Developing Statistical Models for estimating Greenhouse Gas Footprints of Field Tomato Production

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1. Introduction

- Greenhouse gas (GHG) footprinting is increasingly used to support strategies for sustainable sourcing and reduction of environmental impacts within agricultural supply chains.[1,2]
- Cost and challenges of inventory data collection lead to the need for use of proxies and extrapolated datasets → Creates uncertainties that remain acknowledged but not quantified.[3]

Goal

To develop a regression-based methodology to predict farm-specific GHG footprints in the absence of farm-specific inventory data, using open-field tomatoes as a case study.

Source: alamy.com

2. Footprint calculation

- 447 farm-specific data points of open-field tomato production from 2013-2015 were obtained from farmers in Africa, Asia, Australia, Europe and North and South America.
- The greenhouse gas footprint was determined for each farm using a functional unit of **1 tonne of fresh tomatoes** (Figure 1).

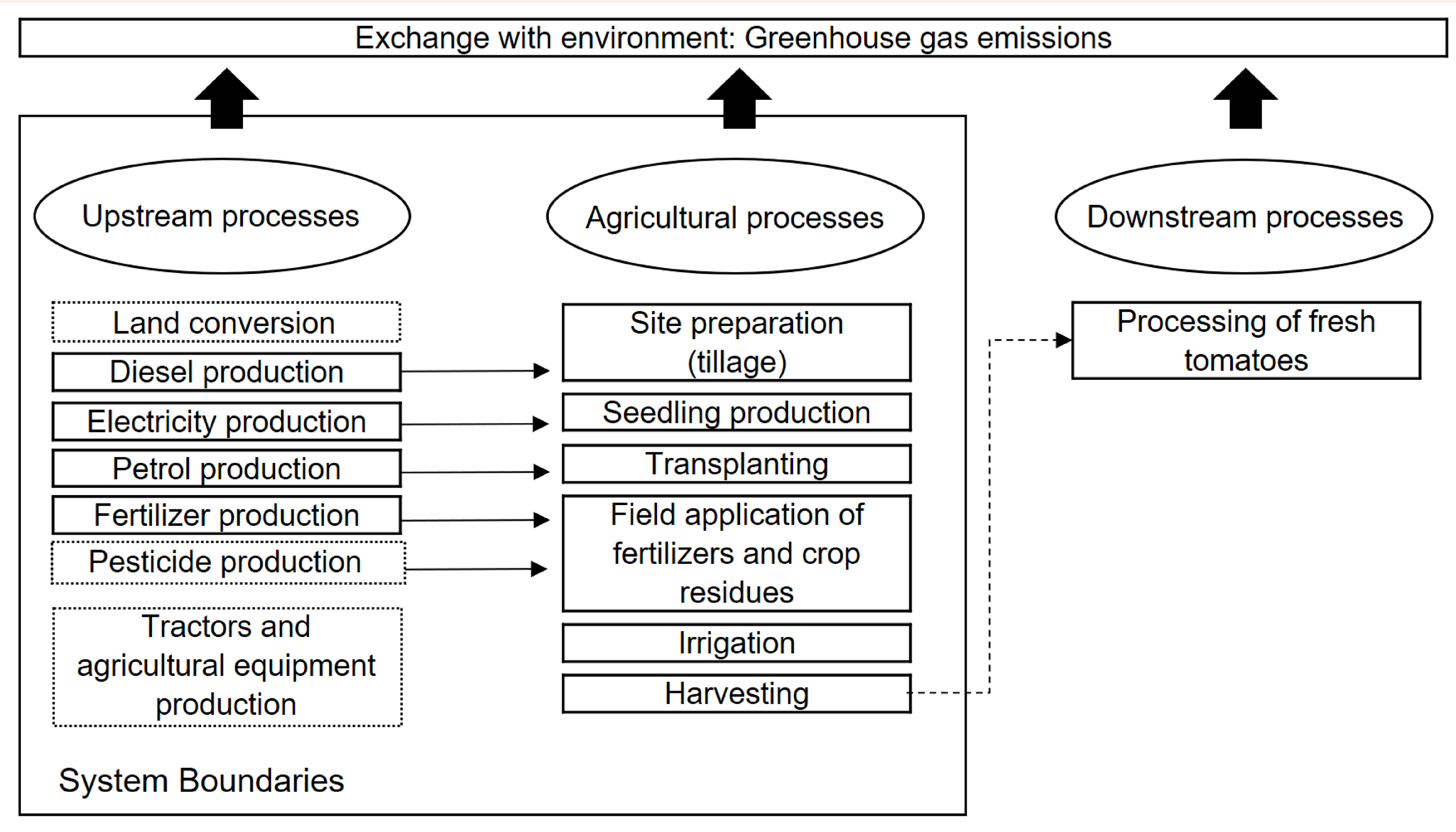
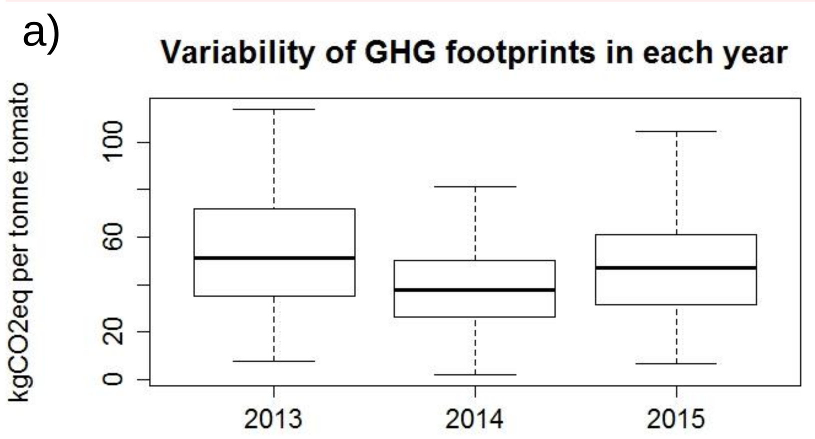


Figure 1: System boundaries for greenhouse gas footprinting from cradle to farm gate (solid lines). Emissions from land conversion, capital goods production, pesticide production and transportation from farm gate are not within the system boundaries.

3. Assessment of Current Footprint



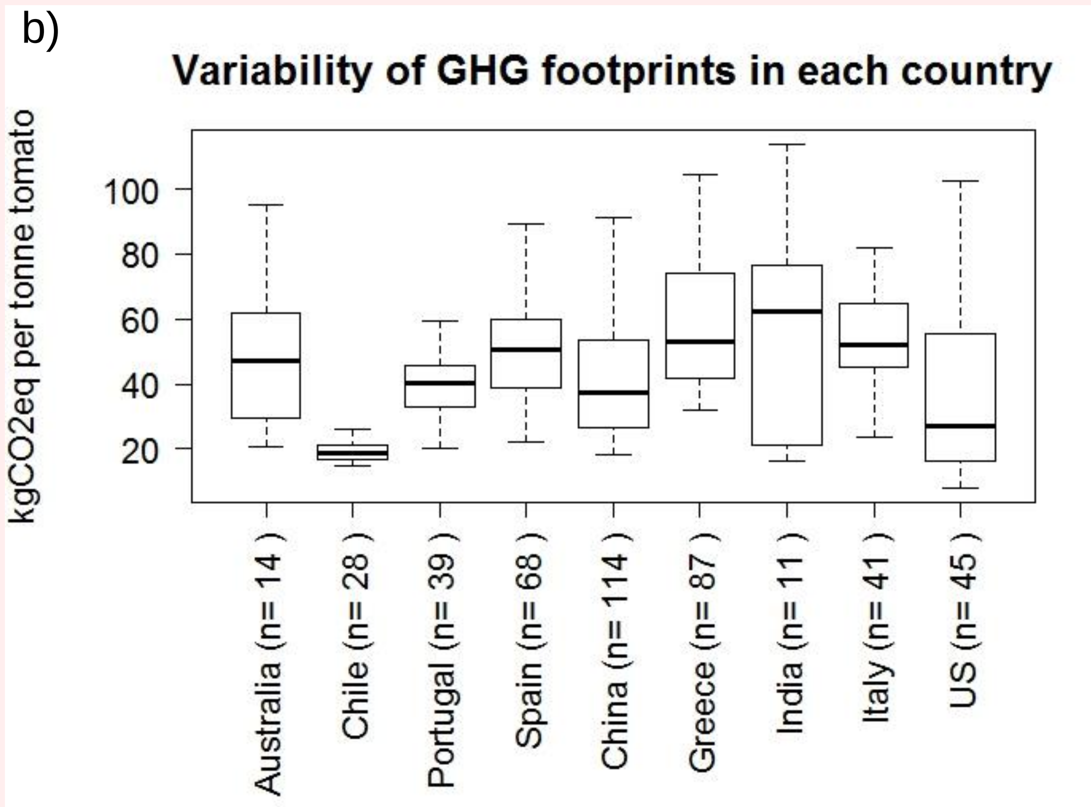


Figure 2: Variability of GHG footprints between a) Year 2013 to Year 2015 and b) between countries. n represents the number of farm data points in each country.

- Each source of emission, i.e. energy consumption, fertilizer production, field nitrous oxide emissions contributes to a different extent to the overall variability of GHG footprints depending on the country: energy consumption is on average the largest contributor (79%).

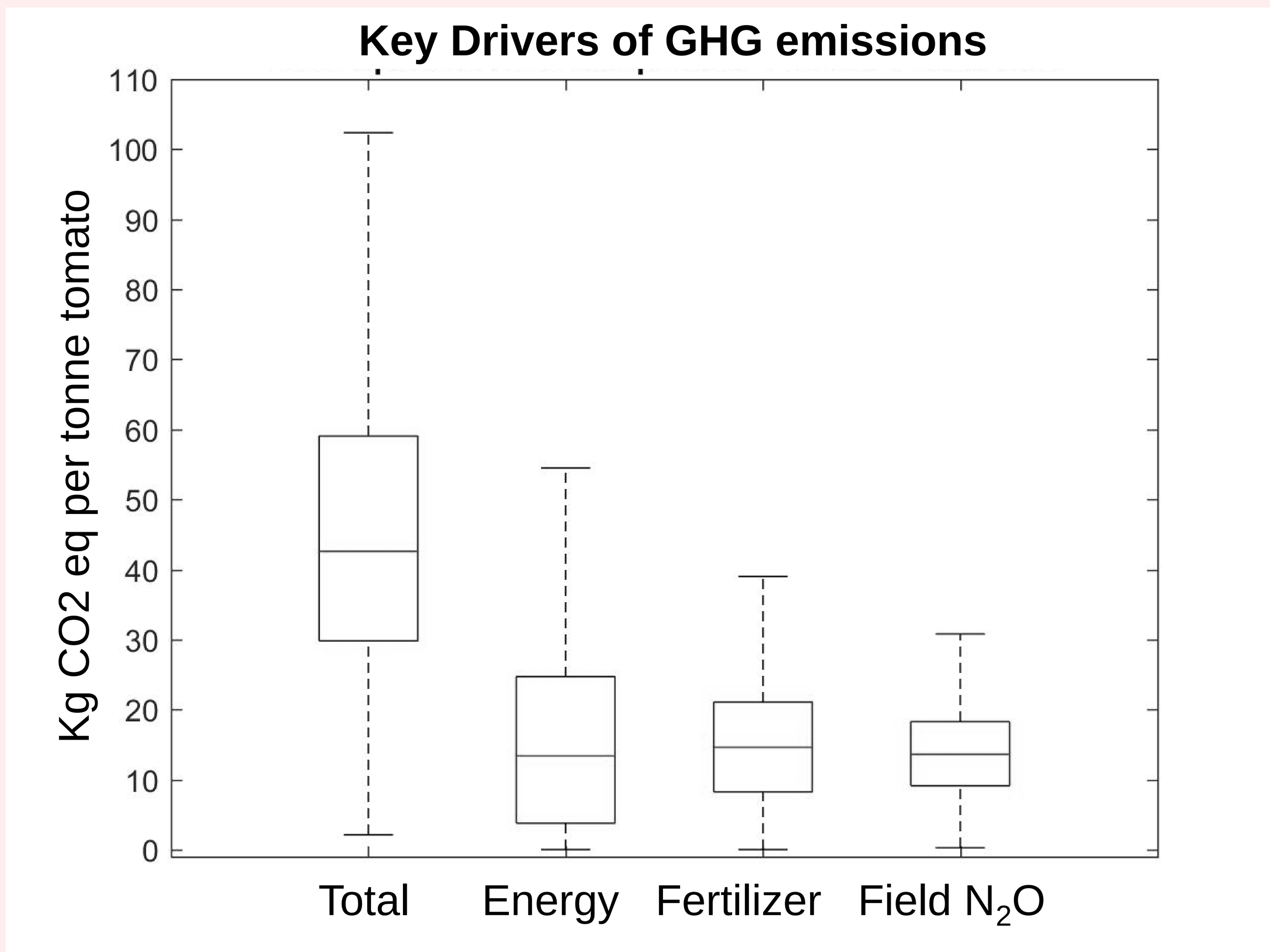


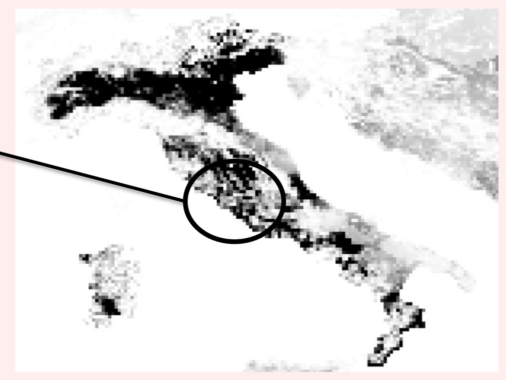
Figure 3: Variability of total GHG footprints and that contributed by each type of emissions: energy consumption, fertilizer production, field nitrous oxide emissions for the full dataset (Sample size= 447).

4. Next steps: Model Building

Response variable: Natural Log GHG footprint (kg CO2eq. per tonne)

Potential fixed predictors	
➢ ln Farm Area ➢ ln GDP per capita ➢ Area equipped for irrigation ➢ Mean, Minimum and Maximum monthly precipitation within growing season ➢ Mean, Minimum and Maximum monthly temperature within growing season ➢ Number of consecutive no-rain days	➢ Number of days below/above a temperature range ➢ Topsoil organic carbon ➢ Soil nitrogen ➢ Topsoil clay content ➢ Cationic exchange capacity of topsoil clay content ➢ Soil pH ➢ Mean elevation

1. Linear mixed models at the grid level to account for potential autocorrelation within nested dataset and heterogeneity due to country, farm and year differences.



2. Model application at the spatial scale of national and global level by grid averaging

3. Comparison of model outcomes to those derived from other models using a different set of predictor variables, e.g. MEXALCA[4] (farming processes from MEXALCA vs biophysical parameters in this study).

References

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4. Nemecek et al (2011) Modular Extrapolation Approach for Crop LCA MEXALCA: Global Warming Potential of Different Crops and its Relationship to the Yield, in: Finkbeiner, M. (Ed.), Towards Life Cycle Sustainability Management. Springer Netherlands, pp. 309-317.

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