global farm-specific data set of 890 observations across 14 countries over a three-year period (2013–2015) was obtained from farms grown under Unilever’s sustainable agricultural code. It represents on average 3% of the annual global production of processing tomatoes: insights can be used to help inform corporate sourcing strategies and certification schemes. The median GHG footprint ranged from 18 in Chile to 61 kg CO2-equiv per tonne of tomatoes in India, lower than results reported in other studies. We found that footprints are more consistent within countries than between them. Using linear mixed effect models, we quantified the relative influence of environmental conditions and farm management factors. Key variables were area of production and the method of fertilizer application. GHG footprints decreased with increasing area of production to a threshold of 17.4 ha. Farms using single fertilizer application methods in general had a larger GHG footprint than those using a combination of methods. We conclude that farm management factors should be prioritized for future data collection, and more stringent guidance on acceptable practices is required if greater comparability of outcomes is needed either within a scheme, such as the Unilever’s sustainable agriculture code, or between schemes.

INTRODUCTION

Greenhouse gas (GHG) calculators and footprinting can be used by companies to inform management strategies within agricultural supply chains.1 The impacts of the agricultural phase in the life cycle of biobased products are highly variable and subject to many influencing factors, especially in open-field cultivation systems.2−5 Variability in GHG footprints (kg CO2-eq per tonne) of crop production is directly related to variation in factors such as fertilizer use, machine use, irrigation, and yield.2,5,6,7 These sources of variability are interrelated and influenced by environmentally related factors, such as climate, soil properties and elevation as well as other farm-related factors such as area of production and fertilizer application methods.5,6,7

Previous life cycle assessment (LCA) studies investigating variability of agricultural production focused on factors directly used in GHG footprint calculations as the major contributors to variability in GHG footprints.2,3,5,6,9 For field tomato production, Clavreul et al.5 conducted intra- and interyear variability analysis of GHG footprints of cultivation using data from 189 farms from 2012 to 2015 in the Extremadura region in Spain and Portugal. The GHG footprints, ranging from 29 to 89 kg CO2-eq per tonne of tomatoes, were found to be most sensitive to the variability in yield, followed by farm practices such as the extent of pump irrigation and choice and amount of fertilizer used. Pishgar-Komlehy7 quantified variability of GHG footprints of field tomato production using data from 204 farms in Iran and obtained GHG footprints ranging from 100 to 400 kg CO2-equiv per tonne of tomatoes. They also found the variability of GHG footprints to be mainly driven by the variability in yield, followed by fertilizer application. While Clavreul et al.5 attributed the importance of interyear variability in GHG footprints to variability in weather conditions, there was no formal quantification of the relationship between climatic and soil conditions and the GHG footprint of the tomatoes.

Linear mixed models (LMM), also known as linear mixed-effects models, are able to incorporate a wide variety of correlation patterns in their random effects structure, and this flexibility provides accurate estimates of the fixed effects in the presence of correlated errors due to data hierarchy and repeated measurements.10,11 This approach is particularly suitable for data sets that have several observations nested within each country, and repeated measurements from farms in different years, and offers a systematic approach to analyze the
importance of other environmentally and farm-related factors, such as soil, climate, and fertilizer application method, in contributing to the variability in GHG footprints of crop production. Analyzing the variability of the GHG footprints at the farm level and understanding the drivers of the variability is necessary to identify possible areas of GHG reduction and to enable more targeted GHG mitigation strategies within agricultural supply chains.

The goal of this study was to (1) assess the variability (between farms, countries, and years) of the GHG footprint of commercially grown field tomatoes globally and (2) understand the relationship between GHG footprints of commercially grown field tomatoes and environmental factors, such as climate and soil characteristics, and farm related factors, such as production area and fertilization method. The data set represents farms that were compliant with the Unilever’s Sustainable Agriculture Code (SAC) and covers 14 countries that represent approximately 80% of global production of field-grown tomatoes and includes the top five producing countries, namely the United States of America (USA), China, Italy, Spain, and Turkey.\(^1\)\(^2\)\(^3\) First, we assessed the variability in GHG footprints and quantified, with a partial correlation analysis, the relative importance of factors that are used in standard GHG footprint calculations of tomato production, namely (i) tomato yield, (ii) emissions from fertilizer production and field application, and (iii) emissions from energy use. Second, we used LMM to quantify the relative influence of environmental conditions and farm management factors on the variability of GHG footprints for global tomato production. The first analysis was conducted using field tomato production data from 890 farm-specific observations across 14 countries and measured over three years (i.e., 2013–2015).\(^4\)\(^5\) The second analysis was based on a subset of 719 observations with unique geolocations and complete description of farm management factors.

---

**MATERIALS AND METHODS**

**GHG Footprint.** Following the system boundaries illustrated in Figure 1, the GHG footprint of field-grown tomato production on a specific farm \(x\) in a specific year \(y\) (GHG\(_{\text{tomato}}\) in kg CO\(_2\)-equiv tonne\(^{-1}\) tomato produced) including GHG emissions from energy use by machinery and irrigation (GHG\(_{\text{energy}}\) in kg CO\(_2\)-equiv ha\(^{-1}\)), GHG emissions from fertilizer production and field nitrous oxide emissions from application of nitrogen fertilizers and crop residues (GHG\(_{\text{fertilizer}}\) in kg CO\(_2\)-equiv ha\(^{-1}\)) per unit of tomato produced (Yield in tonne ha\(^{-1}\)) was defined as (eq 1):

\[
\text{GHG}_{\text{tomato,}x,y} = \frac{\text{GHG}_{\text{energy,}x,y} + \text{GHG}_{\text{fertilizer,}x,y}}{\text{Yield}_{x,y}}
\]

Data for GHG footprint calculations (Table S1) were collected from the Cool Farm Tool,\(^6\) but footprints were calculated outside of the data collection software.\(^7\) Amount of energy and fertilizer consumption were provided in the data collection sheet as aggregate values by their respective types (MJ of electricity, diesel and petrol for energy consumption, and kilograms of different types of fertilizers for fertilizer consumption), without further breakdown of the consumption in each agricultural process illustrated in Figure 1. As specific land use history for the farms was not available in the extracted data set, biogenic GHG emissions from land use change were considered following the approach originating from Mila I Canals,\(^8\) and recommended by Nemecek et al.\(^9\)\(^10\)\(^11\) Upon analysis of the historical land cover data (FAOSTAT\(^12\) over the past 20 years), no land use change arising from tomato production was found in the sample of countries considered. Thus, emissions from land use change were considered to be zero in this analysis.\(^12\) GHG emissions from pesticide production were excluded, as many farms did not provide sufficient information on type and amount of pesticide use. This is likely to have limited impact in the calculation of GHG footprints, as previous studies have indicated pesticide production and application represents less than 5% of the GHG footprint of field-grown tomatoes.\(^12\)\(^13\)\(^14\) GHG emissions from capital goods production were also omitted, as their contribution to the GHG footprint of agricultural products is typically low.\(^15\) Temporary carbon sequestration by tomato plants was also not taken into account due to regular harvest of the tomato crop compared to perennial crops, as well as the short-lived nature of the tomato-based products.\(^15\) Carbon dioxide (CO\(_2\)), methane (CH\(_4\)), and nitrous oxide (N\(_2\)O) emissions were summed using global warming potentials (GWP) of 1, 30, and 265 CO\(_2\)-equiv, respectively, representative of a 100-year time horizon.\(^16\) The GHG emission factors, expressed as kg CO\(_2\)-equiv per unit of material or energy consumed, were derived from secondary sources, mainly ecoinvent version 3.2\(^17\) (Table S5). See section

---

**Figure 1.** System boundaries for greenhouse gas footprinting from cradle to farm gate (solid lines). Emissions from pesticides production and capital goods production were excluded (dotted lines).
We calculated annual GHG footprints of 890 farm-specific observations from 14 countries: Australia, Chile, China, Egypt, Greece, India, Israel, Italy, New Zealand, Poland, Portugal, Spain, Turkey, and the USA for the three-year period 2013–2015. The summed production volume of the farms relative to the annual global tomato production in each year was about 3%.12 The farms in this study applied conventional farming methods (not organic) and were sampled randomly for self-assessment according to the scheme rules13 from farms operating in compliance with Unilever’s Sustainable Agriculture Code (SAC).13 In certain countries, farms were concentrated in specific regions; these included California in the USA, Extremadura region in Spain, and Xinjiang region in China. Farm data were collected via spreadsheets from the Cool Farm Tool14 in an unaudited format, and they were processed and cleaned prior to analysis (section S1 of SI). A data quality score for each observation, ranging from 1 to 12, with lower scores representing more unique and complete information, was applied in accordance with the criteria as specified in section S3 of SI. Only farms that have unique and complete information for area, yield, fertilizer, and energy consumption were given data quality scores less than or equal to 7 and were included in the cleaned data set of 890 observations (section S3 of SI).

Variability and Correlation Analysis. A data set of 890 farm observations was used for the analysis of variability of GHG footprints, as well as for the relative contribution to variability of the factors used in the GHG footprint calculations, i.e., GHGenerg, GHGfertilizer, and yield. Variability in GHG footprints was quantified using the interquartile range and coefficient of variation at four spatial and temporal scales, namely (1) within each country in each year, (2) within each country in all years, (3) within all countries in each year, and (4) within all countries in all years (overall data set). Only countries with data for at least 10 farms per year were included in the variability analysis at level 1, and only countries with data for at least 10 farms over the three years were included in the variability analysis at level 2 (see S1 of SI for number of farm observations in the 14 countries by year). This helps to ensure that the analysis at the country level is based on a sufficient number of observations within a single country. At levels 3 and 4, the full data set across all 14 countries was used as appropriate. We also quantified the variability of GHG footprints (5) between each year in each country and (6) between each country covering all years. We then calculated Spearman’s rank and partial correlation coefficient between the GHG footprint and yield, GHGfertilizer, and GHGenerg at the first four spatial and temporal levels (ppcor package, R 3.3.1 software15). The rank correlation provided an indication of the relative influence of each factor on the variability of the GHG footprints while considering the interaction between them.

Linear Mixed Model. We used LMM to assess variations in GHG footprints as a function of a set of environmental conditions and farm management factors at the global level. In this analysis, we only included observations with unique geocoded locations and for which data on farm management factors were available (N = 719, see S3 of SI). For each observation, we obtained information from the Cool Farm Tool14 on two farm management factors, namely the area of production and fertilizer application method (Table 1). Farmers employ a variety of single and multiple fertilizer application methods, and thus we classified farms accordingly into single fertilizer application methods, i.e., “incorporation”, “apply in solution”, “subsurface drip”, and “broadcast”, and multiple methods, i.e., “incorporate-subsurface drip”, “incorporate-broadcast”, “broadcast-apply in solution”, “incorporate-apply in solution”, and “combination of three unique methods” (nine types of fertilizer application methods in total). In addition, farm-specific environmental characteristics for climate conditions and soil type were obtained from spatially explicit maps using ArcGIS22 (see Table 1 for the spatial resolution) (see S5 for detailed procedure of farm geolocation and spatial data extraction). Climate parameters were obtained for the growing season of open-field tomatoes in each country, e.g., mid-April to mid-October for Spain (see section S4 of SI for the country-specific growing seasons). Soil parameters were obtained for the topsoil fraction (top 30 cm of soil) in which the roots of field tomatoes are typically concentrated23,24 and where soil parameters influence growth of tomatoes.25,26 We chose extreme climate parameters to capture extreme events, such as droughts which could have a large impact on GHG footprints due to increased irrigation demands.

In our linear mixed model (eq 2), Yi is the response variable (GHG footprint), X and β represent the fixed effect variables (environmental conditions and farm management factors in Table 1) and their coefficients, Za and b represent the random effect variables and their coefficients, and ε is the error term. i, j, and k represent each farm data point, each fixed effect variable, and each random effect variable, respectively. To account for variability between the countries, years and farms that may be influenced by factors other than the fixed variables, we included country, year, and farmID as random variables. We chose a random intercept structure of (1|country/farmID)+(1|Year) (denoted in lme4 syntax), as farms were nested within countries and both farms and countries were represented by three years of data.

\[
Y_i = X_i \beta + Z_{a,k} + \epsilon_i
\]  
(2)
Prior to model building, we assessed the normality of the response variables and the homogeneity of response variables across the explanatory variables. Both the GHG footprint and area of production were log_{10}-transformed to correct for skewness, and area was included as a quadratic term. We assessed multicollinearity between explanatory variables using variance inflation factors (VIF). All VIFs were lower than 10, so all variables were retained for model selection. Each explanatory variable was standardized before model fitting. Models were fitted using all possible variable combinations with the packages MuMIn and lme4, and ranked according to the corrected Akaike’s Information Criterion (AICc). We
selected models with delta AICc less than 2 and conducted model averaging based on Akaike weights.\textsuperscript{35,36} The goodness of fit of the averaged model was assessed using the weighted marginal and conditional $R^2$, which represent the respective explained variance by the fixed effect variables and the full model (fixed + random effect variables). The explained variance by the random effect variables was obtained by subtracting marginal $R^2$ from the conditional $R^2$. We attributed a fraction of the marginal $R^2$ to each fixed effect variable in proportion to its sum of squares obtained from the analysis of variance (ANOVA) of the model. Likewise, the explained variance by each random variable was attributed in proportion to its variance obtained from the summary of the model. The relationships of GHG footprints with fixed effect variables found to be important at the global level were further examined at the country level using Spearman’s rank correlation coefficient and variability analysis for continuous and categorical fixed effect variables, respectively. As in the case for variability analysis, only countries with data for at least 10 farms were included for the analysis at the country level.

\section*{RESULTS}

\textbf{GHG Footprints and Variability Analysis.} The annual mean GHG footprints of tomatoes weighted by production volume within all 14 countries in the years 2013, 2014, and 2015 (level 3) are 63, 50, and 47 kg CO₂-equiv per tonne of tomatoes, respectively. This represents on average a 25% decrease in GHG footprints within the sampled data set over the three years. The GHG footprint shows large variability between countries and farms and a slightly lower variability between years (Figure 2 and section S6 of SI). The median GHG footprint within each country in all years (level 2) ranges from 18 to 61 kg CO₂-equiv per tonne of tomatoes, with Chile having the smallest median and India the largest median GHG footprint. The weighted mean GHG footprint within each country in all years (level 2) ranges from 19 to 59 kg CO₂-equiv per tonne of tomatoes, with Chile showing the smallest and China the largest weighted mean GHG footprint. The coefficient of variation of GHG footprints within each country in all years (level 2), ranges from 33% in Portugal to 50% in USA; this is larger than the coefficient of variation of GHG footprints between each year in each country (level 5), that ranges from 8% in Greece to 159% in USA. See section S7 of SI for variability diagrams of yield, fertilizer, and energy consumption.

\textbf{Correlation Analysis.} Figure 3 shows that variability in $\text{GHG}_{\text{energy}}$, $\text{GHG}_{\text{fertilizer}}$, and yield contribute fairly equally to the variability in GHG footprints within all 14 countries in each year (level 3) and within all 14 countries in all years (level 4). This is different when looking at the variability within each country in all years (level 2) (Figure 3a). In this case, only 10

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure4}
\caption{Modeled relationship between GHG footprints and area of production for the global data set of 719 observations in logarithmic scale on both axes, holding other factors constant at their median values. The bold line represents the fitted value, and the gray dashed lines represent the 90% confidence interval. The data points represent the 719 farm-year combinations used for model-building.}
\end{figure}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure5}
\caption{Modeled relationship between GHG footprints and fertilizer application method at the global level, holding other factors constant at their median values. The squares represent the fitted values, and the lines with caps represent the 90% confidence interval. Farms that used a single, double, and triple number of fertilizer application methods are grouped as such; $N$ refers to the number of observations for each fertilizer application method.}
\end{figure}
countries (i.e., Australia, Chile, China, Egypt, Greece, India, Italy, Portugal, Spain, and USA) have data for at least 10 farms over the three years of the data set and were included in the analysis. In Chile and the USA, variability in GHG$_{energy}$ contributes most to the variability in the GHG footprint. Yield, on the other hand, is an important driver of variability in the GHG footprints in India, Australia, and, to a lesser extent, Italy. Between the different years, most countries have only 2 years worth of data with at least 10 farms in each year for comparison. Only China, Greece, Spain, and USA have data for at least 10 farms in each year from 2013 to 2015. The relative contribution of the different sources of variability remains relatively consistent over the years for farms within each country and for farms within all countries; i.e., they remain in the same region of the triplots. Exceptions occur for China in 2013 and USA in 2015. China moves from the higher contribution of yield and energy in 2013 to the middle region in 2015. USA moves from the middle region in 2013 to the higher contribution of yield and energy in 2015. The median GHG footprints of field tomato production in China in 2013 and USA in 2015 are also notably higher than those in the same country in other years (Figure 2).

**Linear Mixed Model.** The marginal and conditional $R^2$ of the best averaged model are 29.6% and 64.2%, respectively, and includes area of production (13.8% explained variance), method of fertilizer application (10%), rain day frequency (3%), and minimum temperature (2.9%) as fixed effects variables. At the global level, the relationship between GHG footprints and area of production is nonlinear, with GHG footprints decreasing with increasing area of production up to a threshold of 17.4 ha and then increasing for farms with larger areas of production (Figure 4). Among the fertilizer application methods, those farms using single fertilizer application methods in general have a larger GHG footprint than those using a combination of methods (Figure 5). Among the nine fertilizer application methods, "apply in solution" is associated with the largest GHG footprints, while the combination "incorporate-apply in solution" results in the lowest GHG footprints. Fertilizer application methods other than these two extremes appear to be similar in their fitted values when considering the 90% confidence interval. See S9 of SI for country-specific variability of GHG footprints with area of production (Spearman’s correlation coefficient) and method of fertilizer application (median GHG footprints for each method of fertilizer application). Regarding the random effect variables, these explain 34.6% of the total variance of GHG footprints, with "country" being the most important (33.8% explained variance), followed by "farm" (0.5%) and then "year" (0.3%). 35.8% of the variability of GHG footprints remains unexplained by the model.

**DISCUSSION**

This study is, according to the authors’ knowledge, the first to provide an integrated analysis of the variability of GHG footprints of global production of a crop, namely commercial field-grown tomatoes for processing. In addition to quantifying the relative importance of GHG$_{energy}$, GHG$_{fertilizer}$ and yield on the variability of GHG footprints of field tomato production, we further explored the relationships of GHG footprints with additional farm and environmental factors not normally considered in the GHG footprint calculations, using linear mixed effect models. In the sections below we highlight the implications for GHG footprint reduction strategies within the field tomato supply chains.

**GHG Footprints of Field Tomato Production.** The weighted mean GHG footprints of field tomato production in this study range from 19 to 59 kg CO$_2$-equiv per tonne of tomatoes in Chile and China, respectively. This is comparable to the values ranging from 29 to 89 kg CO$_2$-equiv per tonne of tomatoes reported previously for Spain and Portugal in 2012−2015 using the same data platform. Compared to the range of GHG footprints of field tomatoes reported in other literature, i.e., 100−400 kg CO$_2$-equiv per tonne in Iran in 2014−2015, and 82 and 130 kg CO$_2$-equiv per tonne in Italy in 2007 and 2011, respectively, the GHG footprints in our study and that of Clavreul et al. are lower. The comparatively large footprints of Pishgar-Komleh could be explained by the fact that natural land was used as a reference state and carbon dioxide emissions from the conversion of natural land to agriculture were included. The differences may also be explained by the fact that the sample of farms in this and Clavreul’s study complied with the Unilever Sustainable Agriculture Code (SAC). The SAC requires improvements in GHG management practices, and the findings may be indicative of improved performance. Indeed, the 25% decrease in the annual weighted mean GHG footprint over the period 2013 to 2015 is also suggestive of the potential effectiveness of the SAC in reducing the GHG footprint of tomato production through education and enforcement of sustainable practices within supply chains. The efficacy of sustainability codes and certification schemes is often neglected due to their principal focus on management practices rather than performance. However, due to crop rotation and supply chain sourcing practices, it is not possible to attribute the reduction in GHG footprint compared to noncertified sources solely to compliance with the SAC.

Another reason for the differences in GHG footprints compared to earlier studies may be from the use of different emission factors (e.g., emission factors from earlier versions of ecoinvent (v2.3, v2.2, and v3.1) instead of v3.2) and changes in the IPCC-recommended GWPs values for GHG (e.g., GWP values of N$_2$O of 298 CO$_2$-equivalents from IPCC 2007, 296 CO$_2$-equivalents from CML2001, and 265 CO$_2$-equivalents from IPCC 2013). Indeed, the use of higher GWPs (296 CO$_2$-equivalents for the GWP of N$_2$O for a 100-year time horizon) by Clavreul et al. from within the Cool Farm Tool resulted in slightly higher GHG footprints than those from the same countries in our study, i.e., Portugal and Spain (38 to 41 in our study vs 53 kg CO$_2$-equiv per tonne of tomatoes in Clavreul et al. However, the data set for Spain and Portugal from Clavreul et al. also included an additional year (i.e., 2012) compared to our study. In the study by Pishgar-Komleh, the use of higher GWP of N$_2$O, coupled with the exceedingly high level of nitrogen input (up to 3000 kg N ha$^{-1}$), could explain the higher GHG footprints in Iran when compared to our study (range: 5 to 623 kg N ha$^{-1}$, median: 210 kg N ha$^{-1}$) and Clavreul et al. (range: 66 to 505 kg N ha$^{-1}$, median: 188 kg N ha$^{-1}$). Lower yield (71 t ha$^{-1}$ to 74 t ha$^{-1}$) in the studies by Manfredi et al. and Theurl et al. on the other hand, could explain the higher GHG footprints compared with those in our study (range of yield: 49 to 132 t ha$^{-1}$, median = 85 t ha$^{-1}$) and Clavreul et al. (29−148 t ha$^{-1}$, median = 86 t ha$^{-1}$) despite the lower nitrogen inputs (130 to 143 kg N ha$^{-1}$) in that study.
Variability of GHG Footprints between Farms, Years, and Countries. The wide variability of GHG footprints within our study shows the potential for further reduction in the GHG impact of tomato production. In the correlation analysis, we found that the relative contribution to variability of GHG footprints by each factor, i.e., $\text{GHG}_{\text{energy}}$, $\text{GHG}_{\text{fertilizer}}$ and yield, is different between the different countries. On the other hand, it is consistent within the same countries and years except for USA in 2015 and China in 2013, where the contribution by $\text{GHG}_{\text{energy}}$ and yield, respectively, are the most important. This suggests that footprints are more consistent within countries than between them. One reason could be that tomato production tends to be concentrated in certain regions in countries that make up a large proportion of the data set; they include Xinjiang in China, California in USA, and Extremadura region in Spain and Portugal. The farms within the same countries are hence likely to experience similar climate and soil conditions as well as more similar farm management practices. The fact that farms in Australia, India, and to a smaller extent Italy can be found within the yield side of the triplet (i.e., region ii in Figure 3a), suggests that not all farms are operating at the most efficient levels. Farms in India have the lowest median yields (see section S7 of SI) despite levels of fertilizer application and energy consumption that are comparable to or higher than those in other countries (see section S7 of SI). Farms in Australia, on the other hand, have the largest median yield. However, the large variability in yields (see section S7 of SI) within the country implies that some farms had much lower yields compared to their counterparts. It is therefore important to look into the reasons for the low yields so as to improve the production as well as environmental performance of these farms.

The shape of the curve describing the relationship between farm area and GHG footprint suggests that production area may need to reach a certain minimum size before achieving economies of scale through the use of machinery and irrigation practices and through more effective “learning-by-doing”. Most countries display negative relationships between GHG footprints and the area of production (S9 of SI). India, with the lowest median area of production (0.6 ha) among the different countries, is also the country with the lowest median yields and highest median GHG footprints (S7 of SI). Only USA has large positive relationships between area of production and both GHG footprint and $\text{GHG}_{\text{energy}}$ suggesting that exceedingly large farms (median area of production = 150 ha) may not always be performing optimally. Nevertheless, compared to other countries, USA has one of the lowest median GHG footprints (S7 of SI).

In the linear mixed model, farms that adopted “apply in solution” as their fertilizer application method may have the highest GHG footprints due to large wastage from fertilizer flows that did not get retained in the root system; i.e., higher fertilizer dose is needed to achieve the same uptake by roots and yield leading to larger GHG footprints. The combination “incorporate-apply in solution”, however, results in the lowest GHG footprints. This may be due to the synergistic effect such that the initial incorporation of solid fertilizers helps build up a strong root system that could better absorb the liquid fertilizers from the application of fertilizers in solution. In Australia, farms using “incorporate-subsurface drip” as the method of fertilizer application have higher yields, lower $\text{GHG}_{\text{energy}}$, and lower GHG footprints than farms that use “subsurface drip” (S9 of SI). This explains the large variability of yields within the country and suggests that a shift from purely liquid-based methods to combination of solid- and liquid-based methods may help to increase yields and lower GHG footprints.

The GHG contribution from energy was most important to the variability in the GHG footprints of production in USA in 2015. The state of California, where the majority of USA farms were located, experienced its fourth consecutive dry year in 2015, with more than 60% of the land experiencing exceptional drought. We noticed a shift in the data set from “subsurface drip” in 2013 to “broadcast” and “apply in solution” in 2015 as the most commonly used methods of fertilizer application in USA. This could indicate that in the face of drought, farmers switched to more water-intensive irrigation methods to reduce water deficit of the crop. The result was larger GHG median footprints because farms consumed more energy to operate irrigation pumps. Overall, the farms in the USA were successful in responding to changing weather conditions, as the variability in yields in 2015 remained similar to previous years (see S7 of SI).

Farms in China, however, were less successful in responding to drought conditions, which were the strongest in 2013 in Northern Xinjiang, where the majority of the tomato farms in China were located. High variability in yield in 2013 (most important contributing factor for the variability of GHG footprints in China in 2013) occurred despite higher energy consumption (S7 of SI), suggesting that such interventions may not always have produced higher yields in times of drought. Indeed, we saw a shift in the most commonly used methods of fertilizer application among the sample farms from “broadcast-apply in solution” in 2013 to “incorporate-apply in solution” and “incorporate-broadcast” in 2014 and 2015 (see S9 of SI), with the earlier method associated with higher volume of water use. Further examination of factors influencing the differences between China in 2013 and USA in 2015 may provide guidance for future drought-intervention practices.

Inherent differences between countries (“country” as a random effect variable) that are not captured by the fixed effect variables explained 33.8% of variability in GHG footprints in the global data set. This could suggest a divergence of GHG footprints between countries due to their unique political and economic situations, e.g., country-specific fertilizer policies, legislative limits, subsidies, or taxes. Moreover, farmers from the same country may learn more easily from each other, leading to a convergence of practice. Such differences are expected to persist unless changes are made at the country-level through policy improvements and technological transfers. Differences between farms and years are less pronounced and may suggest that most of these differences have been captured by the fixed effect variables.

Implications for Sustainable Sourcing. Corporate and governmental policies for sustainable sourcing often promote certain sets of management practices without quantification of their actual impacts. In Unilever, the Sustainable Agriculture Code (SAC) provides a mechanism for monitoring quantitative farm-level data over time. The findings of this study provide some evidence of a reduction in GHG emissions over time, but repeated sampling of the same farms over an extended number of years is required to fully understand the benefits of the scheme. The large variability of GHG footprints within this study for sustainably sourced tomatoes partially reflects the range of management practices that are acceptable in the Unilever SAC. If greater comparability of outcomes is required, either within a scheme such as the Unilever SAC or between...
schemes, then more stringent guidance on acceptable practices would be required. However, highly prescriptive approaches to certification could hinder adoption by farmers and reduce the push for continuous improvement across the sector.

**Implications for Development of Data Collection Platforms and GHG Calculators.** As the energy and fuel consumption were reported as single figures, the impact of specific management practices, e.g., irrigation, harvesting, tilling, etc., could not be quantified. Moreover, information for factors that have significant influence on variability in GHG footprints, e.g., such as genetic resources (varieties) and farmers knowledge and habits (e.g., on fertilizer application, planting dates, pest and disease control), was not available. We also relied on village or city names for geolocation of farms, leading to uncertainty in the extraction of spatial-temporal parameters. Data collection platforms, such as the Cool Farm Tool, could seek to facilitate the gathering of this information. This would improve the identification of drivers of GHG variability and allow development of more specific GHG management strategies. Indeed, in the latest online version of the CFT, the user is able to input information regarding the energy consumed for each type of agricultural process, including machine usage and irrigation. However, there is a trade-off between obtaining more data for detailed analysis and increasing the burden on farmers for further data collection and reporting. On the basis of this study, we suggest prioritizing data collection related to types and quantities of farm management practices rather than aggregate energy consumption. The data collected should include the types and number of passes for soil preparation activities or the types of irrigation and the amount of water use.

Data quality issues related to the CFT were discussed by Keller (2016) and Clavreul et al. (2017). However, there was no methodological guideline regarding how to assess the quality of the data before this analysis. The methodology developed in this study, specifically the assignment of a data quality score based on the general criterion of uniqueness and completeness of the observation, could be considered by the developers of data collection platforms and for future data analysis by others.

### ASSOCIATED CONTENT

**Supporting Information**

The Supporting Information is available free of charge on the ACS Publications website at DOI: [10.1021/acs.est.7b04361](https://doi.org/10.1021/acs.est.7b04361).

Data processing and cleaning methodology. Detailed methodology for derivation of emission factors and calculation of GHG footprints. Data inclusion criteria for the different types of analysis. Literature review of the typical growing period of open-field tomato production in different countries. Methodology of the geocoding of farm locations and extraction of spatial-temporal parameters from spatial maps. Results of the variability of GHG footprints. Results of the variability of yield, fertilizer application, and energy use. Results of the linear mixed model analysis. Results of the variability of GHG footprints with area of production and method of fertilizer application (PDF)

### AUTHOR INFORMATION

**Corresponding Author**

*Phone: +31 (0)24—356 20 60; e-mail: lamwanyee@science.ru.nl.*

**ORCID**

Wan Yee Lam: 0000-0001-7879-4320

**Notes**

The authors declare no competing financial interest.

**ACKNOWLEDGMENTS**

The study is part of the RELiability of product Environmental Footprints (RELIEF) project, which is funded by the European Union’s Horizon 2020 research and innovation program under the Marie Sklodowska-Curie grant agreement no. 641459. The authors thank Isabela Butnar, Lau Tambjerg, Valerio Barbarossa, Zoran Steinmann, and Mirza Cengic for their support in data extraction and technical advice. We also thank three anonymous reviewers for their valuable input.

### REFERENCES

(12) Hillier, J.; Walter, C.; Malin, D.; Garcia-Suarez, T.; Milá i Canals, L.; Smith, P. A farm-focused calculator for emissions from crop


(22) ESRI. *ArcGIS Desktop: Release 10.3.1; Environmental Systems Research Institute: Redlands, CA, 2015.*


(56) Foster, A. D.; Rosenzweig, M. R. Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. J. Political Econ. 1995, 103 (6), 1176–1209.
