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▶ To cite this version:

Allan Hayato Shimako, Ligia Tiruta-Barna, Aras Ahmadi. Operational integration of time dependent toxicity impact category in dynamic LCA. Sciences of the total Environment, 2017. hal-04335384

HAL Id: hal-04335384 https://hal.science/hal-04335384

Submitted on 11 Dec 2023

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1 Operational integration of time dependent toxicity impact category in dynamic LCA

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11 Abstract

Life Cycle Assessment (LCA) is the most widely used method for the environmental evaluation 12 of an anthropogenic system and its capabilities no longer need to be proved. However, several 13 limitations have been pointed out by LCA scholars, including the lack of a temporal dimension. 14 The objective of this study is to develop a dynamic approach for calculating the time dependent 15 impacts of human toxicity and ecotoxicity within LCA. A new framework is proposed, which 16 includes dynamic inventory and dynamic impact assessment. This study focuses on the 17 dynamic fate model for substances in the environment, combined with the USEtox® model for 18 19 toxicity assessment. The method takes into account the noisy and random nature of substance 20 emissions in function of time, as in the real world, and uses a robust solver for the dynamic 21 fate model resolution. No characterization factors are calculated. Instead, a current toxicity is calculated as a function of time i.e. the damage produced per unit of time, together with a time 22 23 dependent cumulated toxicity, i.e. the total damage produced from time zero to a given time horizon. The latter can be compared with the results obtained by the conventional USEtox® 24 25 method: their results converge for a very large time horizon (theoretically at infinity). Organic substances are found to disappear relatively rapidly from the environmental compartments (in 26 the time period in which the emissions occur) while inorganic substances (i.e. metals) tend to 27 persist far beyond the emission period. 28

25	
30	Keywords: dynamic Life Cycle Assessment, fate model, toxicity, ecotoxicity
31	
32	Highlights:
33	A method is proposed for calculating time dependent toxicity and ecotoxicity.
34	• Resolution of the dynamic fate model is combined with the USEtox [®] toxicity model.
35	• A current toxicity and a cumulated toxicity are calculated in function of time.
36	• The dynamic toxicity calculation is integrated in a dynamic LCA framework.
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39 **1. Introduction**

Life Cycle Assessment (LCA) is a method that calculates potential impacts associated with 40 products, processes and services over their entire life cycle. ISO standards14040-14044 41 42 specify the guide for conducting a LCA study, i.e. the four operational steps: the definition of the goal and scope, the construction of the Life Cycle Inventory (LCI) based on mass and 43 44 energy balances over the whole system life cycle, the Life Cycle Impact Assessment (LCIA) based on various impact calculation models, and the interpretation step (ISO, 2006a; ISO, 45 46 2006b). Currently LCA is the most widely used methodology for evaluating the environmental performance of any anthropogenic system. Its capabilities no longer need to be proved but 47 48 several limitations have been pointed out by LCA scholars. Among them, the lack of a temporal 49 dimension is intrinsically related to the LCA background. In a state of the art review, Finnvenden et al. (2009) argued that "the LCI results are also typically unaccompanied by 50 51 information about the temporal course of the emission or the resulting concentrations in the receiving environment... The impacts, which can be calculated under such boundary 52 conditions, thus represent the sum of impacts from emissions released years ago, from 53

emissions released today and from emissions released sometime in the future." Here, two
levels can be distinguished, which are related to the LCI and LCIA calculation steps in LCA.

Another time dependent aspect concerns the prospective evolution of systems over time, e.g. changes at the level of technologies or economic sectors. Such issues are resolved either by considering different scenarios at different time periods or by a radically different methodology i.e. Consequential LCA. This aspect is beyond the scope of this work, which focuses on the time dependency of inventory and impacts in Attributional LCA. Including the time dimension in LCA models is a challenge that has been taken up only recently and very little research is currently in progress.

The time dimension in the LCI step has been studied by Beloin-Saint-Pierre et al. (2014). These authors developed an approach called Enhanced Structure Path Analysis, in which environmental interventions (elementary flows, i.e. emissions and natural resources consumed) are distributed over time by considering the convolution product between temporal distributions related to the processes flows and temporal distributions related to elementary flows. However, this method still lacks a full and complete relationship with an LCA database.

To the best of our knowledge, only Tiruta-Barna et al. (2016) have provided a dynamic method for LCI, dealing with the complex supply chain and processes presented in an LCA study and linking the method to traditional LCA tools (databases). It enables easier implementation of temporal characteristics by LCA practitioners. In a recent study, Shimako et al. (2016) applied this method to bioenergy production from microalgae by calculating temporal LCI and coupling them with a temporal model of climate change.

In fact most studies dealing with temporal aspects in LCA are dedicated to climate change impact. For example, Cherubini et al. (2011) performed a calculation considering dynamic carbon removal by the biomass, which is a step prior to the calculation of the climate change impact. However, dynamic results for midpoint or endpoint climate change impact are not given as the calculated results are integrated in a single unit-based index. Levasseur et al. (2010) and Kendall (2012) studied time dependency in climate change impact by calculating temporal
characterization factors (CF) for substances and applying them to dynamic emissions.
Nonetheless, the authors focused on the LCIA step and modelled simple systems that did not
present a complex network of processes (and emissions) as most LCA studies do. The fixed
time step and simple input of data for the LCI did not allow the application of a more complex
and complete dynamic LCI in their methods.

In traditional LCA, the mass of the emitted substance is proportionally linked to the impact by 86 using characterization factors as proportionality constants, even though the fate of chemicals 87 in the environment is determined by time-dependent processes such as mass transfer and 88 89 chemical reactions, which produce non-linear distributions of remaining mass of substances in environment. An infinite time horizon is generally used for the calculation of CF for toxicity 90 91 impact. This assumption is important for taking all long lasting impacts into account. However, predicting impacts for eternity is also illogical. Also, the consideration of an infinite time horizon 92 93 may hide the potential impacts occurring over short periods of time in the assessment of a system, because of the different nature of substances considered in the assessment 94 (Huijbregts et al., 2001). The evidence of such shortcomings determined LCA scholars to 95 consider CFs for different time horizons. For toxicity calculations, Huijbregts et al. (2000a, 96 2000b, 2001) proposed characterization factors based on the USES-LCA model, which 97 comprises fate, exposure and effect calculations. CFs for 20, 100 and 500 years were 98 calculated to be in accordance with the horizon times used in global warming potentials as it 99 was considered that they provided a useful interval for policy decisions. 100

Another method, proposed by Hellweg et al. (2003), tackles the lack of time influence by applying a discounting method, which considers that toxicity impact diminishes with time. Calculation of time dependent CFs was also the approach proposed by Lebailly et al. (2014) by evaluating the dynamics of substance fate in the environment. They used the USEtox[®] model and calculated the dynamic behaviour of substances for an initial unit load of substance by solving the fate model for these particular conditions. These authors calculated 107 characterization factors at different time steps (starting from the initial emission), and used 108 them for a temporal evaluation of the freshwater ecotoxicity of metals. They applied this 109 method to the use of zinc as a fertilizer in agriculture in order to assess the temporal behaviour 110 of the impact. Although it implements dynamics in the fate calculation for metals, the study 111 lacks information on organic substances and, also, it does not implement complex, temporal 112 LCIs, which may present dynamic features related to unit processes and supply chains 113 involved in the life cycle of processes.

In conventional LCA, several toxicity models have been developed and used over the years. 114 The Life Cycle Initiative (http://www.lifecycleinitiative.org/) programme of the United Nations 115 116 Environment Program (UNEP) and the Society for Environmental Toxicology and Chemistry (SETAC) developed the USEtox[®] consensual toxicity model for LCA. USEtox[®] development 117 118 was based on the comparison of several toxicity models and on experts' recommendations (Jolliet et al. 2006; Lighart et al. 2004; McKone et al. 2006). USEtox® provides toxicity 119 120 characterization factors for human toxicity and freshwater ecotoxicity that are recommended 121 by LCA scholars.

The objective of this study is to develop a dynamic approach for calculating time dependent 122 toxicity and ecotoxicity impacts within LCA. The USEtox® model was chosen and adapted to 123 include the time dimension. In the first part of the paper, the theoretical development is 124 presented. Then, the method is applied to a testbed case, i.e. grape production, in order to 125 emphasize the results of the proposed framework. This testbed case was chosen for a variety 126 127 of reasons: i) agriculture employs potentially hazardous substances in the different production stages, so a temporal analysis of the LCI and environmental impacts is justified; ii) various 128 substances are emitted into the environment by agricultural operations, i.e. metals and organic 129 compounds with different types of harmful effects on humans and ecosystems. 130

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133 **2. Method**

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2.1. Toxicity Impact Assessment – USEtox[®] method

This subsection gives a brief presentation of the principles of the toxicity calculation methods 135 in LCA, particularly for the USEtox® method. The toxicity calculation methods usually follow 136 the approach used in methods for assessing chemical risk to human and ecosystem health, 137 based on three steps following the causal chain: i) evaluation of the fate of chemicals in the 138 environment, which leads to different concentrations/quantities of substances in different 139 environmental compartments; ii) evaluation of the exposure of humans or ecosystems to a 140 141 given substance, and iii) the effects that exposure might have on human or ecosystem health (Hauschild et al., 2008). Specific modelling approaches characterize each step, and have 142 given rise to commonly used LCIA methods like IMPACT 2002 (Jolliet et al., 2003; Pennington 143 et al., 2005), ReCiPe (Goedkoop et al., 2008) or USEtox[®] (Hauschild et al., 2008). All the 144 145 methods cited are based on a similar framework consisting of the calculation of characterization factors for substances as the result of multiplying a fate factor, an exposure 146 factor and an effect factor together, each of them being the result of one of the three 147 corresponding modelling steps cited above (Huijbregts et al, 2005a and 2005b). 148

Rosenbaum et al. (2007) proposed a framework in which the characterization factor was calculated as the product of matrices representing fate, exposure and effect factors:

$$\mathbf{CF}_{s} = \mathbf{EF}_{s} \cdot \mathbf{XF}_{s} \cdot \mathbf{FF}_{s}$$
(1)

where the index s represents the substance of concern, **CF** is the characterization factor vector in which each row represents a compartment, **FF** is the fate factor matrix representing the environmental removal and transport processes of a certain substance in the different environmental media, **XF** is the exposure factor matrix representing the increase in human consumption of a particular substance based on the increase of the substance concentration in a certain medium (for human toxicity) or the bioavailability of a certain substance (for ecotoxicity), **EF** is the effect factor matrix, which express the effect on humans or ecosystems per unit of concentration (Rosembaum et al., 2007). The USEtox[®] calculation tool (available at
 http://www.usetox.org/) is based on this flexible matrix algebra.

161 Finally, for toxicity impact calculations, the characterization factor is multiplied by the 162 aggregated environmental intervention of certain substance over its entire life cycle:

163
$$n_{s,i} = CF_{s,i} g_{s,i}$$
 (2)

where index i represents the emission compartment, g represents the environmental intervention (aggregated mass, which is the result of the LCI step) and n is the toxicity impact value for a certain substance s emitted in compartment i.

167

2.1.1. Fate modelling

Fate modelling uses a concept developed in the 1980s (described in many publications, e.g. Mackay, 2002; Van de Meent, 1993), which considers the environment as connected, well mixed, homogeneous boxes (named environmental media or compartments). The mass/concentration of a substance varies with time due to transport between compartments, reaction processes (e.g. degradation), and removal (immobilization in different media). In this model, the mass balance of a substance in the environment is described by a system of ordinary differential equations (ODE):

$$_{175} \quad \frac{\mathrm{dm}_{s}}{\mathrm{dt}} = \mathbf{K}_{s}\mathbf{m}_{s} + \mathbf{g}_{s} \tag{3}$$

where **K** is the square matrix of rate constants (related to removal, degradation and transport processes) in each compartment i (day⁻¹), **m** is the mass vector of substance s in the respective environmental compartments (kg), **g** is the vector of emission flows in each compartment (kg day⁻¹), t is time.

180 The nested multimedia fate concept is also used in LCIA methods but in the very simplified 181 condition of equilibrium or steady state. Physically the fate factor (day) represents the persistence of a chemical in the environment. It is mathematically defined as the resident mass
(kg) in a certain compartment per unit of constant flow (kg.day⁻¹) emitted into the environment.
In terms of the ODE system (equation 3) that signifies no variation of the
concentrations/masses, in all compartments:

186
$$\frac{\mathbf{d}\mathbf{m}_{s}}{\mathbf{d}\mathbf{t}} = \mathbf{0} = \mathbf{K}_{s}\mathbf{m}_{s} + \mathbf{g}_{s} \text{ then } \mathbf{F}\mathbf{F}_{s} = \frac{\mathbf{m}_{s}}{\mathbf{g}_{s}} = -\mathbf{K}_{s}^{-1}$$
(4)

The USEtox[®] 2.0 model is based on the steady-state condition described by equation (4). The following scales and compartments are defined (Hauschild et al., 2008): global scale (air, freshwater, ocean, natural soil, agricultural soil), continental scale (rural air, freshwater, sea water, natural soil, agricultural soil), local scale (urban air, household indoor air and industrial indoor air).

192

2.1.2. Exposure modelling in USEtox[®]

The exposure factor represents the relationship between the quantity of substance present in a certain compartment and its intake by humans. It can be divided into direct (i.e. direct consumption of an environmental compartment) and indirect exposure (e.g. meat, dairy produce, vegetables, etc.), represented respectively by equations 5 and 6 (Rosembaum et al., 2007).

$$198 XF_{s,xp,i}^{direct} = \frac{IR_{xp,i} \cdot P}{\rho_i \cdot V_i} (5)$$

$$199 XF_{s,xp,i}^{indirect} = \frac{BAF_{s,xp,i} \cdot IR_{xp} \cdot P}{\rho_i \cdot V_i} (6)$$

where XF^{direct} (day⁻¹) represents the average direct intake rate of the polluted medium i via direct ingestion. The parameter ρ is the bulk density of medium i (kg .m⁻³), V (m³) is the volume of medium i related to the exposure pathway xp, IR (kg.day⁻¹) is the ingestion rate of medium i via exposure pathway xp at population level and P is the population head count. For XF^{indirect} (day⁻¹), IR (kg.day⁻¹) represents the individual intake rate of food substrate correlated to pathway xp and BAF= C_{xp}/C_i (kg.kg⁻¹) is the bioaccumulation factor (the steady state concentration ratio between food substrate corresponding to exposure pathway xp and compartment i). For ecotoxicity, the exposure factor represents the relationship between the quantity of the substance in environmental compartments and its available fraction (truly dissolved fraction) (Rosenbaum et al., 2011).

210

2.1.3. Effect modelling in USEtox®

The effect factors represent the relationship between the intake quantity and the possible negative health effect of substances for living organisms. The effect factor for humans (cancer and non-cancer effects) can be calculated by equation 7. A linear dose-response function was assumed for each disease endpoint and intake route (Rosenbaum et al., 2011).

$$EF_{s} = \frac{0.5}{ED50_{s}}$$
⁽⁷⁾

where EF is the effect factor for humans (cases. kg⁻¹) for substance s, ED50 is the lifetime daily
dose resulting in a probability of effect of 0.5 (Henderson et al., 2011).

The effect factor for ecotoxicity (PAF.m³.kg⁻¹) represents the change in the Potentially Affected
 Fraction (PAF) of species due to change in concentration:

$$EF_{s} = \frac{0.5}{HC50_{s,EC50_{s}}}$$
(8)

where HC50 is defined by the hazardous concentration at which half of the target population is exposed above its EC50 (concentration for which 50% of the population is affected) (Henderson et al., 2011).

225 **2.2.** Time consideration in toxicity impact assessment

Among the factors included in a toxicity calculation, the fate is the one for which the dynamic 226 aspects are the most evident. It is well-known that the fate of substances in the environment 227 depends on their nature. Organic substances can be degraded by the environment, which 228 leads to their disappearance. On the other hand, inorganic substances (metals) tend to be 229 230 persistent and stay in different compartments for a long time (Hauschild et al., 2008). It is important to account for the dynamic behaviour of substances in the environment by 231 considering all the phenomena involved, such as mass transfer, degradation of substances, 232 removal, etc., as described by the mass balance system of equations (equation 3). Therefore, 233 234 considering the steady state condition, as is the case in conventional LCA, may lead to loss of consistency. The dynamic mass balance model provided, once adapted, can be resolved by 235 236 numerical methods. It should be noted that the environmental intervention \mathbf{g} (equation 3) represents emission flows with complex temporal behaviour which requires a rigorous 237 resolution approach. The input data **g** can be defined as a time dependent function in an 238 analytical manner or as numerical values at given times. Moreover, the rate-constants matrix 239 **K** contains values of different orders of magnitude (in day⁻¹) which signify the combination of 240 slow and rapid kinetics, with very different slopes. This condition imposes the use of finite 241 difference solvers with a very narrow discretization of the time dimension that has to be 242 investigated, or solvers with variable, adaptive, time steps. In this work, the Python odeint 243 integrator (SciPy Python library) was employed to solve initial value problems. It automatically 244 switches between an Adams predictor-corrector method for non-stiff problems and a backward 245 246 differentiation formula method for stiff problems. In this work, the mass balance model in equation (3) was used with the specific data provided by the USEtox[®] model, i.e. kinetic 247 constants, exposure and effect factors for the defined environmental scales and 248 compartments. 249

The result of the ODE is a vector of 13 elements that represents the current masses of substance s in each compartment i at a specific time t. By the end of the calculation, a mass vector (13 values corresponding to each compartment) is obtained for each discrete time value.
For the toxicity results, following the matrix approach proposed by Rosenbaum et al. (2007),
each mass vector is multiplied by the exposure matrix (**XF**) and effect matrix (**EF**):

255
$$\mathbf{n}_{\text{human,s}}(t) = \mathbf{m}_{s}(t) \times \mathbf{XF}_{\text{human,s}} \times \mathbf{EF}_{\text{human,s}}$$
 (9)

256 $\mathbf{n}_{human}(t)$ is the vector that represents human toxicity (cancer and non-cancer, cases.day⁻¹) for 257 a certain substance s in different compartments, at a given moment t in time.

$$\mathbf{n}_{eco,s}(t) = \mathbf{m}_{s}(t) \times \mathbf{XF}_{eco,s} \times \mathbf{EF}_{eco,s}$$
(10)

259 $\mathbf{n}_{eco}(t)$ represents the ecotoxicity, (PAF.m³.day).day⁻¹, due to an emission into a specific 260 compartment for a certain substance s at a given moment in time t.

The result for the aggregation of all substances s and compartments i, for a given time t, is given by equations (11) and (12) for human and eco-toxicity, respectively.

263
$$n_{human}(t) = \sum_{s} \sum_{i} n_{human,s,i}(t)$$
 (11)

264
$$n_{eco}(t) = \sum_{s} \sum_{i} n_{eco,s,i}(t)$$
 (12)

The cumulated values, $n_{human,cumul}$ (cases) and $n_{eco,cumul}$ (PAF.m³.day), for human toxicity and ecotoxicity can be calculated using equations (13) and (14) respectively.

₂₆₇
$$n_{\text{human,cumul}} = \int_{t=t_0}^{HT} n_{\text{human}}(t) dt$$
 (13)

$$n_{\text{eco,cumul}} = \int_{t=t_0}^{HT} n_{\text{eco}}(t) dt$$
(14)

where t_0 represents the time of the first emission released into the environment, HT is the time horizon for which the impact is investigated.

The objective of this work is the adaptation of USEtox[®] steady-state model for a dynamic 271 representation of the chemicals fate. The USEtox[®] 2.0 physical parameters were used without 272 modifications. Nevertheless, the authors are aware about the limitations and simplifications in 273 274 the LCIA methods. The chemicals fate in environment reveals much more complexity than that described by the multimedia fate models used in LCIA. Examples of influence factors are: local 275 characteristics of environmental media which depend, besides the geological parameters, on 276 specific climate factors and biota (e.g. Hertwich, 2001a; Daly and Wania 2004), chemical 277 278 speciation and its dependence on the above cited factors (Gandhi et al, 2011), and global modifications at long term of all these parameters. Obviously, a more accurate representation 279 280 should consider time and region dependent transport and kinetic parameters in a more complex nested multimedia. 281

Dynamic aspects can also be found in exposure and effect factors. Exposure of organisms to 282 a specific pollutant during a long time period may lead to high mortality and morbidity in the 283 first years. However, it may also lead to a genetic adaptation of organisms or a structural 284 285 change in the species composition of the ecosystem, decreasing mortality and morbidity (Heijungs et al., 2004). Temporal aspects may also occur in the indirect intake of pollutants via 286 the food chain, which normally delays the moment of pollutant intake with respect to the current 287 288 pollution state. However, these processes are not considered in this study as the prediction of 289 such behaviour is complex and uncertain, and remains beyond the scope of this work. Here, the conventional exposure model (equations 5, 6), and linear dose-response functions 290 (equations 7, 8) are used. 291

292

2.3.

Integration in a Dynamic LCA framework - DyPLCA

Introducing the time dimension into the LCIA step, in particular for toxicity calculation, is not
 sufficient to provide a relevant temporal assessment in LCA. A reliable time dependent LCI

must be set up. Recently, a novel conceptual and computational framework for including time 295 dependency in LCI was proposed by Tiruta-Barna et al. (2015). This method considers the 296 297 temporal behaviour of the foreground processes and of the supply chain. It takes temporal characteristics such as residence time of processes, lifetime of infrastructures, delivery 298 scheduling of products and latent time in the supply chain into account (more details in the 299 Supplementary Information document SI-S6). Each process is characterized by a production 300 301 flow function and an emission flow function. In order to distribute the environmental 302 interventions over time, the life cycle network of processes is described as a graph in which the nodes represent the processes and the arcs the exchange of products. For the computation 303 of the time-resolved environmental interventions, a tracking (graph search) algorithm is 304 implemented in a Web software named DyPLCA (http://dyplca.univ-lehavre.fr/). In terms of 305 results, the new approach provides time dependent LCI expressed as: i) a time function for 306 307 individual emissions (or resource consumption) for individual processes, ii) an aggregated time function for a given environmental intervention. The results are obtained in the form of 308 309 numerical data for discrete time values, over the time span of the life cycle under study (i.e. 310 past activities in background, present and future activities for fore- and background processes, e.g. 100 years). The proposed approach and tool are generic and fully compatible with all 311 dynamic LCIA methodologies and were recently used with a dynamic climate change approach 312 313 by Shimako et al. (2016).

Three different tools were interconnected in order to obtain a modelling and computational 314 framework for dynamic toxicity in LCA (Figure 1). SimaPro® LCA software was used for the 315 316 traditional LCI resolution. This software delivers the LCI results in matrix form: a technological matrix and an environmental intervention matrix (emissions by compartments and processes). 317 Those results were then used in the DyPLCA platform together with all the temporal 318 characteristics of processes and supply chains (defined by the practitioner prior to calculation). 319 320 This tool delivered a time vector and the associated emissions vector (kg.day⁻¹) in different environmental compartments, which were then used in the dynamic toxicity model proposed 321

by this study. A Python program treats data interpolation, choice of time step for calculation,
and sends the data to the ODE solver together with all the necessary USEtox[®] parameters,
then retrieves and treats the toxicity results. The complete dynamic framework was applied to
a testbed case.

326



327

328 Figure 1- General framework for the calculation of a dynamic LCA

329

330 **2.4.** Practical application to a testbed case

The process of "grape production, GLO" in version 3.2 of the ecoinvent database was considered as testbed case in order to exemplify the dynamic evaluation of toxicity using USEtox[®]. Conventional and dynamic LCA were performed and the results were compared.

334 2.4.1. <u>Conventional Life Cycle Assessment of grape production</u>

335 Goal and scope definition

From an LCA point of view, the objective of this study is to evaluate the toxicity impacts for the production of 1 kg of grapes (the functional unit). Cradle to gate boundaries are considered following the ecoinvent dataset "grape production, GLO" with attributional allocation.

This dataset (presented in SI-S3) covers the processes starting from the initial maintenance of the vineyard just after the previous crop, to the harvest and storage of the grapes produced, and includes fertilizer acquisition and application, pesticide acquisition, electricity use and irrigation. More details can be found in Stoessel et al. (2012).

343 *Life cycle inventory*

Global geography (GLO) is the only geography available in ecoinvent 3.2 and was chosen for 344 this study. For this reason, several improvements were necessary to match agricultural 345 practices better at regional scale. Regarding organic substance emissions, few substances 346 347 could be found in the "grape production" dataset. The emissions were accounted for in the process "pesticides, unspecified" in the technosphere. However, some important pesticides 348 currently used in agriculture were not considered. In Europe, France was the main agricultural 349 pesticides producer in 2013. It ranked second for absolute sales of pesticides, with a share of 350 almost 19% in 2014, and ranked third for grape production (Eurostat, 2016). In this sense, the 351 French market was chosen to represent the quantities of pesticides to be taken into account. 352 For this purpose, the dataset "pesticide, unspecified" and the emission "pesticide, unspecified" 353 were modified to fit the values available for the French market (MEDDE, 2016 - French national 354 sales data base - provides the French market distribution for pesticides). For this study, only 355 34 compounds were selected, corresponding to 55% of the French market in 2014 (Table 1). 356

357

Table 1 – Share of pesticides in French market - substances that contribute more than 0.5%
to the market (classified by their abundance in 2014).

Substance	2013	2014	Substance USEtox [®]	Substance ecoinvent
Sulfur	19.7%	17.9%	n.a.	Sulfur
Glyphosate	14.3%	13.4%	Glyphosate	Glyphosate
Mancozeb	5.24%	7.02%	Mancozeb	Mancozeb
Metam-sodium	3.12%	3.31%	Methyldithiocarbamic acid, Na salt	Metam-sodium
Prosulfocarb	2.16%	3.27%	Prosulfocarb	
s-Metolachlor	0.00%	2.89%	Metolachlor	Metolachlor
Chlormequat	2.78%	2.84%	Chlormequat	Chlormequat
Isoproturon	2.10%	2.48%	Isoproturon	Isoproturon
Folpet	2.49%	2.31%	Folpet	Folpet
Chlorothalonil	2.12%	2.03%	Chlorothalonil	Chlorothalonil
Iron sulphate	2.17%	1.98%	n.a.	n.a.
Paraffin oil	1.49%	1.69%	n.a.	n.a.
Chlorotoluron	1.89%	1.63%	Chlortoluron	Chlorotoluron
Metiram	1.65%	1.55%	Metiram	Metiram
Pendimethalin	1.28%	1.32%	Pendimethalin	Pendimethalin
Copper from copper sulphate; Copper from tetracopper tricalcium sulphate	1.39%	1.21%	Cu(II)	Copper
Metaldehyde	1.72%	1.18%	Metaldehyde (tetramer)	Metaldehyde
Aclonifen	1.30%	1.16%	Aclonifen	Aclonifen
Dimethenamid	1.08%	1.09%	Dimethenamid	Dimethenamid
МСРА	1.36%	1.05%	MCPA - Sodium salt	MCPA
Metazachlor	1.25%	1.00%	Metazachlor	Metazachlor
Napropamide	1.00%	0.91%	n,n-Diethyl-2-(1- naphthalenyloxy)propana mide	Napropamide
2,4-d	0.96%	0.89%	2-(2,4- dichlorophenoxy)acetic acid	2, 4 -D

Prochloraz ; Prochloraz manganese	1.02%	0.86%	Prochloraz	Prochloraz
Prothioconazol	0.96%	0.84%	n.a.	Prothioconazol
Tebuconazole	0.81%	0.80%	Tebuconazole	Tebuconazole
Metamitron	0.85%	0.78%	Metamitron	Metamitron
Pronamide	0.64%	0.73%	Pronamide	Pronamide
Amitrol	0.64%	0.68%	Amitrole	
Mineral oils	0.30%	0.61%	n.a.	n.a.
Copper from copper hydroxide	0.72%	0.61%	Cu(II)	Copper
Thiram	0.64%	0.55%	Thiram	Thiram
Imidacloprid	0.45%	0.52%	Imidacloprid	Imidacloprid
Boscalid	0.64%	0.52%	n.a.	n.a.

360 n.a. = not applied

361 *LCIA*

The application case focuses on human toxicity and ecotoxicity impacts generated by the substances emitted in the life cycle. The USEtox[®] 2.0 method was used for the conventional LCIA. In conventional LCIA toxicity impacts are calculated in steady-state condition, i.e. for an infinite time horizon.

366

2.4.2. Dynamic toxicity assessment

367 Dynamic LCI

As noted in subsection 2.3, a certain number of temporal parameters are needed in order to 368 369 compute dynamic LCI. The duration of one production cycle of grape is taken to be 12 months in permanent culture, the period defined as starting in January of each year. The lifetime of the 370 production field is regarded as 25 years as recommended by Bordelon et al., 2000. The main 371 application of pesticides takes place between April and July and they are applied every 7-14 372 days in general (Bordelon et al., 2000). For this study, an interval of 7 days was chosen. Direct 373 emissions (i.e. N₂O) of soil fertilisation to the air are considered to occur continuously during 374 the production cycle. Fertilizers and pesticides are considered to be delivered to the process 375

of grape production twice a year. The process related to the application of fertilizer, "fertilizing, by broadcaster", has the same temporal characteristics as the pesticides application. For this study, the harvest month was set as September, as it usually occurs between August and Octorber. The grape produced is stored for 2 months (Nemecek and Kägi, 2007) after the harvest and irrigation was considered to be continuous between April and October.

Based on this information, the temporal characteristics of processes involved in the life cycle of grape production were defined in the dynamic LCI method proposed by Tiruta-Barna et al. (2015) (listed in SI-S6). The inventory quantitative data from ecoinvent and the temporal parameters were used with the DyPLCA tool in order to build the temporal LCI.

385 Dynamic LCIA

386 Here only toxicity and ecotoxicity impacts were evaluated using the dynamic approach 387 developed in section 2.2.

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3. Results and Discussion

Tis section is structured in two sub-sections. In the first part the feasibility of the new method
and the comparison with the conventional method is discussed through two simple examples.
The second part presents and discuss the results for the testbed case.

393 3.1. Discussion of the dynamic toxicity approach

An organic substance (chloroform) and an inorganic one (mercury) were analysed here. For each substance, an emission was considered over 20 years in the agricultural soil compartment, described by a simple step behaviour (Figure 2.A): 0.04 kg.year⁻¹ constant flow during the first 10 years, then a constant flow of 0.06 kg.year⁻¹ between years 10 and 20. The total mass of emission is 1kg (time integral of the emission flow).



Figure 2 – (A) Emission profile of chloroform and mercury into agricultural soil at continental scale. (B) Chloroform fate in environment over 100 years and (C) Mercury fate in environment over 500 years. Legend: home.airl = household indoor air, occ.airl = industrial indoor air, airU = urban air, airC = continental rural air, fr.waterC = continental freshwater, sea.waterC = continental sea water, nat.soilC = Continental natural soil, agr.soilC = Continental agricultural soil, airG = global air, fr.waterG = Global freshwater, oceanG = ocean, nat.soilG = Global natural soil, agr.soilG = Global agricultural soil.

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In order to convert the dynamic emission into a dynamic toxicity calculation, the first step is to calculate the fate of the substance. Figures 2.B and 2.C show the current mass of chloroform and mercury in the environmental compartments, for a calculation time of 100 years and 500 years respectively. The very different behaviours found for the two substances depend on the different mechanisms included in the USEtox[®] model. Accordingly, the remaining mass of

chloroform drops considerably after the last emission around year 25. For non-persistent 413 organic substances, kinetics of removal and degradation usually present a high order of 414 magnitude, which explains the fast depletion of chloroform in the environment. The dynamics 415 of mercury removal in the environment is still slow and the sum of the remaining mass of 416 mercury in all compartments at year 500 represents 71% of the total emitted mass. It should 417 be noted that, after an accumulation during the emission period, the mass decreases in the 418 emission compartment (agricultural soil) while it increases in others, e.g. ocean. All transfer 419 420 and removal processes are slow, explaining the slow, long-term evolution of mercury quantities. 421

Figure 3 shows the current dynamic toxicity impacts (n_{human} (t), $n_{eco}(t)$ – equations 11, 12), calculated for 100 years in case of chloroform and for 500 years in case of mercury.

424



Figure 3 - Current dynamic toxicity impacts calculated for 100 years in case of chloroform and for 500 years in case of mercury. Ecotoxicity (n_{eco}) for chloroform (A) and mercury (B); Human toxicity (n_{human}) for chloroform (C) and mercury (D).

429

For both substances, the shapes of ecotoxicity (Figures 3.A and 3.B) and human toxicity curves (Figures 3.C and 3.D) are similar to those obtained for the mass in the fate calculation (Figure 2), which is explained by the fact that the dynamic aspects are related only to the fate step. Exposure and effect steps, being considered independent of time, are characterized by constant values. In case of chloroform, the value of toxicity drops considerably after about 20 years from the first emission, leading to the conclusion that toxicity impact occurs for the time frame in which the emissions exist.



Figure 4 - Cumulated dynamic toxicity calculated over 500 years for chloroform emission (●)
and mercury emission (■) (mission during 20 years). Ecotoxicity n_{eco,cumul} – A; Human toxicity
n_{human,cumul} - B

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438

Figure 4 shows the values of cumulated toxicity (equations 13, 14), for chloroform and mercury, for a time horizon of 500 years. This kind of result should be interpreted as the total impact generated from time zero to a given time horizon HT, and, for sufficiently large HT, the results should be similar to those calculated by the conventional method (USEtox[®], infinite HT). In case of chloroform (non-persistent substance) ecotoxicity and human toxicity stabilize after the end of the emission period. In case of mercury, the cumulated toxicity is still increasing significantly as the substance remains in the environment for a long period. In conclusion, the dynamic method demonstrates that mercury generates toxicity in the long term as a consequence of its persistence in the environment, with a variable intensity culminating at the end of the emission period (maximum of mass accumulation in the emission compartment).

Table 2 shows the conventional toxicity results and the cumulated values (obtained for 100 453 and 500 years integration time) obtained from the dynamic toxicity model, for both analysed 454 substances. In case of chloroform, the values found through the dynamic evaluation are similar 455 456 to those obtained from the conventional (infinite time horizon) method, thus validating the structure of dynamic calculations for toxicity. In the case of mercury, the results for 500 year 457 458 time horizon are lower than the conventional results. This can be explained by the fact that the chosen time horizon might not be sufficient to reach the complete removal of the substance. 459 However, it can be noted that the value tends to the traditional toxicity value when HT is 460 461 increased.

462

463 Table 2 – Toxicity results for the emission of chloroform and mercury.

- 464
- 465

		Conventional	Dynamic 100 years	Dynamic 500 years
Mercury	Remaining mass (kg)		9.4E-01	7.2E-01
	Ecotoxicity, cumulated (miliPAF.m ³ .day)	1.6E+07	9.8E+05	4.7E+06
	Cancer toxicity, cumulated (cases)	3.7E-02	2.3E-03	1.1E-02
	Non cancer toxicity, cumulated (cases)	4.3E+00	2.7E-01	1.3E+00
Chloroform	Remaining mass (kg)		0.0E+00	0.0E+00
	Ecotoxicity, cumulated (miliPAF.m ³ .day)	9.3E E+02	9.3E+02	9.3E+02

Cancer toxicity, cumulated (cases)	3.1E-07	3.1E-07	3.1E-07
Non cancer toxicity, cumulated (cases)	9.0E-07	9.0E-07	9.0E-07

466

As a general conclusion, the behaviour of different substances is determined by the transport 467 and reaction processes in the fate step. The rate constants of these processes are gathered 468 in the constants matrix K (available with the USEtox® tool). All of them are compartment and 469 substance sensitive. When steady state conditions are considered in the toxicity calculation, 470 important information is lost or hidden. The equilibrium state in conventional LCA leads to 471 overestimation of CFs for toxicity, especially for persistent substances. This aspect of the 472 pollutant persistence and its associated toxicity is not visible in conventional LCIA methods, 473 474 i.e. it is not possible to evaluate if toxicity acts for a short period affecting people for several 475 years (as in the case of chloroform) or for a long period affecting several generations (example of mercury). 476

477 Lebailly et al. (2014) also proposed a dynamic freshwater ecotoxicity assessment for metals 478 in LCA. After studying the behaviour of several metals, the authors reached the same 479 conclusion as the present work: the integrated toxicity approaches the conventional value for large time spans, depending on the substance and compartment. However, in their method, 480 481 the behaviour of non-persistent organic substances was not investigated. Concerning 482 methodological aspects, their method is based on the time dependent calculation of CFs by solving equation (3) for an initial unit load of substance (i.e. a pulse input, g = 1kg at t =zero 483 and g=0 for t>0). CFs (instantaneous and cumulated) were calculated with a 1-year time step. 484 485 Then, ecotoxicity impact (instantaneous and cumulated) was calculated at a given HT using 486 the sum of the products g(t)*CF(HT-t). The method proposed by Lebailly et al. (2014) differs 487 from our method by the mathematical approach chosen for resolving the dynamic fate model.

Given that g(t) is expected to be noisy with a complex shape representing the emission of a substance by many processes shifted in time, over a large time span covering the life cycle of a system, the most rigorous approach is to directly solve the ODE system, which was carriedout in the present work.

492 The second solution could be to consider the mathematical properties of a linear system, i.e. 493 the convolution product between an impulse response function of the system and the input perturbation signal. In our case, the system is the environment, the perturbation input signal is 494 495 a substance entering the environment (a temporal emission g(t)), and the impulse response function IRF is the response of the environment (all environmental mechanisms taken 496 together) at a pulse unit input (g=unit at t=0, g=0 for t>0), i.e. a particular initial condition. This 497 approach is similar to that of Lebailly et al. (2014): the CFs(t) represent IRFs, and the toxicity 498 499 calculation procedure they propose corresponds to a convolution product. Well before Labailly et al, Hertwich (2001b) proposed, in a context different from LCA, to solve dynamic multimedia 500 501 fate models by using the convolution approach, combined, in addition, with the Laplace transforms of equations and source function g(t) in order to avoid numerical integration 502 503 (possible only if g(t) is analytically defined by a function).

The toxicity results obtained by the different mathematical methods presented (direct resolution of ODE and convolution approach) should be very similar, within the limit of inherent errors induced by the numerical resolution. However, given the behavioural complexity of the systems studied in the context of LCA, the convolution approach is more limiting while it requires specific mathematical conditions to be respected.

As regards the practicability of either of these approaches, again due to the complexity of the g function, the direct integration of dynamic mass balances is more practical and easier to handle in a modelling platform where dynamic LCI and dynamic impact calculations are coupled (as described in paragraph 2.3 and shown in Figure 1). In addition, if the toxicity model should evolve by adding more dynamic phenomena, variable parameters in time and space, or spatial dimension, the direct resolution of a complex system of differential equations remains the only solution. Moreover, the calculation of time dependent CFs becomes unnecessary since the large number of values (many thousands for a single substance, depending on the granulometry of the time scale) make it unfeasible to use them in the spirit of conventional LCA (where only a single CF characterizes a substance/compartment pair). CF was a concept introduced in LCA for the sake of simplicity, in order to gather, in a single constant, the contributions of many environmental mechanisms and phenomena involved in the impact/damage generation. Thus in the dynamic context, characterization factors lose their sense and utility. This is why they are not used in the present study.

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3.2. Testbed case results

First of all, the "grape production" process was modelled in SimaPro[®] and the matrix of environmental interventions was extracted. The data from SimaPro[®] was then used in DyPLCA together with the necessary temporal parameters, resulting in a table containing 742 columns representing substances and compartments, with, in rows, the discrete values of environmental interventions (LCI) for each time step. The time span covered the lifetime of the main process (grape production, 25 years) and 1 year before for background processes (year -1). The time step in the DyPLCA inventory used for this project was 0.5 days.

Then, data harmonization between the ecoinvent and USEtox[®] databases was performed. 531 Environmental compartments in ecoinvent are not defined in the same manner as in USEtox[®]. 532 Thus, the adaptation of compartments led to a different number of combinations with the 533 emitted substances (see SI - S1 and S2 for more details). Moreover, the name and chemical 534 speciation of substances are not the same in the ecoinvent and USEtox[®] databases, e.g. 535 metals do not have an oxidation number in ecoinvent but they do in USEtox[®]. Speciation is 536 one of the most important items of information for toxicity assessment. Finally, a total of 671 537 substance/compartment combinations were considered in this testbed case, covering 538 emissions over the whole life cycle. The results obtained from DyPLCA, with harmonized 539 540 nomenclature, were then used for dynamic toxicity calculation. The same harmonization was used for conventional LCI in order to calculate toxicity with steady-state USEtox[®]. 541

For the sake of clarity, only the results for two selected substances are presented here together 542 with results for organics and inorganics. All numerical results correspond to the functional unit, 543 i.e. 1kg grape production. Figure 5.A presents the emission profile of one chosen substance, 544 prochloraz, identified as one of the most impacting pesticide in this application, while figure 5.B 545 shows its current mass (kg) in different compartments in function of time. The emission profile 546 obtained after computing the dynamic LCI with DyPLCA tool, has peaks corresponding to the 547 periods of application to the vines (see zoom side of the figure). These cycles can be well 548 549 distinguished also on graph 5.B as the pesticide is relatively rapidly degraded in agricultural 550 soil and no major accumulation takes place from one cycle to another.



551

Figure 5 – Case of the prochloraz – results for 1kg grape production. (A): Emission into agricultural soil at continental scale with zoom between years 0 and 2. (B): Mass distribution in different compartments with zoom between years 0 and 2. Legend: home.airl = household indoor air, occ.airl = industrial indoor air, airU = urban air, airC = continental rural air, fr.waterC = continental freshwater, sea.waterC = continental sea water, nat.soilC = Continental natural soil, agr.soilC = Continental agricultural soil, airG = global air, fr.waterG = Global freshwater, oceanG = ocean, nat.soilG = Global natural soil, agr.soilG = Global agricultural soil.

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It should be noted that emissions could occur in the life cycle of the process under study before it started to produce. For example, the production of grapes requires chemicals that are produced before the agricultural process. The start time of the grape production is noted t=0 but background processes had already been working before this time. Therefore, a negative part of the time axis was employed to point out the existence of background emissions in the past.

Figure 6 shows the emission profile (6.A) and the fate (6.B) of copper, another compound present in pesticide products. The remaining mass is predominantly in agricultural soil at continental scale due to the slow transfer towards the other compartments and the very slow removal. The mass in this compartment increases until the last emission and then decreases slowly. About 64% of the mass still remains in the environment by the year 100 and 9% by the year 500.

572 The observed behaviours of the two substances shown similarities to those discussed in 573 section 3.1, i.e. non-persistent organic compounds and persistent metals. Calculated dynamic 574 toxicities follow the fate profile as discussed in section 3.1 (toxicity results presented in SI-S7).



Figure 6 – Case of copper - results for 1kg grape production. (A): Emission profile into agricultural soil at continental scale with zoom between years 0 and 2. (B): Mass distribution in different compartments with zoom between years 0 and 2. Legend: home.airl = household indoor air, occ.airl = industrial indoor air, airU = urban air, airC = continental rural air, fr.waterC = continental freshwater, sea.waterC = continental sea water, nat.soilC = Continental natural soil, agr.soilC = Continental agricultural soil, airG = global air, fr.waterG = Global freshwater, oceanG = ocean, nat.soilG = Global natural soil, agr.soilG = Global agricultural soil.

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Figure 7 presents the results obtained for ecotoxicity in PAF.m³.day.day⁻¹ (fig 7.A) and human toxicity, as cancer (fig 7.B) and non-cancer (fig 7.C) in cases.day⁻¹, in function of time, for all substances emitted by the life cycle system. A highly variable toxicity profile is observed in the first 25 years (which is the lifetime of the foreground process), as a cumulated effect of organics and inorganics. After the end of emissions, the toxicity values drop to those of the remaining metals, and then decrease slowly following the fate of the metals.

592



Figure 7– Current toxicity for the production of 1 kg of grapes. (A) Ecotoxicity $n_{eco}(t)$; (B) Cancer and (C) Non-cancer Human toxicity $n_{human}(t)$.

597

598 Human toxicity and ecotoxicity were also calculated separately for organic and inorganic 599 substances. Regarding the current ecotoxicity and human toxicity of organic substances 600 (Figure 8 A, B and C), marked variations can be noted during the emission period as a result 601 of the substance fate. As previously discussed and shown in the case of prochloraz, the fate 602 of organic substances is driven not only by the emission profile but also by rapid removal and 603 transfer processes. For the organic substances the impact is high during the emission period.

604



Figure 8 – Current Ecotoxicity $n_{eco}(t)$ (A), Cancer (B) and Non-cancer (C) Human toxicity n_{human}(t) of organic substances for the production of 1 kg of grapes

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Regarding the human toxicity and the ecotoxicity of inorganic substances (Figure 9 A, B and C), a large increase can be noted throughout the lifetime of the vineyard, due to the accumulation of substances in agricultural soil as a result of their slow inter-compartment transfer and very slow removal (high persistence). After that period, toxicities slowly decrease asymptotically in time.

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Figure 9 – Current Ecotoxicity $n_{eco}(t)$ (A), Cancer (B) and Non-cancer (C) Human toxicity n_{human}(t) of metals for the production of 1 kg of grapes

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Figure 10 shows the cumulated ecotoxicity in PAF.m³.day (fig 10.A) and the cumulated human toxicity, as cancer and non-cancer in cases (fig 10.B), over the time horizon, for all substances considered together, for organics and inorganics. Cumulated ecotoxicity and non-cancer human toxicity increased progressively with time due to the higher contribution of persistent inorganics. Cancer human toxicity increased strongly during the emission of pollutants and more slowly in the long term. The explanation is the contribution of less persistent inorganics with a high toxicity potential, such as arsenic or mercury (see SI - S5).

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Figure 10 – Cumulated dynamic ecotoxicity $n_{eco,cumul}$ (A) and human toxicity $n_{human,cumul}$ (B) of all environmental interventions (•), organic substances (**•**) and metals (**•**) for the production of 1 kg of grapes.

634

635 Cumulated toxicity for organic substances reflects their fate well. The order of magnitude of 636 the cumulated values for toxicity of organic substances is negligible compared to the cumulated 637 values of toxicity for all substances considered in the testbed case. Toxicity results for inorganic 638 substances show values very close to those obtained for all substances which highlights the 639 importance of inorganic substances in the toxicity impact assessment for this testbed case. Table 3 presents the cumulated values for human toxicity and ecotoxicity, calculated over thetime horizons of 100 and 500 years.

642

Table 3 –Conventional (infinite time horizon) and dynamic (time horizons of 100 and 500 years)
cumulated toxicity impacts for organic, inorganic and all substances emitted in the grape
production testbed case

	Cumulated impact	Conventional	Dynamic 100 years	Dynamic 500 years
	Ecotoxicity (PAF.m ³ .day)	4.8E-01	4.8E-01	4.8E-01
Organic	Cancer toxicity (cases)	5.7E-11	4.6E-11	4.6E-11
	Non-cancer toxicity (cases)	5.6E-11	5.2E-11	5.2E-11
	Ecotoxicity (PAF.m ³ .day)	1.8E+02	4.1E+01	9.9E+01
Inorganic	Cancer toxicity (cases)	1.2E-07	8.8E-09	1.0E-08
	Non-cancer toxicity (cases)	2.0E-07	2.8E-08	5.5E-08
	Ecotoxicity (PAF.m ³ .day)	1.8E+02	4.1E+01	9.9E+01
All	Cancer toxicity (cases)	1.2E-07	8.8E-09	1.0E-08
54851411065	Non-cancer toxicity (cases)	2.0E-07	2.9E-08	5.5E-08

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647

648 When comparing the dynamic and conventional approaches for organic substances, a 649 difference of about 20% can be observed in the case of human cancer toxicity. This difference may come from the inventory steps in conventional and dynamic LCI, which presented about 650 10% of difference. For metals, the gap between dynamic and conventional toxicity results 651 decreases as the time horizon increases. In this work USEtox® was chosen as the database 652 because it is highly recommended by LCA scholars. However, it should be noted that several 653 data used for inorganic substances are of poor relevance (named interim values) and the 654 results should be interpreted with caution. 655

When only the organic substances were evaluated, the following individual contribution results have been found (Table 4, more results in SI-S7). The pesticide that had most influence for ecotoxicity was metam with a contribution of 32% in the dynamic and conventional methods; for dynamic human cancer toxicity, pronamide contributed with 12% in the dynamic method and 10% in the conventional method; for human non-cancer toxicity prochloraz contributed with 16% in the dynamic method and 15% in the conventional method.

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Table 4 – Contribution of distinct pesticides on dynamic (cumulated toxicity at 100 years) and
conventional (infinite time horizon) toxicity impacts generated by all organic substances.
Results for human toxicity (Cancer and Non-cancer) and ecotoxicity (Eco) impacts for the
production of 1 kg of grape.

	Dynamic (100 years)			Conventional		
Substance	Cancer	Non-	Eco	Cancer	Non-	Eco
		cancer			cancer	
Folpet	0.1%	0.2%	8.0%	0.1%	0.2%	8.1%
Thiram	0.0%	0.4%	1.9%	0.0%	0.4%	1.9%
Imidacloprid	0.0%	10.2%	0.7%	0.0%	9.3%	0.7%
Napropamide	0.0%	1.8%	0.1%	0.0%	1.7%	0.1%
Chlorothalonil	0.1%	2.5%	15.0%	0.1%	2.3%	15.2%
Pronamide	12.7%	4.7%	0.2%	10.2%	4.3%	0.2%
Pendimethalin	0.0%	4.7%	2.9%	0.0%	4.3%	2.9%
Metolachlor	0.0%	4.9%	3.7%	0.0%	4.5%	3.7%
Prochloraz	9.9%	16.1%	0.9%	7.7%	14.6%	0.9%
Mancozeb	0.0%	14.1%	14.4%	0.0%	13.0%	14.4%
Metiram	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
МСРВ	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Glyphosate	0.0%	15.0%	1.0%	0.0%	0.0%	0.0%
Chlormequat	0.0%	11.4%	0.0%	0.0%	10.5%	0.0%
2,4-D	0.0%	9.0%	0.0%	0.0%	8.2%	0.0%
Metam-sodium dihydrate	0.0%	0.0%	31.7%	0.0%	0.0%	31.5%

Chlortoluron	0.0%	0.0%	0.3%	0.0%	0.0%	0.3%
Isoproturon	0.0%	0.0%	3.1%	0.0%	0.0%	3.1%
Metamitron	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Metazachlor	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Aclonifen	0.0%	0.0%	7.2%	0.0%	0.0%	7.2%
Dimethenamid	0.0%	0.0%	6.5%	0.0%	0.0%	6.5%

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668

In this testbed case, cumulated toxicity and ecotoxicity are dominated by the inorganic 669 persistent substances, for which conventional methods may give overestimated impact results, 670 as also discussed in section 3.1. The more the HT tends to infinity the closer the value of 671 672 cumulated toxicity comes to the values of a conventional LCA. In contrast, current toxicity diminishes with HT. In other words, the population and ecosystems are less affected by the 673 residual pollution but they suffer the greatest damage in a restricted period corresponding to 674 the end of lifetime of the system (about one generation is strongly affected). These results 675 676 emphasize the importance of the current impact evaluation as a measure of the intensity of 677 possible damage at a given time.

678 Another aspect concerns the distribution in time of the activity of different processes involved 679 in the life cycle of grape production. The dynamic LCI-LCIA approach allows to observe that the main toxicity impact occurs in the present and future time. The explanation is that all 680 chemicals and other commodities are produced and used during the lifetime of the foreground 681 process and no important infrastructure was built in the past. The impact generated in the past 682 by background processes, previously to vineyard activity, is very small when compared to the 683 current impact (past impact is hardly visible on the negative time axis on all figures). However, 684 inorganic substances emissions from the past activities generate persistent impact for the 685 686 present and future time.

From a LCA – decision making point of view, dynamic evaluation provides complementary 687 information helping at discriminating comparable scenarios and at proposing solutions for 688 689 impact mitigation. For equal conventional impact results, time dependent behaviour of toxicity 690 can be different for the compared scenarios. For example, scenario B has more metals contribution than A (all equal otherwise). Impact at the human lifetime scale could be lesser in 691 case of B as the time horizon is a very important parameter for potential cumulated impact in 692 case of persistent chemicals. Scenario B could be preferable for short durations like the 693 694 vineyard lifetime. Solutions for changing the land destination could be envisioned in order to avoid a sensitive use (e.g. for food production) in the future. 695

The existence of variations with different amplitudes on the toxicity curves (figures 5-9) suggests that dynamic toxicity simulation can be used as a forecast tool for, e.g. identifying optimal situations where certain activities should be (temporarily) stopped or, at the contrary, launched, at regional level. For example, to not use a specific substance during the years with forecasted high toxicity pics, or to stop the sensitive use of a certain water resource for a given period, etc.

702

703 **4. Conclusions**

In this study, a mathematical implementation of dynamic toxicity assessment based on the USEtox[®] model was presented. In addition, the study developed a dynamic LCA framework, combining dynamic LCI modelling and toxicity impact evaluation over time. The feasibility of such an approach was demonstrated via a testbed case on grape production.

The main features of the dynamic toxicity calculator can be summarized as follows. The dynamic toxicity model is based on the resolution of the dynamic fate model in USEtox[®]. Exposure and effect factors are unchanged and considered constant in time. Characterization factors are no longer needed as current toxicity and cumulated toxicity are directly calculated in function of time. Instead of using CFs, the dynamic mass balance equations were directly integrated, the behaviour of different substances being determined by the transport and reaction processes in the fate step. The computational method should consider the possibility of a noisy and random shape for the emission function. Therefore, the odeint integrator (Scipy Python), a robust method for ODE resolution that is compatible with stiff systems, was employed in the present work.

The toxicity calculator can be easily coupled with a dynamic LCI tool, in our case DyPLCA,
thus providing a complete dynamic LCA framework.

Regarding the expected results of a dynamic approach, the following outcomes can be mentioned.

The current toxicity (cases.day⁻¹) allows the intensity of the impact at a given time to be evaluated and the critical periods with regard to the potential impact to be identified. The evolution of toxicity in time is similar to the substance fate profile (mass in compartments versus time).

The cumulated toxicity (cases) represents the total damage generated over a given time horizon. This result was compared with the conventional toxicity value. It should be noted that the cumulated toxicity reaches the conventional toxicity value for large time horizons (theoretically at infinite time).

Significantly different behaviours were observed when persistent and non-persistent 731 substances were compared. Non-persistent (generally organic) substances deployed almost 732 733 all their hazard potential during their emission period and disappeared more or less rapidly due to degradation or transfer to sink compartments (removal). In contrast, persistent substances 734 accumulated in environmental compartments during the emission period and their toxicity 735 potential remained high after the cessation of emission, affecting many human generations. 736 737 However, a calculation of toxicity at equilibrium (infinite time in conventional method) 738 overestimated the total impact at the time scale of a human life.

The results obtained by the conventional method - which fixes an arbitrary time horizon - made 739 740 no distinction between persistent and non-persistent pollutants. In contrast, dynamic 741 calculations of toxicity and generally dynamic LCA brought out important information about the period when the potential hazard becomes critical, allowing mitigation of pollution issues, which 742 is not the case in conventional LCA. Dynamic LCI – LCIA can be used as a forecast tool by 743 simulating different scenarios in function of time, identifying optimal situations and scheduling 744 745 the activities, helping in this way decision making. Combination of both dynamic aspects, LCI (share of environmental interventions in time, i.e. the functioning of life cycle processes) and 746 LCIA (environmental mechanisms and specificities of substances), allows thus to obtain 747 detailed case specific information on potential hazard/environmental impact. 748

749

750 Acknowledgements

751 We gratefully acknowledge funding by the French Research Agency ANR-13-IS09-0007-

752 01/DyPLCA and thank Dr. Yoann Pigné for his assistance with the dynamic inventory step in

the DyPLCA tool.

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