Eco-efficiency of tomato from Rwamagana district in Rwanda: from field constraints to statistical significance

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ABSTRACT

On the request of decision-makers, the Life Cycle Assessment (LCA) framework is increasingly applied in agri-food value chains in developing countries under particularly demanding constraints. Based on the cradle-to-farm-gate LCA results of the tomato in Rwamagana district in Rwanda commissioned by the European Union, the main objectives of the paper were to validate statistically the differences in environmental impacts among expert-based types for this crop based on location and season and identify the key-drivers of these impacts. The study was developed thanks to two intensive field visits and a survey of 15 plots. The functional unit was one kg of tomato at farm-gate. Combining several statistical analyses allowed identifying three groups of plots with contrasting input profile and eco-efficiency. For most impact categories, the first group with mainly plots in marshland during wet season had the lowest impacts and the third group with plots in hillside showed the highest impacts. The yield of tomato being significantly different between marshland and hillside plots was an important driver of these results. The second group composed of plots in marshland during the dry season generally showed intermediate impacts due to the withdrawing of water for irrigation. The second group obtained a higher freshwater ecotoxicity due to a more intensive use of toxic insecticides. The factorial analysis for mixed data (FAMD) confirmed the importance of the location and the season for the eco-efficiency of tomato plots and the hierarchical clustering on principle components (HCPC) separated the tomato plots into three clusters. The generalized linear models (GLMs) validated the differences in the environmental impacts per kg of tomato between the clusters. The principal component analysis (PCA) combined to GLM revealed that only the use of water was significantly different between the three groups. Compared to existing datasets, all groups showed high freshwater ecotoxicity impacts due to the use of toxic insecticides and the excessive use of mancozeb. The third group also showed a high freshwater eutrophication in relation to P losses due to erosion and low yield. From a methodological point of view, we demonstrated in this paper that using expert-based typologies combined with adapted statistical analyses constituted a relevant approach under such circumstances.

Keywords: LCA; tomato; Rwanda; statistics; decision-makers

1. Introduction

To support their decisions, public and private decision-makers increasingly demand quantitative and reliable evaluations of social, economic and environmental aspects for agri-food value chains in developing contexts. LCA is recognized as the most consensual and relevant methodology for the assessment of environmental impacts for agri-food value chains. Applying LCA to agri-food products in tropical and developing contexts gives the opportunity to get insight into the highly variable agricultural production systems in these contexts. The variability is caused by differences in the economic and educational situation of farmers, variable landscapes, soil and climate conditions or not optimal infrastructure. The task is however challenging due to the limited awareness and capacities in LCA by stakeholders, the scarcity and often low-quality of statistical data, and the limits imposed to LCA commissioned from abroad in terms of time and budget constraints (Basset-Mens et al., 2018). Indeed, LCA practitioners from abroad must operate in a context that is usually unknown from them, build relevant and reliable partnerships with local experts and collect regionally specific data on complex value chains to produce the most representative and comparable LCA results as possible, in a few weeks.

Although not the only major contributor, the importance of the farm stage in LCA for agri-food value chains is well recognised and has recently been highlighted again by Poore and Nemecek (2018) in a meta-analysis compiling 570 LCA studies for food products. These authors also emphasized the high variations in impact among producers of a given product (Poore and Nemecek, 2018). The effect of farmers' management and variability on LCA results had previously been acknowledged as well by other authors such as Mouron et al., (2006), Mila i Canals et al. (2006) or Perrin et al., (2014). While in LCA the methods and data used should always be adapted to the goal and scope of the study, the importance of accounting of the variability and diversity of farms and practices in LCA studies has not always been well known (Bessou et al., 2013) and can still constitute a weakness of these studies for the representativeness of their results and for the decision-making process. However, the awareness of the importance of accounting for the variability of farming systems and uncertainty in LCA for agri-food value chains is progressively rising. Nowadays, all guidelines dedicated to the LCA of agri-food products provide specifications in terms of data quality (e.g. PEF data quality indicator; EC, 2013), sampling procedures and regarding the importance of defining the representative product (e.g. the Product Environmental Footprint Category rules guidance published by EC in 2018 or the Product category rules according to ISO 14025 for fruits and nuts). The LCA studies of agri-food products using statistical approaches (Mouron et al., 2006; Bersimis and Goergakellos, 2013; Chen et al., 2015) or providing an analysis of the uncertainty of the results (Romero-Gámez et al., 2017; Poore and Nemecek, 2018) remain rare though. The first authors to combine LCA and statistical analyses such as principal component analysis (PCA) and statistical risk assessment were Mouron and colleagues studying the management effect of individual apple farmers in Switzerland (Mouron et al., 2006). More recently, Chen et al. (2015) presented the environmental assessment of trout farming in France combining LCA and bootstrapped PCA. Chen et al. (2015) used the PCA to classify the trout farms into groups based on the size of fish produced and the non-parametric bootstrap technique to test the significance of PCA results.

The three main goals of an LCA study can be defined as: i) identifying the main hot-spots of a product system, ii) exploring the differences of product systems fulfilling the same function from an environmental point of view, iii) producing a representative reference of the environmental impacts for the whole population of a product system. The first goal of an LCA can possibly be achieved by an in-depth analysis of a few individuals from the studied population. The third goal is the most demanding one from a sampling point of view as illustrated by the recommendations made in Environmental Product Declarations (EPD). For the EPD for fruits and nuts for instance (EPD, 2015), "the sample size should be derived from proper statistical analysis based on the actual size of the farms population and the standard deviation [should be] found through historical data". Stratified sampling or sampling based on quotas is the alternative recommended in those guidelines. However, performing either a statistically based sample or a proper stratified sampling would require having available reliable statistics on the studied population. This is most generally not the case for agri-food value chains in developing contexts. In a developing context, in an in-depth work on the LCA of tomato from urban gardens in Benin, Perrin et al. (2017) demonstrated the relevance of designing a representative mean of tomato gardens by using an expert-based stratified sample of 12 fields.

For the second goal finally, a statistically sound typology should ideally be used either a priori, based on technical and descriptive data of the studied system or a posteriori, based on the environmental impacts of the studied system. To this end, statistical approaches currently used in other areas of research such as agronomy, botanic (Zamani et al., 2017), ecology (Nwankwo et al., 2018) or hydrology (Adamovic et al., 2016) could be well adapted due to the shared constraints imposed to the sample size across those various disciplines, in terms of sampling effort and cost. .

Based on the LCA of tomato from the Rwamagana district in Rwanda commissioned by the Directorate General for International Cooperation and Development (DG DEVCO) from the European Commission under important time constraints, the objectives of this paper were:

- To validate statistically the differences of Lifecycle Impact Assessment results between expert-based cropping system types
- To conduct a statistical analysis of key input variables
- To provide recommendations for improving the eco-efficiency of tomato in Rwamagana district

2. Materials and methods

2.1. Tomato from the Rwamagana district

The tomato produced open-field in the Rwamagana district represents an important vegetable supplied to the Kigali market in Rwanda and neighboring countries such as the Democratic Republic of Congo (DRC). As in the rest of Rwanda, farmers cultivate on small plots in Rwamagana district due to a high population density, and Rwanda's hilly topography leads to substantial soil vulnerability (Basset-Mens et al., 2016). In such a context, the application of LCA is of particular interest to help decision-makers identify and favor the most eco-efficient practices and cropping systems. At national level, cabbage and tomato are the most important vegetables in terms of area planted and the weight of production (National Horticulture Policy and Strategic Implementation Plan). However, national tomato production figures vary considerably. According to a local expert from the Rwanda Agricultural Board (RAB), annual tomato production in Rwanda is around 70,000 tons per annum of which about 37,000 tons are produced in Rwamagana district (Kagiraneza, pers. Comm., 2015). The population of tomato producers in the Rwamagana district was estimated at about 10'000 and was mostly constituted of small-scale growers. According to expert advice, tomato producers are spread over producers on hillside producing mostly during the two wet seasons (A and B) and producers on marshland producing mostly in dry season (C) when tomato prices are maximum. Production of tomatoes during other combinations of location and season also exist but are less favorable either technically due to water access on hillside during the dry season (low yield) or economically due to low prices for tomato produced on marshland during the wet season (high yield and high production). Table 1 presents the different seasons of production in Rwamagana district in Rwanda.

Table 1. Seasonality of tomato production in Rwamagana district.

Season/Month		J	F	M	A	M	J	J	A	S	O	N	D	J	F	M
Season A										■	■	■	■	■		
Season B	■	■	■	■	■	■										
Season C						■	■	■	■	■						

2.2. Goal and scope

2.2.1. Goal

The goal of this LCA study was to explore the impacts of the main cropping system types for the tomato produced in the Rwamagana district in Rwanda and to identify the key-drivers of their eco-efficiency.

2.2.2. System boundaries

Given the key objectives of this LCA study, the system boundaries were set from cradle-to-farm-gate and considered the complete crop cycle from land preparation and seed planting to harvest. The production and transportation of all key inputs: fertilizers, pesticides, fuel use for irrigation were included in the analysis as well as their use and emissions on the plots. The manufacturing and transportation of small materials and machines such as chemical sprayers, basins, wheelbarrow, watering cans and pumps were excluded because of little expected impacts. Fuel and water consumptions were included as well as occupation of land. The transportation of mulching materials (bundles of wild grass from the lake) and the transportation of other key inputs (fertilizers and pesticides) from the local agro-dealers up to the farm were partially included due to data gaps. Most inputs are generally transported either on head or by bicycle involving no mechanized transport and therefore no fuel consumption.

2.2.3. Functional unit and allocation rules

The functional unit used to express all impacts was the kg of fresh tomato at farm-gate. Tomato can be sorted by three grades with different prices. However, we allocated the results using a mass allocation since all grades fulfilled the same function of human consumption, 1kg of grade 1 quality receiving the same weight as 1kg of grade 2 and grade 3. The yield asked to farmers was the yield after rejects. Tomato rejects used by farmers for their own needs had no economic value and were therefore considered as leaving the system at no environmental cost.

2.2.4. Data quality

Field surveys

Site-specific primary data were collected between November 2015 and January 2016, covering all cropping stages from sowing to harvesting and including nursery, mulching, irrigation, organic and mineral fertilization, crop protection and harvesting.

The field data collection was done in three steps, namely:

- First meeting and presentation of the study to the different cooperatives
- Face-to-face interviews in December
- Face-to-face interviews in January to fill data gaps and validate certain data.

Data representativeness

The LCA study had to be performed in 30 days all together. We evaluated the maximum feasible size of our sample of plots at 16 (4 farms x 4 cooperatives). The estimated shares of tomato cropping system types in the total population are presented in Table 2. We sampled our 16 plots, reduced to 15 due to one plot showing too many data gaps, among the most typical combinations of locations and seasons. Table 2 also presents our planned and actual samples with corresponding shares for each type.

Table 2. Estimated shares of cropping system types and planned and actual samples.

	Hillside A&B	Hillside C	Marshland A&B	Marshland C	Total
Estimated shares of producers	38%	6%	26%	32%	100%
Planned sample	5 (31.25%)	1 (6.25%)	5 (31.25%)	5 (31.25%)	16
Actual sample	4 (27%)	1 (6%)	5 (33%)	5 (33%)	15

Overall, the 15 open-field plots surveyed were members of the studied population: tomato producers in the Rwamagana district. Four farmers (2 men and 2 women) each from 4 different cooperatives producing open-field tomato production were sampled. The resulting sample of 15 plots showed an important variability in terms of season of production (A, B or C), location (Marshland versus hillside) but also in terms of yield and inputs' use. In the original report prepared for the decision-makers, impact results were presented according to the expert-based cropping system types based on the combination of locations and seasons as follows: Marshland C (n=5), Marshland A&B (n=5) and Hillside A&B (n=4). The Hillside C plot was kept separate as an example of extreme situation of production because access to water is an issue in the hillsides during the dry season.

The statistical significance of our results will be specifically analyzed in this study (see section 2.6).

Data gaps and uncertainties

Across the 15 plots included in our sample, primary data were collected in terms of inputs' use, yield and practices based on farmers' declaration. Some of them had recorded data on their practices, some had not. However, all farmers appeared reasonably comfortable in answering to our questions and could give precise and quantitative information about all their practices, inputs and yield. This does not obviously exclude any risk of mistakes. Certain data gaps existed and assumptions were made. For instance, irrigation volumes often had to be estimated based on the farmer's practice in terms of frequency of watering and container used. Moreover, based on available information, we assumed that the mulching material, the fertilizers and the pesticides were carried by head or bicycle leading to no fuel consumption. This appeared as the most frequent situation. Certain composts used by farmers were quite original and no exact information on their nutrient content was found. For instance, certain farmers used a compost of a mix of cow manure and bundles of grass or harvest residues. In such cases, we assumed the same nutrient content as for the compost of cow manure. The compost of grass was assumed to have the same nutrient content as urban vegetal compost. Certain data gaps had to be filled by using average ratio calculated for other plots when available or by expertise. Two pesticides used by farmers could not be identified. Therefore, they could not be accounted for. They represented each a bottle of 100ml at plot level.

The quality of agronomic data was submitted to several agronomists, experts of tomato cropping systems in Africa. Their critical review allowed us to identify aberrant and extreme values, which we could validate again with farmers.

Table 3 presents key agronomic data for all surveyed plots.

2.3. Environmental inventory

2.3.1. Field emissions

Overall, the most recent or appropriate methods available for estimating field emissions were used. Given the lack of specific data on phosphorus and pesticide emissions in tropical conditions, we followed the recommendations from Nemecek and Kägi (2007) to estimate these emissions which corresponded to the most up-to-date guidelines for agriculture. We also based our estimation of NO_x emissions on these guidelines (21% of N_2O emissions). We used emission factors from IPCC (2006) to estimate direct (1% of nitrogen inputs) and indirect (1% of NH_3 emitted and 0.75% of NO_3 emitted) nitrous oxide emissions (N_2O) and to estimate nitrate (NO_3) leaching (as 30% of nitrogen inputs). Despite the lack of specificity of its emission factors, the IPCC report remains the most consensual method to estimate emissions in our context. For ammonia (NH_3) emissions from mineral fertilizers, emission factors from Bouwman and Van Der Hoek (1997) were used since they correspond to tropical conditions (4% for NPK and 25% for urea). At the transplanting of tomato seedlings, composts were used. They were composts either of cow manure, small animal manure, poultry manure or a mix of cow manure and bundles of grass or crop harvesting residues. Well-matured composts generally do not emit further ammonia emissions after their application on the field, while during the composting phase, a large amount of ammonia is generally volatilized. To account for this ammonia volatilization during the composting process, we used the IPCC emission factors of 20% of N content of the manure. For phosphorous losses to water, three components were included according to Nemecek and Kägi (2007): leaching, runoff and erosion. For estimating P losses due to erosion, the quantity of eroded soil was estimated based on existing literature. Kagabo et al. (2013) measured eroded soil with protection measures (grass strips) of about 30 t/ha in the hillslope versus 10 t/ha in the footslope. Although our cropping systems were different, the mulching material also constitutes a protection measure of the soil. We therefore assumed that eroded soil was 10t/ha/year in marshland and 30t/ha/year in hillslide. The P content of soil was estimated according to Mbonigaba Muhinda et al. (2009) who measured a P content of 525 mg/kg soil in a low altitude soil. For field water fluxes we simply used the volume of water withdrawn as declared by farmers. Finally, gaseous emissions from petrol combustion were calculated according to recommendations from Nemecek and Kägi (2007).

2.3.2. Background processes

Processes inventoried in the Ecoinvent database (version 2.2) available in the SIMAPRO software (version 8.0.5.13), were used as background data for energy production (Dones et al., 2007), fertilizer production (Nemecek and Kägi, 2007) and pesticide production (Sutter, 2010). Due to the complex logistics regarding the importation of energy materials and inputs into Africa and due to the tight timeframe, the transportation stages from the Ecoinvent processes were not adapted to the Rwandan situation and the transport from the regional storehouse to the local agro-dealers was excluded.

2.4. Characterization of environmental impacts

The impact assessment was performed following the recommendations from the ENVIFOOD Protocol which also corresponds to the recommendations from the ILCD Handbook (2011). The following environmental impact categories were considered: climate change (100 years; kg CO_2-eq, IPCC, 2007), acidification (mol H+-eq, Seppäla et al., 2006; Posch et al., 2008), freshwater and marine eutrophication (g P-eq and g N-eq respectively, based on the nutrient-limiting factor of the aquatic environment, Struijs et al., 2009), human toxicity – cancer effects and non-cancer effects (Comparative Toxic Units for humans, CTUh, USEtox, Rosenbaum et al., 2008), freshwater ecotoxicity (Comparative Toxic Units for Ecosystems, Rosenbaum et al., 2008), and Resource Depletion – mineral, fossil (Kg antimony (Sb)-eq, van Oers et al., 2002). The water deprivation potential (WDP, expressed in m^3 equivalent) was calculated using the water stress index (WSI) from Ridoutt and Pfister (2010). The water deprivation potential results from the quantification of water consumptions during the life-cycle of a product, related to the water scarcity index (WSI) of the area where the water was withdrawn. According to this method, the Water Stress Index for Rwanda is low at: 0.0135 m^3-eq/m^3. We decided to exclude the land use impact category from Mila i Canals et al. (2007) because it is recommended by ILCD with a level III meaning it has to be used with caution.

2.5. Comparison with other LCA studies

We compared our results with the results of two of our own datasets already published but initially using different impact assessment methods. The first LCA study evaluated the environmental impacts of peri-urban open-field tomato production in South Benin (Perrin, 2013; Perrin et al., 2017). The second LCA study evaluated the environmental impacts of an off-season tomato grown in-soil under an unheated greenhouse in the Souss Massa region in Morocco for the French market (Payen et al., 2015). LCIA results for both LCA studies were recalculated with the characterization methods recommended by ILCD.

Table 3. Agronomic data for 15 tomato plots in Rwamagana district, Rwanda

	Unit	Plot 1	Plot 2	Plot 3	Plot 4	Plot 5	Plot 6	Plot 7	Plot 8	Plot 9	Plot 10	Plot 11	Plot 12	Plot 13	Plot 14	Plot 15
General informations																
Plot size	m^2	1800	6000	1200	300	1500	1200	750	300	1200	1800	2500	780	2000	2500	1200
Location		M	H	M	M	M	M	M	M	H	H	H	H	M	M	M
Season		B	A	B	B	A	C	C	C	C	B	A	A	C	C	B
Crop duration	days	180	135	135	180	180	150	180	150	180	180	150	150	180	180	150
Yield	$kg.ha^{-1}$	27111	7700	13000	40000	12733	32500	26667	21000	10750	9583	19030	13750	36100	11200	25000
Fertilization																
N org	$kg.ha^{-1}$	12	56	12	93	28	93	95	79	41	107	16	18	29	0	17
P_2O_5 org	$kg.ha^{-1}$	6	28	5	46	14	46	47	39	29	50	3	9	14	0	9
N NPK	$kg.ha^{-1}$	28	15	1	45	1	52	45	17	72	48	20	20	21	26	37
P_2O_5 NPK	$kg.ha^{-1}$	28	15	1	45	1	52	45	17	72	48	20	20	21	26	37
N urea	$kg.ha^{-1}$	0	0	5	61	0	0	2	0	0	0	0	0	0	0	0
N tot	$kg.ha^{-1}$	40	70	18	199	29	145	141	96	113	155	36	37	50	26	54
P_2O_5 tot	$kg.ha^{-1}$	34	42	7	91	15	98	92	56	101	98	23	28	36	26	45
Irrigation																
Water volume	$m^3.ha^{-1}$	128	16	80	267	400	1177	947	2099	602	59	324	323	86	521	306
Fuel consumption	$kg.ha^{-1}$	0	94	0	0	17	84	112	84	84	0	0	0	134	37	77
Pest management																
INS-Dimethoate	$kg.ha^{-1}$	0.00	0.27	0.33	0.00	1.07	4.33	2.67	2.67	0.00	4.67	1.68	0.00	1.00	0.00	0.00
INS-Dichlorvos	$l.ha^{-1}$	0.00	0.00	0.00	20.00	2.67	5.83	8.60	0.00	0.00	0.00	0.00	0.00	5.00	4.00	0.00
INS-Profenofos	$l.ha^{-1}$	0.00	0.00	0.00	0.00	0.80	0.00	2.67	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
INS-Cypermethrine	$l.ha^{-1}$	0.00	0.00	0.00	0.00	0.08	0.00	0.27	0.40	0.17	0.00	0.00	0.26	0.00	0.02	0.00
INS-Abamectin	$l.ha^{-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	2.58
INS-Acetamiprid	$l.ha^{-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
FONG-Mancozebe	$kg.ha^{-1}$	208.33	58.75	21.88	83.53	32.50	190.63	105.00	76.25	77.99	114.78	75.75	113.78	95.63	46.50	80.83
FONG-Metalaxyl	$kg.ha^{-1}$	0.00	0.00	0.00	1.07	0.00	0.00	0.00	0.00	0.37	0.62	0.00	0.00	0.00	0.00	0.00
FONG-Sulphur	$kg.ha^{-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.20	35.90	0.00	0.00	0.00

M: Marshland; H: Hillside

2.6. Statistical analyses

The statistical framework included two steps. Firstly, we identified the plot groups according to all their potential environmental impacts per kg of tomato (as described in section 2.4), their location and the season of production. We used a factorial analysis for mixed data (FAMD) followed by a hierarchical clustering on principle components (HCPC). FAMD analyzes simultaneously quantitative variables using principal component analysis (PCA) and qualitative variables using multiple correspondence analysis (MCA) (Pagès, 2004, 2014). HCPC, based on the Euclidean distance and the Ward's method, allows to build a hierarchical tree and to define the clusters (Husson et al., 2010). Before the analysis, data were processed into standardized data; for each variable, data values were both mean-centered and divided by the standard deviation. Then, we validated the clusters according to the environmental impacts using a generalized linear model (GLM) with Gaussian or Gama distribution followed by pairwise post-hoc comparisons with the Tukey method. Secondly, we selected the main input variables using a Principal Components Analysis (PCA) with a set of 16 continuous variables and cluster index as supplementary categorical variable; we excluded "N tot" and "P_2O_5 tot" because they were strongly correlated to the other variables of fertilization ($r>0.7$). We retained each PCA-axe for which the Lambda value was above 2.92; this parameter was calculated according to the formula of Karlis et al. (2003) that takes account of the sample size. We considered that only the input variables with a contribution greater than or equal to 10% (for a given component) explained this component (Dormann et al. 2013). Then, we compared these input variables between the clusters using GLM with a Gaussian or Gama distribution followed by pairwise post-hoc comparisons with the Tukey method. Statistical tests were performed using the R software version 3.4.4 (R Core Team, 2018) and Factominer (Le et al., 2008), Emmeans (Lenth 2017) and R commander (Fox and Bouchet-Valat, 2018) packages.

3. Results and discussion

3.1. Statistical typology of tomato plots in terms of eco-efficiency (impact per kg tomato)

The first two FAMD components explained 80% of the total inertia of the results and clearly discriminated tomato plots among production seasons (dry/wet) on one hand and locations (hillside/marshland) on the other (Figure 1).

Figure 1.

In Figure 2, the cluster dendrogram is presented. It was cut off at 1.3 Euclidean distance units to separate the plots into three clusters: G1, G2 and G3.

Figure 2.

Table 4 shows the distribution of plots among the three groups in terms of location and season. G1 was mainly constituted of plots located in Marshland during wet seasons. In G2 all plots were located in Marshland and produced during the dry season. In G3, all plots were located in Hillside and tomatoes were cultivated mostly during a wet season.

Table 4. Location and season of tomato production according to the groups defined by HPCP

Group	Plot	Location	Season
G1	1	Marshland	Wet
G1	3	Marshland	Wet
G1	4	Marshland	Wet
G1	5	Marshland	Wet
G1	11	Hillside	Wet
G1	13	Marshland	Dry
G1	15	Marshland	Wet
G2	6	Marshland	Dry
G2	7	Marshland	Dry
G2	8	Marshland	Dry
G2	14	Marshland	Dry
G3	9	Hillside	Dry
G3	2	Hillside	Wet
G3	10	Hillside	Wet
G3	12	Hillside	Wet

As already explained, in the original report of the study for decision-makers, results were calculated for 3 cropping system types: marshland during the wet seasons A and B, marshland during the dry season C and hillside during the wet seasons A and B. Plot 9 producing on hillside during the dry season was kept separate as example of extreme situation (Basset-Mens et al., 2016). Although clear distinctions between types were obtained in terms of eco-efficiency with this expert-based typology, no statistical significance could be commented. The statistical typology based on the eco-efficiency of tomato plots validates in this case study the relevance of the local expert-based typology combining locations and seasons. Both locations and seasons are important for the eco-efficiency of tomato plots. The yield also varied significantly between the groups (GLM Gamma: $F = 6.04$; $p<0.01$). The yield of G3 (plots on hillside) was two times less than that of the two other groups (plots mostly in marshland) (Figure 3). In the next section, we present and comment on the statistical significance of the three statistically-based groups in terms of environmental impacts per kg tomato.

Figure 3.

3.2. Eco-efficiency of tomato plots in Rwamagana (impact per kg of tomato)

The environmental impacts varied significantly between most groups (GLM – p value<0.05) (Figure 4). Climate change was significantly different among the three groups, with G3 showing the greatest impact, G1 the least and G2 having an intermediate impact. For all other impact categories, at least two groups obtained significantly different impacts:

- For marine eutrophication, acidification and human toxicity cancer, G1 obtained significantly less impact than G3.
- For water resource depletion, G1 showed significantly less impact than G2 and G3.
- For freshwater eutrophication, Mineral, fossil and renewable resource depletion and human toxicity non-cancer, G3 had significantly greater impacts than G1 and G2.
- For freshwater ecotoxicity, G2 had a significantly greater impact than G3.

Except for climate change and water resource depletion, impacts were similar for G1 and G2. Except plot 11, both groups are composed of plots in marshland. The main difference between G2 and G1 is the season of production. One hypothesis to explain the difference of climate change and water resource depletion between G1 and G2 is that the need for irrigation during the dry season in G2 leads to greater use of fuel for pumping water and to greater water use. Producing tomato in marshland whatever the season appears as more favorable. Additionally, producing tomato in marshland during the wet season is clearly the best option in terms of eco-efficiency. On the contrary, G3 obtained the greatest impacts for all impact categories (except freshwater ecotoxicity) meaning that producing on hillside is not favorable for the eco-efficiency of tomato production.

Figure 4.

The effect of location can be related to the fertility of soils and access to water. The erosion phenomenon is widespread in Rwanda due notably to important slopes and intensive use of land (König, 1994). This issue has consequences on the soils' productivity as observed in our sample of plots where tomato yield for marshland plots is significantly greater than that of hillside plots (Figure 3). Furthermore, on hillside plots, water access is generally more difficult which explains the scarcity of hillside plot production during the dry season (only plot 9). The wet season is obviously more favorable to tomato production whatever the location due to the water requirements of the crop.

It is important to highlight that, despite the small group sizes the dispersion within each group was large and can probably be explained by the variations in farmers' skill and local conditions of production prevailing for each plot.

Results for our three plot types were compared with results for two other LCIA results for tomato production in Morocco (Payen et al., 2015) and Benin (Perrin et al., 2017). The comparison between these different LCA results for tomato globally allows validating the orders of magnitude of the results for this study. However, the comparison yielded quite different conclusions depending on the group. For a majority of impact categories, the tomato from Rwamagana obtained less impacts per kg tomato compared to the tomato from Benin and similar or worse compared to the tomato from Morocco (climate change, human toxicity, acidification, marine eutrophication). Except for water resource depletion, the unheated greenhouse tomato from Morocco can be considered a quite eco-efficient production compared to other systems such as heated greenhouses in France (Payen et al., 2015). On the contrary, the tomato from Benin has been recognized as having a poor eco-efficiency due to low and variable crop yields, high fuel consumption for irrigation, large emissions of nutrients and an excessive use of insecticides (Perrin et al., 2017).

Except for freshwater ecotoxicity where G1, G2 and G3 had the worst impacts compared to tomato from Morocco and even Benin, for most impact categories, the tomato from Rwamagana had more impacts (or similar) compared to the tomato from Morocco but less compared to the tomato from Benin. For freshwater eutrophication and Mineral, fossil & renewable Resource depletion, G3 showed the worst results of all compared systems. Interestingly, plots from G3 had a similar yield compared to tomato plots from Benin. Overall, tomato plots from Rwamagana rely mostly on manual labour. However, according to our data, farmers consumed either no fuel at all or a great amount of fuel for irrigation. One farmer even declared transporting jerricans of water on his motorbike. The data for fuel use is uncertain and would need to be validated since it was even greater than fuel use by tomato farmers from Benin (Perrin et al., 2017). Farmers from Rwamagana use quite reduced fertilizer rates.

This comparison allows us to conclude that G3 has a particularly high impact in terms of freshwater eutrophication and all tomato plots from Rwamagana (G1, G2 and G3) have particularly high impacts in terms of freshwater ecotoxicity. Acidification and marine eutrophication were also quite high for all groups which could be linked to the important use of compost. High freshwater eutrophication (limited by P) for G3 can be linked to the important erosion from hillside plots accounted for in this study and leading to large P losses. Important freshwater ecotoxicity for all groups and particularly for G1 and G2 can be linked to a great use of toxic insecticides in addition to a very high use of mancozeb. In the next section, we propose an analysis of the key input variables for each group.

3.3. Key-drivers of the eco-efficiency of tomato cropping systems

Four PCA-axes explained 87% of the total variation (36% for Dim1, 26% for Dim2, 14% for Dim3 and 10% for Dim4). Two clusters G1 and G2 were discriminated on the two first axes wheras there was a great variation within G3, where we observed two sub-clusters (Figure 5). G1 was represented by Dim1 and Dim2 (cos2 of centroid = 0.49 & 0.32, respectively) wheras G2 was represented by Dim2 (cos2 of centroid = 0.63). PCA axes well represented 11 input variables, i.e. 69% of variables, and eight input variables were well represented by the two first axes including organic and chemical fertilizers, water use, and certain pesticides (Profenofos, Cypermethrine and Metalaxyl).

Figure 5.

The radar diagram in figure 6 reveals that the three groups had contrasted input use profiles. Combined with their respective yield, these profiles are key elements of the eco-efficiency of the tomato plots.
Except for N. urea, the G1 farmers used less inputs per ha than the two other groups. The G2 farmers used more water and more insecticides Profenofos and Cypermethrine than the two other groups and they did not use Sulphur and Metalaxyl. The G3 farmers used more Sulphur and Metalaxyl than the two other groups and they did not use N. Urea and Profenofos. However, only the use of water was significantly different between the three groups (GLM Gamma, $F=8.47$, $p<0.01$) ; farmers of G2 using five times more water than those of the two other groups with a mean of 1186 ±333 m^3/ha.

Beyond the actual volume of water consumed among the different stages of the life cycle of the tomato, what matters here for evaluating the impact is the "local" water stress index used where the ingredients/products are manufactured. The water stress index used for water from Rwanda at country and annual scales in the water resource depletion method recommended by ILCD is low. This could be further refined by looking for a water stress index calculated on a monthly basis and maybe for a smaller region than the whole country (Ponsioen and van der Werf, 2017).

Figure 6.

Mancozeb is consistently used across all tomato plots at rates between 10 and 100 times the recommended rate (Table 2). From our contribution analysis (not shown), this fungicide can clearly be identified as a hot-spot for all tomato plots with great potential for improvement. Both profenofos and cypermethrine were identified as key input variables differentiating the groups from the PCA results and this is important since both active ingredients present high toxicity factors: profenofos: 453’000 CTUe/kg a.i., cypermethrine: 70’000 CTUe/kg a.i..

3.4. Recommendations and outlook

3.4.1. For tomato crop in Rwamagana region in Rwanda

Compared to LCA results for other tomato crops, our results revealed that for all groups, impacts were very high for freshwater ecotoxicity, and quite high for acidification and marine eutrophication. Group 3 exclusively composed of hillside plots also showed a very high freshwater eutrophication. Key-drivers for these hot-spots have been identified and include the high use of toxic insecticides, the great use of fuel for irrigation, the use of composts and the important P losses due to erosion for hillside plots. Despite the fact that producing tomato in marshland, particularly in a wet season clearly appeared more favorable in terms of eco-efficiency than in hillside, all systems have margins for improvement. In Rwanda the demand for food is important due to the great population density and the availability and productivity of land is a critical issue. Therefore, abandoning hillside plots is clearly not an option. Working on soil conservation and fertility is more than ever important. Different mechanical soil protection techniques have been tested such as slow-forming terraces (Kagabo et al., 2013) but are still perfectible. The complexification of cropping systems through the association of various species of trees, hedges, crops and the association of crops with legumes appear as promising practices to both enhance soil fertility and limit erosion (König, 1994). Access to water should also be facilitated through diverse investments and efficient irrigation techniques should be promoted. Fertilizer use did not appear to be excessive and even below recommendations. Conversely, pesticide use is excessive in many cases especially for mancozeb which is used at a rate between 10 and 100 times the recommended rate. The choice of insecticides should be based on their intrinsic toxicity and the recommended dosage should be strictly respected. Alternatives to currently used toxic insecticides should be searched for. Furthermore, education of both farmers and technical advisors and agro-dealers, often providing technical advice, is required to help farmers select and use properly the most eco-friendly molecules to manage pests and diseases. A lot of farmers expressed their wish to have a greenhouse to protect their crop. In the original study, two extreme situations of greenhouse production were assessed and revealed that they were worse in terms of human toxicity impacts especially related to the greenhouse infrastructure and could be either better for other impacts or worse depending on the local conditions and the quality of the farmers' management.

Picture 1.

Picture 2.

3.4.2. For best practices in LCA studies under similar constraints

In LCA studies, the requirements on data and, sample size should be adapted to the goal and scope of each study. Where an in-depth analysis of a few individuals can be sufficient to explore potential hot-spots, in other LCA studies aiming at producing a representative reference for the studied system, a proper sampling covering the diversity of situations should be designed In this LCA study, the objective was to explore the different cropping system types and validate statistically an expert-based typology from an environmental point of view. Statistical analyses were conducted allowing to classify individual plots into three groups from an eco-efficiency point of view and an input use profile was associated to each group. Many impacts were significantly different between groups allowing to validate the relevance of the original typology of systems based on local expertise and combining location and season. However, these analyses also revealed the great variations of results and input variables of the studied sample.

Beyond the comparison of the different cropping system types, the expert-based typology provided in this paper could also have permitted to calculate a reference environmental impact for the total population by weighting the results for each type according to its share in the overall population as demonstrated by Perrin et al. (2017) for the tomato from urban gardens in Benin. From a strict statistical point of view, the optimum size of the sample should be defined according to the population size and its inherent variability regarding the studied parameters. However, working with an ideal sample size is not always feasible. In such cases, and when no adapted typologies already exist on the studied population, using expert-based typologies to identify the main cropping system types and design a stratified sampling constitutes the best available option as demonstrated in this study and also by Perrin et al. (2017).

4. Conclusions

In this study, it proved possible to develop a complete LCA study in a tight timeframe for the open-field tomato from the Rwamagana district in Rwanda. Combining original LCA results based on an expert-based typology with a proper statistical analysis allowed identifying three groups of plots with contrasted input profiles and eco-efficiency. The three groups confirmed the importance of the location: marshland versus hillside and the season: wet versus dry, in the eco-efficiency of the tomato plots. The statistical analysis confirmed the relevance of the original typology of plots based on local expertise and combining location and season of production. The location is important on the eco-efficiency of plots most probably due to the differences of intrinsic soil fertility between marshland and hillside plots leading to large variations of yield, water accessibility and P losses due to erosion. The season is also important in relation to the water requirements of the crop and maybe also to the differences in pest pressure across seasons. Consequently, for most impact categories, the first group with mainly plots in marshland during wet season had the least impacts, the third group with plots in hillside showed the worst impacts. The second group composed of plots in marshland during the dry season generally showed intermediate impacts due to the withdrawing of water for irrigation. The second group obtained a greater freshwater ecotoxicity due to a greater use of toxic insecticides. Compared to existing datasets, all groups showed high freshwater ecotoxicity impacts due to the use of toxic insecticides and to an excessive use of mancozeb. The third group also showed a high freshwater eutrophication in relation to P losses due to erosion and low yield. From a methodological point of view, when working with an ideal sample size is not feasible, we demonstrated in this paper that combining an expert-based typology to design a stratified sampling procedure and appropriate statistical analyses constitutes the most relevant option. This approach can be relevant for both exploring the diversity of cropping systems from an environmental point of view and producing representative environmental impacts for the whole population.

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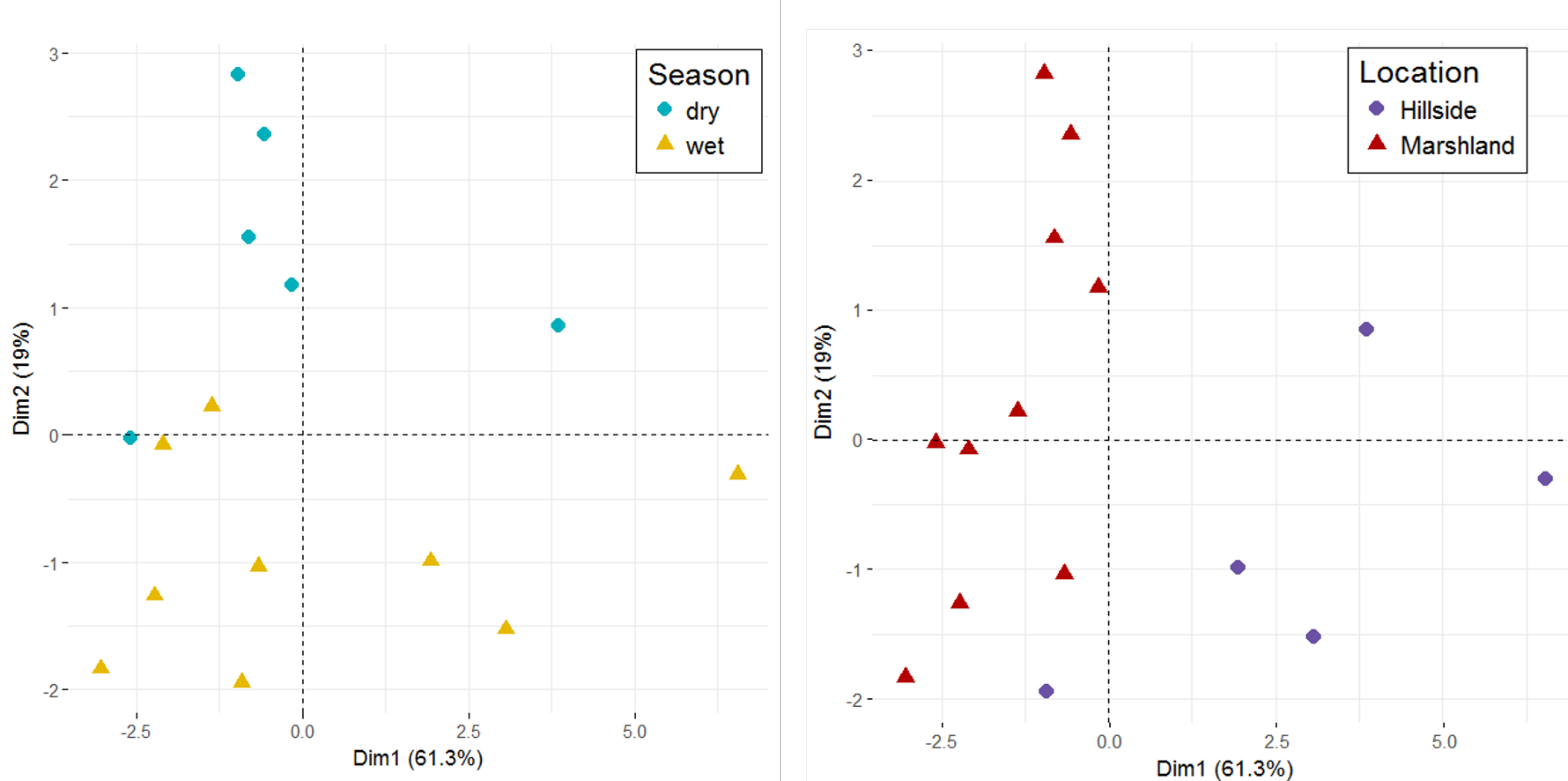
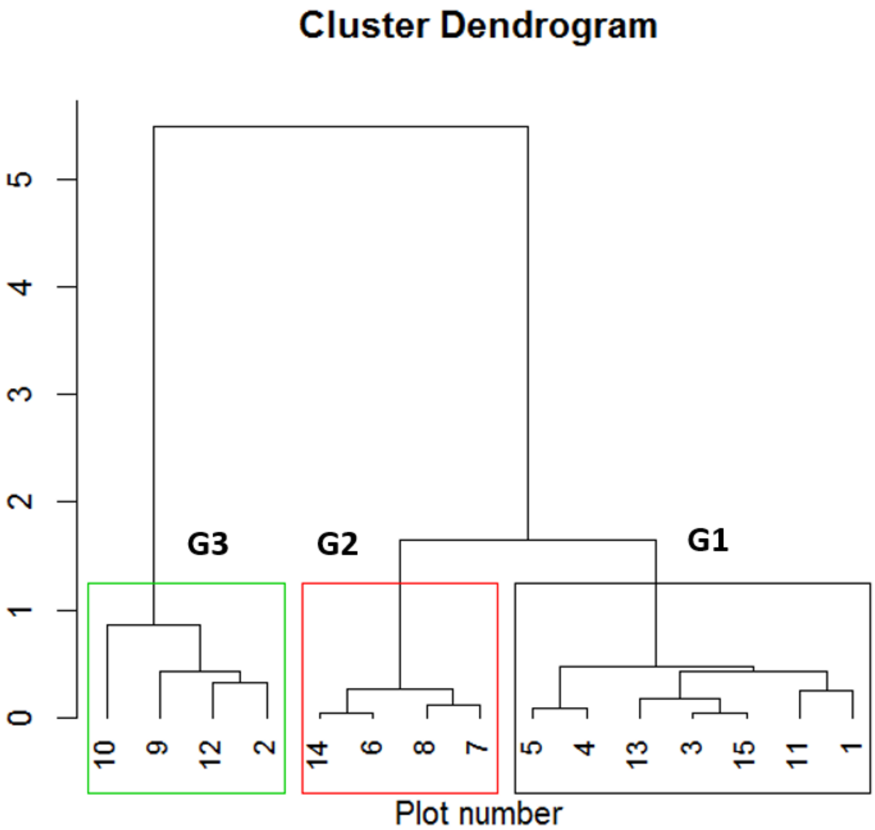
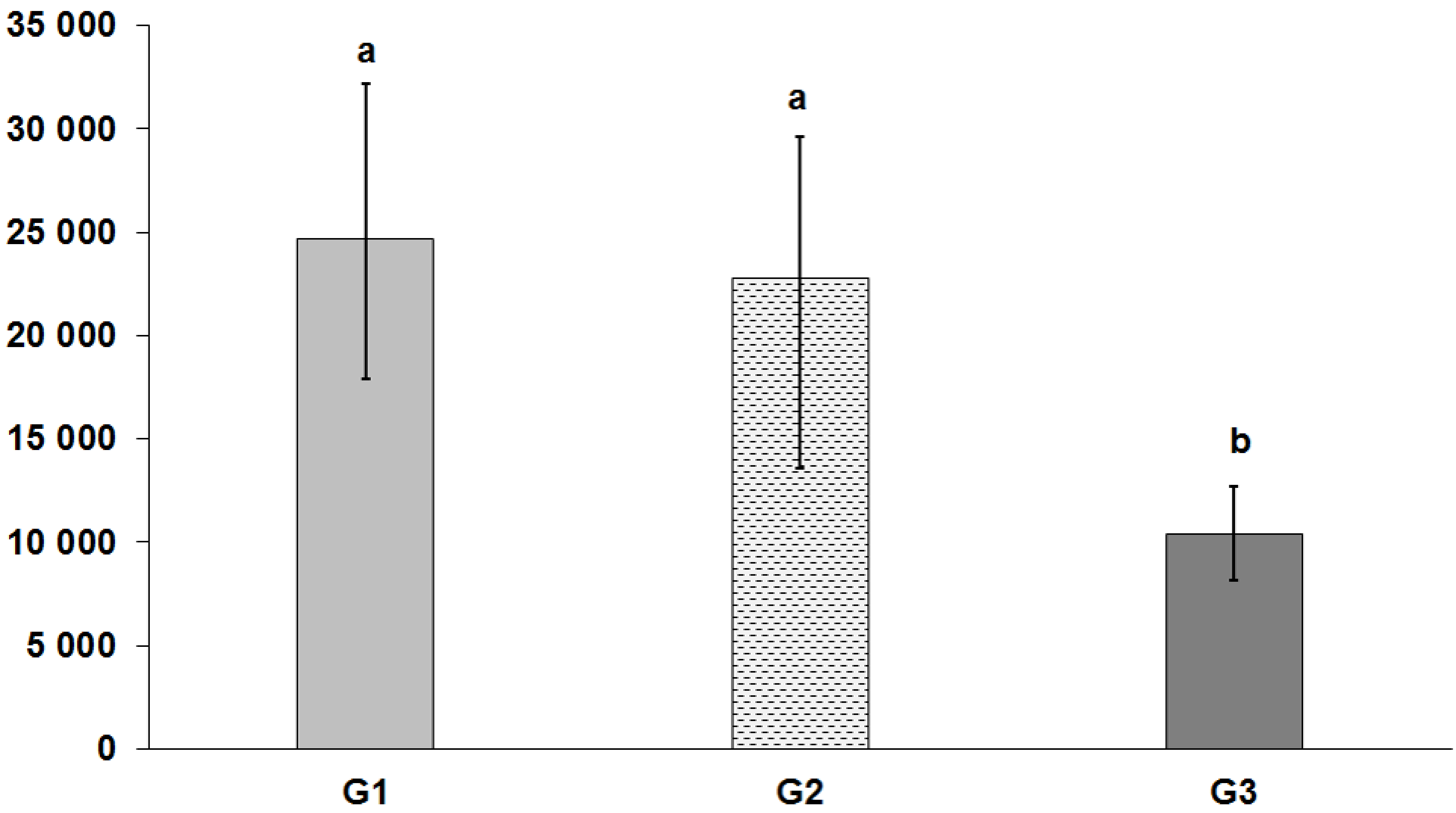
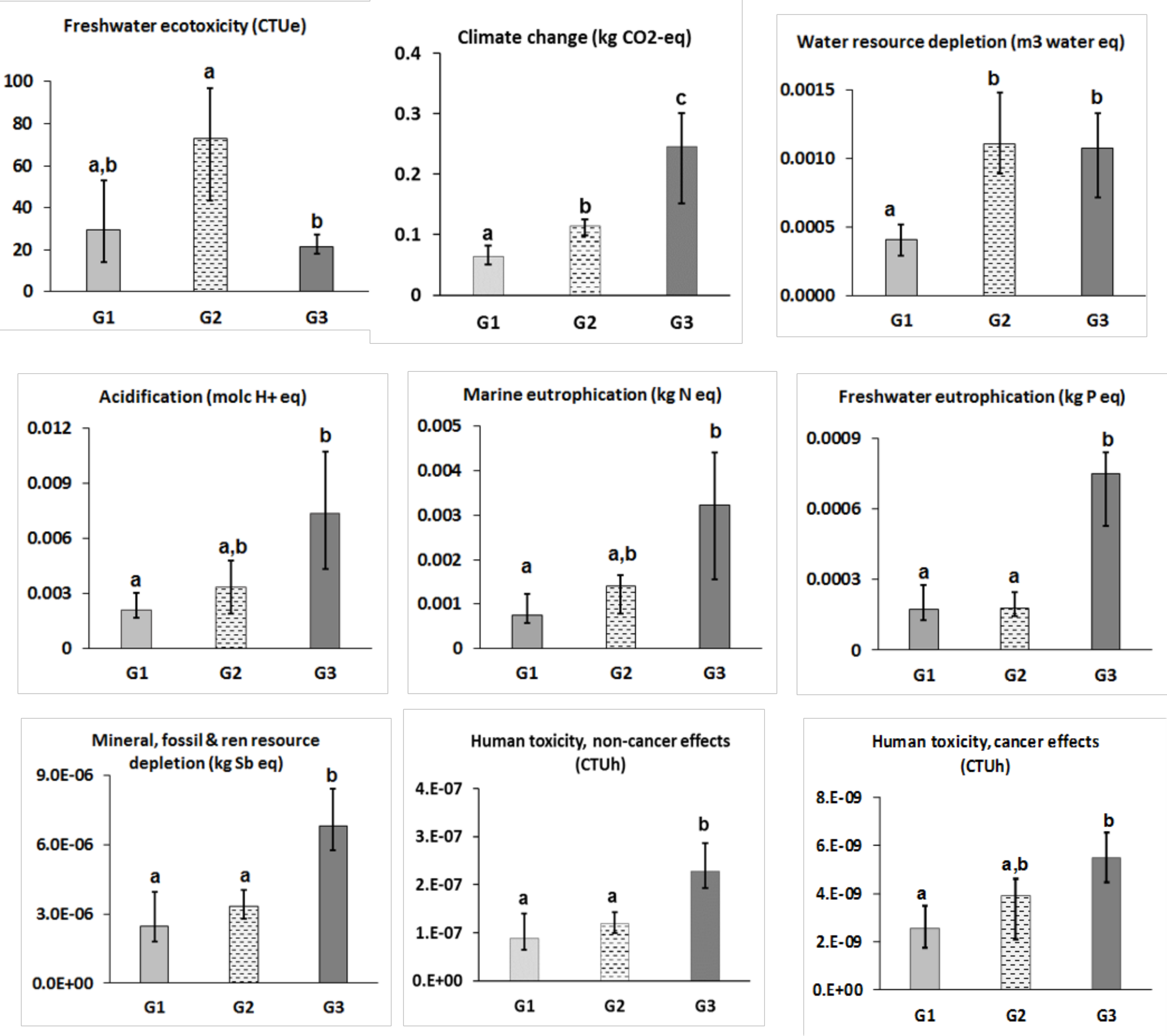


Season
dry
wet
Dim2 (19%)
Dim1 (61.3%)
3
2
1
0
-1
-2
-2.5
0.0
2.5
5.0
Location
Hillside
Marshland
Dim2 (19%)
Dim1 (61.3%)

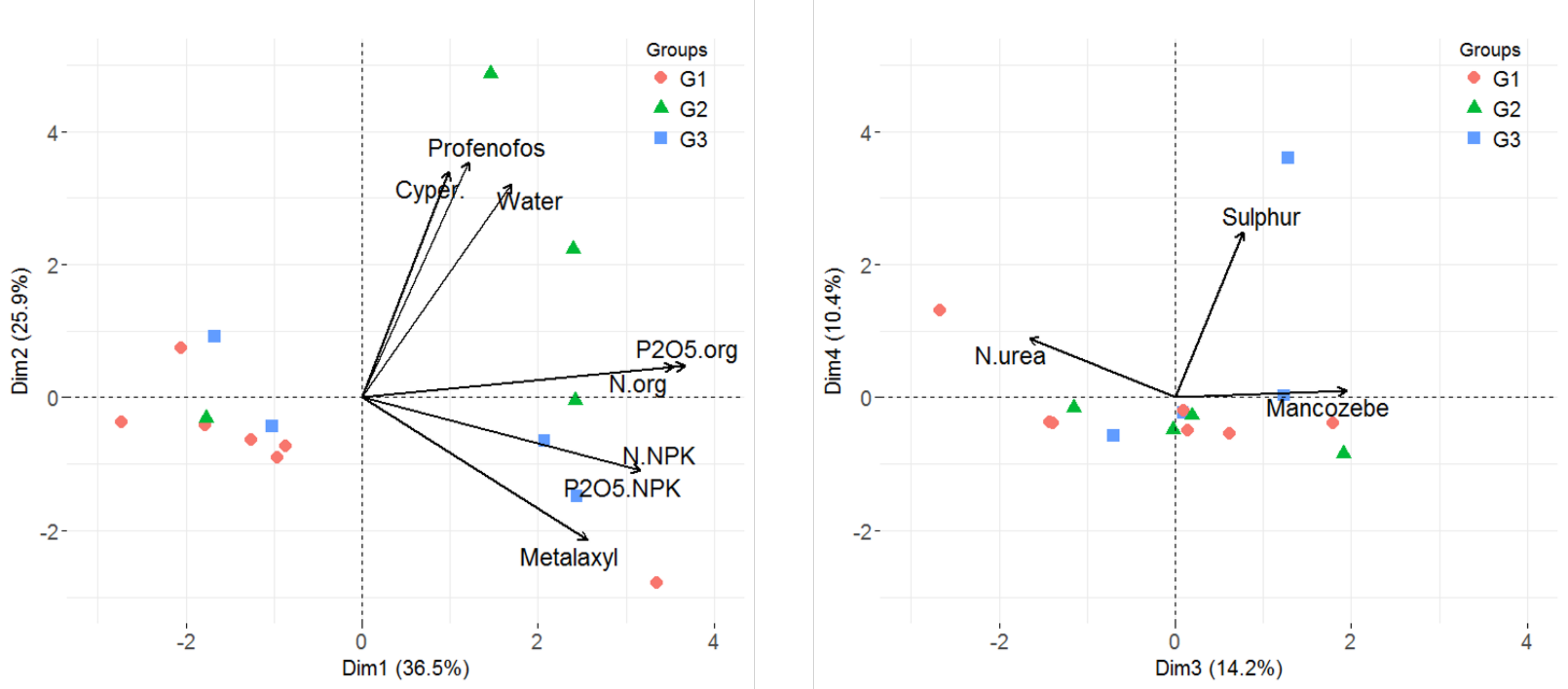

Cluster Dendrogram
0
1
2
3
4
5
G3
G2
G1
10
9
12
2
14
6
8
7
5
4
13
3
15
11
1
Plot number

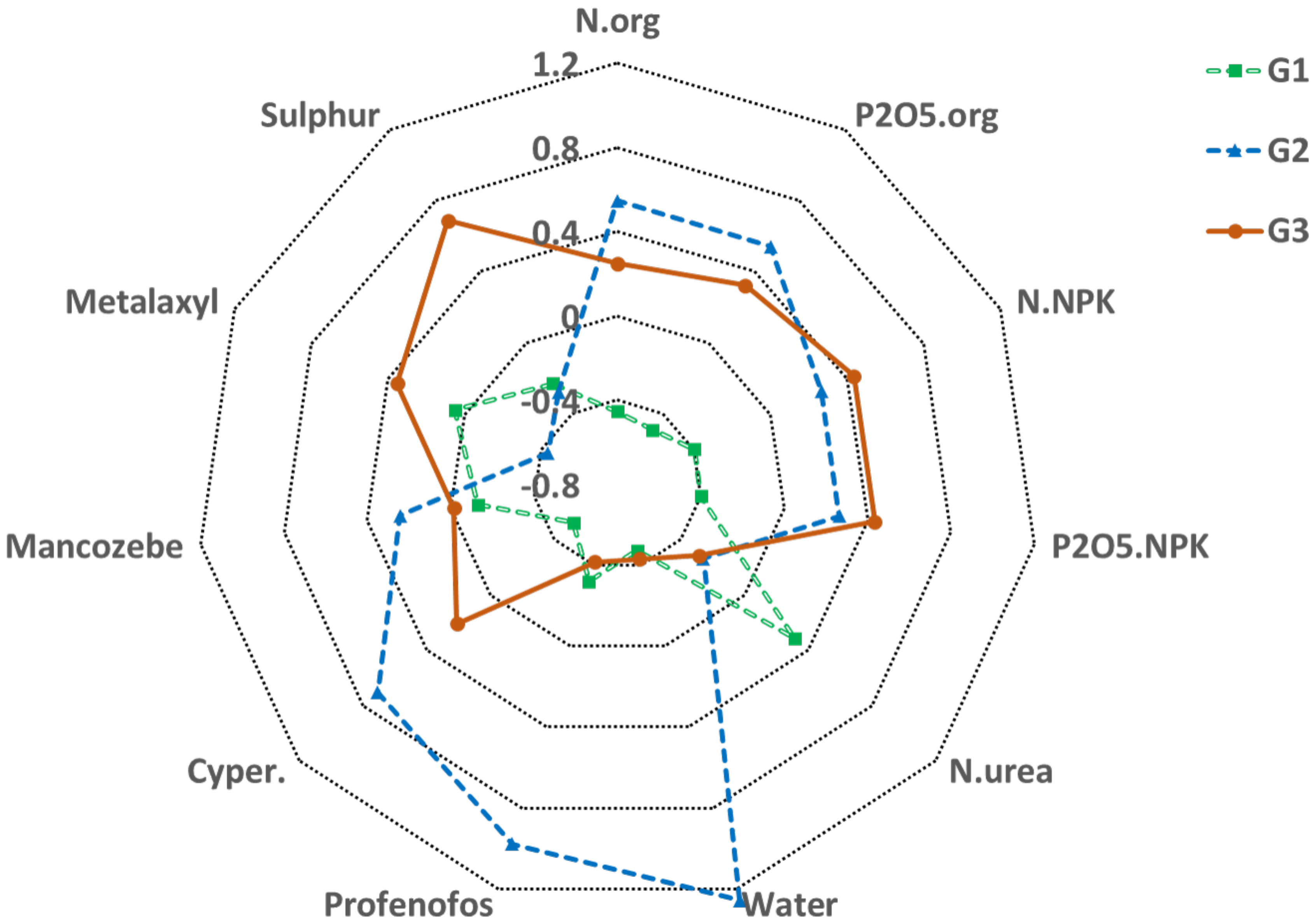


35 000
30 000
25 000
20 000
15 000
10 000
5 000
0
a
a
b
G1
G2
G3



Freshwater ecotoxicity (CTUe)
100
80
60
40
20
0
a,b
a
b
G1
G2
G3
Climate change (kg CO2-eq)
0.4
0.3
0.2
0.1
0
a
b
c
G1
G2
G3
Water resource depletion (m3 water eq)
0.0015
0.0010
0.0005
0.0000
a
b
b
G1
G2
G3
Acidification (molc H+ eq)
0.012
0.009
0.006
0.003
0
a
a,b
b
G1
G2
G3
Marine eutrophication (kg N eq)
0.005
0.004
0.003
0.002
0.001
0
a
a,b
b
G1
G2
G3
Freshwater eutrophication (kg P eq)
0.0009
0.0006
0.0003
0
a
a
b
G1
G2
G3
Mineral, fossil & ren resource depletion (kg Sb eq)
9.0E-06
6.0E-06
3.0E-06
0.0E+00
a
a
b
G1
G2
G3
Human toxicity, non-cancer effects (CTUh)
4.E-07
3.E-07
2.E-07
1.E-07
0.E+00
a
a
b
G1
G2
G3
Human toxicity, cancer effects (CTUh)
8.E-09
6.E-09
4.E-09
2.E-09
0.E+00
a
a,b
b
G1
G2
G3


Groups
G1
G2
G3
Profenofos
Cyper.
Water
P2O5.org
N.org
N.NPK
P2O5.NPK
Metalaxyl
Dim1 (36.5%)
Dim2 (25.9%)
Sulphur
N.urea
Mancozebe
Dim3 (14.2%)
Dim4 (10.4%)



N.org
P2O5.org
N.NPK
P2O5.NPK
N.urea
Water
Profenofos
Cyper.
Mancozebe
Metalaxyl
Sulphur
1.2
0.8
0.4
0
-0.4
-0.8
G1
G2
G3