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4 **Influence of spatial differentiation in impact assessment for LCA-based decision**
5 **support: implementation of biochar technology in Indonesia**

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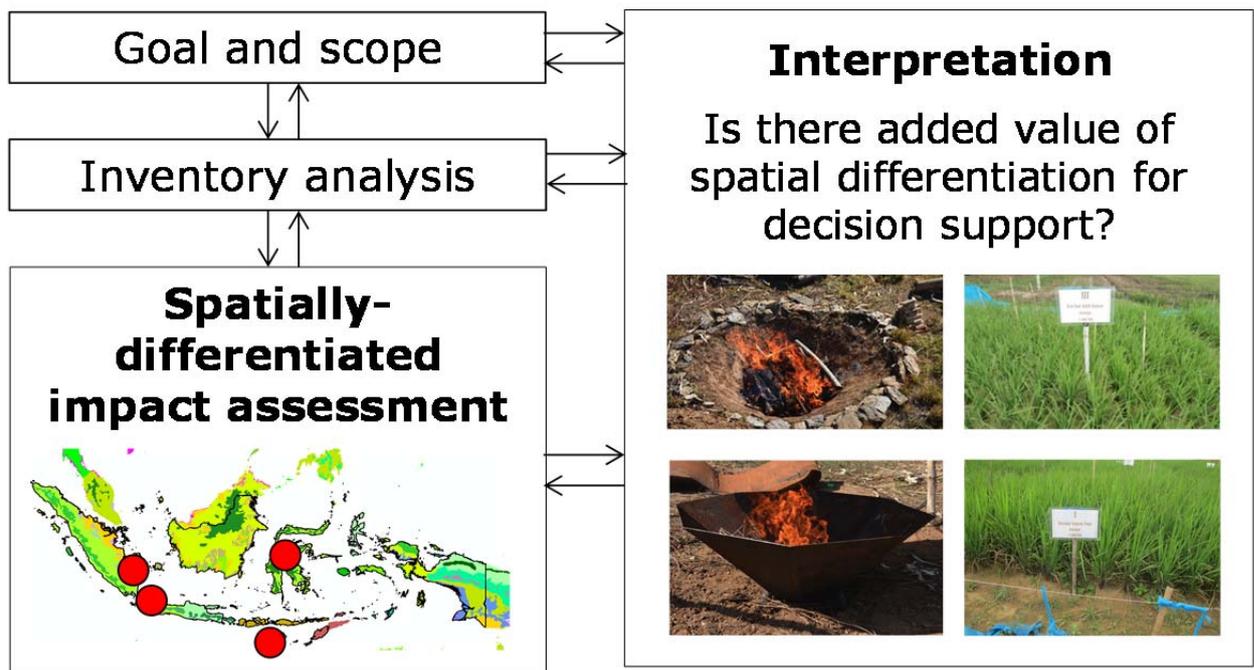
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- 20 • Spatial differentiation was found important for total damage to human health
- 21 • Spatial differentiation was less relevant for total damage to ecosystems
- 22 • Tradeoffs between impact categories influenced total scores
- 23 • Geographical variations in inventory flows influenced comparisons
- 24 • Spatial differentiation did not necessarily lead to better decisions



25

26 Graphical abstract

27 **Abstract**

28 Spatial differentiation in evaluation of environmental impacts in life cycle assessment (LCA) may
29 give more accurate and realistic results, especially in cases where impacts occur at a local or
30 regional scale and where sensitivity of receiving ecosystems differs from generic conditions.
31 However, from a decision maker's perspective it is of interest to investigate whether the use of
32 spatially differentiated impact assessment methods in addition leads to better decisions. Biochar
33 production and agricultural utilization in Indonesia is an example of a micro-level decision-support
34 case where spatial differentiation could be relevant.

35 To study the influence of spatial differentiation on implementation of biochar as a waste
36 management strategy and the choice of best performing biochar production techniques, agricultural
37 utilization systems and geographic locations, comparisons were made between four communities
38 living on different Indonesian islands, three biochar production techniques and two types of
39 fertilizer.

40 Results showed that the differences in impact scores between generic and spatially
41 differentiated impact scores were an order of magnitude different for some of the considered impact
42 categories. These differences influenced the identification of which system performed best when
43 considering total damage to human health, which was mainly due to differences in accounting for
44 impacts arising from water use. By contrast, trade-offs between impact categories combined with
45 relatively small contribution of some spatially differentiated impacts rendered spatial differentiation
46 less relevant with regard to total damage to ecosystems. Total impact scores were influenced to a
47 greater extent by variations in inventories determining environmental burden and benefits, than by
48 differences between generic and spatially differentiated characterization factors. Hence, irrespective
49 of the scenario and type of damage considered, both generic and spatially differentiated assessments

50 showed that implementing biochar technology in Indonesia is expected to bring environmental
51 benefits.

52 It was shown that spatial differentiation in impact assessment did not necessary lead to
53 better decisions in this case study. This may suggest that depending on the goal of the LCA,
54 practitioners should consider potential benefits of implementing spatially differentiated life cycle
55 impact assessment methods as opposed to potential benefits from collecting site-specific
56 inventories.

57 **Keywords**

58 decision-making, decision-support, LCA, LCIA, regionalization, spatialization

59

60 **1. Introduction**

61 Life cycle impact assessment (LCIA) the part of life cycle assessment (LCA) in which the life cycle
62 inventory of a system's material flows is translated into their potential contributions to the
63 environmental impacts. LCIA supports the interpretation phase of the LCA, where questions posed
64 in the goal definitions are answered (Hauschild and Huijbregts, 2015). Spatially differentiated life
65 cycle impact assessment (LCIA) methods enable execution or regionalized life cycle assessment
66 (LCA) studies as they take into consideration local conditions and sensitivities of receiving
67 ecosystems. In contrast to generic methods, which should be valid on a global scale (at the expense
68 of higher spatial uncertainty), spatially-differentiated LCIA methods are more accurate as they
69 operate at either regional or local scales, corresponding to site-dependent and site-specific
70 assessments, respectively (Potting and Hauschild, 2006). In this paper, we studied the influence of
71 the choice of spatially differentiated LCIA methods on the interpretation phase of an LCA.

72 The development of spatially differentiated LCIA methods has intensified in the past few
73 years (Patouillard et al., 2018; Rosenbaum et al., 2018; Verones et al., 2017). A review of

74 characterization models included in spatially differentiated LCIA methods, like IMPACT World+
75 (Bulle et al., 2012) or LC-Impact (Verones et al., 2016), is given in Rosenbaum (2018).
76 Examinations of these models shows, that depending on the impact category, geographic variability
77 in characterization factors (CF) can be higher than differences in characterization factors between
78 substances covered by the method. Applications of such methods in LCA studies results in more
79 accurate and realistic evaluations of environmental impacts, as was demonstrated for the few
80 regionalized LCA studies published to date (Anton et al., 2014; Heidari et al., 2017; Henderson et
81 al., 2017a; Mutel et al., 2011).

82 LCA is a decision support tool. Two (out of three) commonly used archetype goal situations
83 (namely, situation A for micro-level decision support and situation B for meso/macro-level decision
84 support) involve a decision context (Bjørn et al., 2018a; European Commission, 2010). It is
85 therefore of interest to investigate whether the use of spatially differentiated LCIA methods leads to
86 better decisions, in addition to more accurate and realistic LCIA results. Our research question is
87 therefore: does spatial differentiation in life cycle impact assessment lead to better decisions? The
88 answer to this research question is not obvious. Even large differences in impact scores for
89 individual impact categories might become less influential for decision support. This could be due
90 to potential trade-offs between impact categories (Heidari et al., 2017), due to a larger influence of
91 spatial variability in inventory flows compared to spatial differences in characterization factors
92 (Henderson et al., 2017b), or due to a smaller contribution of spatially-differentiated impact
93 categories to total damage. The influence of spatial differentiation in impact assessment on LCA-
94 based decision support has not previously been investigated.

95 Spatial differentiation may be particularly important for application of biochar systems in
96 tropical rural areas like Indonesia, where conditions with regard to biodiversity or water availability
97 can vary significantly from generic characterization factors used in traditional LCA (Boulay et al.,

98 2011; Chaudhary et al., 2015). Biochar is typically used as soil conditioner, increasing crop
99 productivity while contributing to climate change mitigation through carbon sequestration and
100 storage (Lehmann, 2007; Woolf et al., 2010). Biochar is produced from biomass residues, and in
101 developing and middle-income countries often small-scale, low-cost pyrolysis technologies
102 traditionally based on earth-mound kilns are used (Nsamba et al., 2015). Alternatively, more
103 innovative and cleaner flame curtain (“Kon-Tiki”) kilns or retort kilns made out of bricks and steel,
104 can be used (Cornelissen et al., 2016; Sparrevik et al., 2015). Experimental studies have shown that
105 biochar production leads to emission of toxic organic compounds and greenhouse gases
106 (Cornelissen et al., 2016; Sparrevik et al., 2015). Environmental impacts from biochar systems have
107 previously been assessed using LCA (e.g. Galgani and Delft, 2012; Gwenzi et al., 2015; Sparrevik
108 et al., 2014). However, the relative immaturity of spatially differentiated LCIA approaches and their
109 limited implementation into LCA modelling software, have restricted the use of spatially
110 differentiated methods in these studies.

111 The objective of this study was therefore to assess implications of spatial differentiation in
112 LCIA on decision support related to implementation of a biochar systems in Indonesia. For this
113 purpose, generic and spatially differentiated impact scores were calculated and compared using a
114 suite of relatively recent LCIA methods, which offer spatially differentiated characterization factors
115 at the damage level. Firstly, the influence on an *absolute scale*, i.e. whether the conversion of
116 biomass residues to biochar and its subsequent use in agriculture provides has a net positive effect
117 compared to the current situation (no treatment of biomass residues), was investigated. Secondly,
118 when selecting management strategies, decision makers must know in which geographic locations
119 biochar systems are expected to perform optimally, and furthermore which biochar production
120 technique and biochar application conditions (inorganic vs. organic fertilizer based agriculture)
121 perform best from an environmental point of view. Thus, the effect of spatial differentiation on the

122 *relative importance* for ranking of subsystems and technologies was assessed. Finally, decision
123 makers may be interested in identifying potential improvements for biochar systems, and a process
124 contribution analysis, i.e. identifying the processes with the largest environmental burden, can be
125 used for this purpose. Thus, the impact of spatial influence on *process contribution* was examined.

126 **2. Methods**

127 **2.1. Goal and scope**

128 The goals of the LCA were three fold: The first goal was to assess and compare life cycle impacts
129 of biochar systems in Indonesia in order to support decision making related to the implementation
130 of biochar as a waste management strategy in four Indonesian island communities. The second goal
131 was to identify the best biochar production technique and agriculture practice in these communities.
132 The third goal was to identify improvement potentials for the biochar systems. The results of this
133 LCA are used to discuss the effect on spatial differentiation for LCA-based decision support in the
134 Indonesian context.

135 The LCA was carried out following the requirements of the ISO standards and the
136 guidelines of the International Reference Life Cycle Data System (ILCD) handbook (European
137 Commission, 2010; European Committee for Standardization, 2006a, 2006b) According to the
138 ILCD guidelines, the current study is a micro-level decision support (type-A) situation, and the
139 assessment carried out applies an attributional approach in accordance with the recommendations of
140 the ILCD guidelines for this decision support type. A system expansion (through crediting) using
141 average processes in this attributional approach, consistent with both ILCD and the ISO hierarchy
142 for solving multifunctionality, was therefore applied (Bjørn et al., 2018b).

143 *2.1.1. Functional unit and system boundaries*

144 The primary function of the biochar systems in this context is to utilize biomass waste to produce
145 biochar and use of this biochar as a soil conditioner. Thus, the functional unit was defined as the
146 “treatment of 1 kg of biogenic carbon from biomass residues in rural areas in Indonesia”. This
147 definition allows for a fair comparison between residues treated using different techniques. A
148 secondary function of biochar when used as soil conditioner is its ability to support crop growth. In
149 this case, the benefits from increasing yields are modelled as avoided production of crops (mainly
150 fertilizer use). In addition, system boundaries included the complete underlying biochar production
151 life cycle, including the construction of the biochar kilns and production of biochar from biowaste
152 (Fig. 1). Avoided impacts from current waste management system are also relevant to considered,
153 but in this case there is no treatment of biomass residues, which are allowed to decompose in
154 aerobic conditions. Thus, following Sparrevik et al., (2014) no net emissions of carbon dioxide and
155 no emission of methane during decomposition of biomass residues were assumed.

156 Fig. 1.

157 2.1.2. Biochar systems investigated

158 The influence of spatial differentiation was studied by using site specific inventory data from four
159 distinct geographic locations of Indonesia (Ngata Toro on the island of Sulawesi, Napu on Sumba,
160 Lampung on Sumatra, and Lamongan on Java) (see SI, Section S1 for details). On the basis of
161 previous work in Nepal and Zambia, the most promising method for the production of biochar in
162 the four villages was considered to be the flame curtain technique (Table 1, scenarios 1-4)
163 (Cornelissen et al., 2016; Schmidt et al., 2014). This novel production technology was compared to
164 biochar systems based on other available alternative production technologies, such as retort kilns
165 (the Adam retort) (Adam, 2009) and simple non-retort earth-mound kilns (Table 1, scenarios 5-12).
166 Inorganic fertilizers (N, P, K, and urea) are used in all villages, except for Napu where compost is
167 used. Thus, comparisons were made with compost as the sole source of nutrient input in Ngata

168 Toro, Lampung, and Lamongan, and with inorganic fertilizers as the source of nutrient input in
 169 Napu (Table 1, scenarios 13-24).

170 Table 1. Overview of the compared biochar systems.

# Scenario	Sensitivity parameter	Geographic location (production and use) ^a	Biochar production technique ^b	Fertilizer type and amount ^c
1	Baseline	NT	“Kon-Tiki” flame curtain kiln	NPK and urea fertilizers
3-4	Geographic location of biochar production and use	N, LS, LJ	“Kon-Tiki” flame curtain kiln (all locations)	NPK and urea fertilizers (NT, LS, LJ); compost (N)
5-12	Biochar production technique	NT, N, LS, LJ	retort kiln (all locations); earth mound kiln (all locations)	NPK and urea fertilizers (NT, LS, LJ); compost (N)
13-24	Fertilizer type and amount	NT, N, LS, LJ	“Kon-Tiki” flame curtain kiln, retort kiln; earth mound kiln (all locations)	compost (NT, LS, LJ); NPK and urea fertilizers (N)

171 ^a NT: Ngata Toro; N: Napu; LS; Lampung, Sumatra; LJ: Lamongan, Java

172 ^b retort kiln made from bricks and steel (Adam retort) and earth-mound kiln were alternatives to
 173 steel-made “Kon-Tiki” flame curtain kiln

174 ^c in Lampung and Lamongan NPK and urea fertilizers were applied in higher amounts compared to
 175 Ngata Toro (see SI, Section S2 for details)

176

177 **2.2. Life cycle inventory analysis**

178 Data for background processes, like construction of kilns or (avoided) production of inorganic
179 fertilizers are based on generic processes available in Ecoinvent, version 3.3 (Weidema et al.,
180 2013). Ecoinvent is currently one of the most comprehensive databases of life cycle inventories.
181 Consideration of spatial differentiation in LCIA for these generic processes was not possible, as it is
182 not known where emissions occur in the background system. Data for foreground processes in the
183 biochar system, such as biochar production or soil application, should be represented as accurately
184 as possible and were thus based on primary data measured in Indonesia and reported previously
185 (Sparrevik et al., 2014), or collected specifically in surveys carried out for this work. Spatial
186 differentiation was used in the LCIA in all relevant processes in the foreground system. All
187 inventory data were site-specific representative field data aggregated from seven years of biochar
188 research activities. This data, which included biochar properties, biochar application rate, irrigation
189 and agricultural yields, varied between sites. Outdoor emissions resulting from the production of
190 biochar, concentrations of CO₂, CO, CH₄, NMVOC, and PM₁₀ and nitrous oxides, measured in
191 Cornelissen et al., (2016) and Sparrevik et al., (2015) were used. Emissions of nitrate, phosphate,
192 phosphorus and metals (co-contaminants) to soils, and emissions of GHG to air from organic and
193 inorganic fertilizers were taken from generic Ecoinvent process for production of maize.
194 Differences in fertilizer amounts between the Ecoinvent process and amounts in these case studies
195 were corrected for, assuming that composition of fertilizers with regard to metal content was the
196 same. Site-specific data related to the mineralization kinetics of biochar in soil were not available
197 for this study and as such were assumed to follow bi-exponential decay kinetics and average
198 (geometric mean) kinetic parameters measured for six biochars representing a wide range of
199 mineralization rate constants were therefore used (Zimmerman and Gao, 2013). Based on Woolf
200 and Lehmann, (2012) a negative priming equal to 45% increase in soil organic carbon stock in the

201 long-term (100 years) was used. Model parameters and underlying data are presented in the [SI](#),
202 [Section S2](#). Unit processes for the foreground system are given in the [SI](#), [Section S3](#).

203

204 **2.3. Life cycle impact assessment**

205 To answer the research question (does spatial differentiation lead to better decisions?), spatially
206 differentiated LCIA methods must be applied to all relevant categories of environmental impacts
207 and must express impacts in common units. Hence, the following set of criteria was applied to
208 choose LCIA methods: (i) a method must be published in peer-reviewed literature; (ii) it must offer
209 modelling at damage level; (iii) it must allow a calculation of spatially-explicit impact score at
210 sufficient resolution to be made (e.g. country- or Southeast-Asia level for regional impact categories
211 like photochemical ozone formation, and island- or biome-level for local impact categories like land
212 use); and (iv) it can be further adapted to specific geographic situation based on available details of
213 the case study (e.g. adapting the particulate matter (PM) model to local exposure parameters). A
214 comparison of impact assessment methods based on their environmental relevance or scientific
215 robustness was not carried out here and no preference was given to one method over another for this
216 study. Damage scores were computed allowing for weighting of impact categories contributing to
217 total damage in two important areas of protection in LCIA: (i) human health, where impacts are
218 expressed in disability adjusted life years, DALY; and (ii) ecosystem quality considering terrestrial,
219 freshwater, and marine ecosystems, where impacts are expressed as loss of biodiversity (in species-
220 years) (Hauschild and Huijbregts, 2015). The full list of LCIA methods with details of the spatial
221 scales considered is given in [Table 2](#). A detailed description of each method is presented in the [SI](#),
222 [Section S5](#).

223 [Table 2](#). Generic and site-explicit LCIA methods for the impact categories considered in this study.

Impact category	Area of protection	Impact score unit	Geographical and temporal reference unit	Reference
Climate change	Human health	DALY	Indonesia; 1-yr time steps	Levasseur et al., 2010); ReCiPe2016 (Huijbregts et al., 2016); IPCC (2013); Cherubini et al., (2016)
Climate change	Ecosystems (freshwater)	species×year	Indonesia; 1-yr time steps	
Climate change	Ecosystems (terrestrial)	species×year	Indonesia; 1-yr time steps	
Ozone depletion	Human health	DALY	Global	ReCiPe2016 (Huijbregts et al., 2016)
Ionizing radiation	Human health	DALY	Global	ReCiPe2016 (Huijbregts et al., 2016)
Particulate matter formation	Human health	DALY	Outdoor rural: Southeast Asia Indoor: air exchange rate for open building and no attenuation, measured village-specific exposure parameters (see Table S1)	(Fantke et al., 2017b)
Land use	Ecosystems (terrestrial)	species×year	Village-specific	Chaudhary et al., (2015)
Water use (distribution)	Human health	DALY	Watershed/Indonesia ^a	Boulay et al., (2011)
Water use	Ecosystems (terrestrial)	species×year	Watershed	ReCiPe2016 (Huijbregts et al., 2016), based on Pfister et al., (2009)
Water use	Ecosystems (freshwater)	species×year	Indonesia ^b	ReCiPe2016 (Huijbregts et al., 2016), based on Hanafiah et al., (2011)
Toxicity (cancer and	Human health	DALY	Outdoor: Southeast Asia Indoor: household indoor exposure settings based	USEtox 2.02 (Fantke et al., 2017a)

Impact category	Area of protection	Impact score unit	Geographical and temporal reference unit	Reference
non-cancer effects)			on non-OECD archetype combined with village-specific exposure parameters (see Table S2)	
Freshwater ecotoxicity	Ecosystems (freshwater)	species×year (converted from PDF×m3×d)	Southeast Asia	USEtox 2.02 (Fantke et al., 2017a)
Terrestrial ecotoxicity	Ecosystems (terrestrial)	species×year (converted from PDF×m3×d)	Village-specific for metallic elements; Global for organic chemicals	ReCiPe2016 (Huijbregts et al., 2016); (Owsianiak et al., 2017; Owsianiak et al., 2013) for metallic elements
Marine ecotoxicity	Ecosystems (marine)	species×year (converted from PDF×m3×d)	Indonesian Sea marine ecosystem for metallic elements; Global for organic chemicals	ReCiPe2016 (Huijbregts et al., 2016) for organics; Dong et al., (2016) for metallic elements
Freshwater eutrophication	Ecosystems (freshwater)	species×year	Indonesia	ReCiPe2016 (Huijbregts et al., 2016)
Marine eutrophication	Ecosystems (marine)	species×year	Village-specific	Cosme et al., (2017; Cosme and Hauschild, 2017); Roy et al., (2014)
Terrestrial acidification	Ecosystems (terrestrial)	species×year	Village-specific	ReCiPe2016 (Huijbregts et al., 2016)
Photochemical ozone	Human health	DALY	Region comprising Indonesia, Papua New Guinea, and East Timor	ReCiPe2016 (Huijbregts et al.,

Impact category	Area of protection	Impact score unit	Geographical and temporal reference unit	Reference
formation				2016)
Photochemical ozone Formation	Ecosystems (terrestrial)	species×year	Region comprising Indonesia, Papua New Guinea, and East Timor	ReCiPe2016 (Huijbregts et al., 2016)
Mineral resource scarcity	Resources	USD2013	Global	ReCiPe2016 (Huijbregts et al., 2016)
Fossil resource scarcity	Resources	USD2013	Global	ReCiPe2016 (Huijbregts et al., 2016)

224 ^a although watershed-specific characterization factors were calculated by Boulay et al., (2011) for main watersheds (ca.

225 600 in total), all four villages are located outside main watersheds and thus assigned the same characterization factor

226 ^b although watershed-specific characterization factors were calculated by Hanafiah et al., (2011) for well-known river

227 basins above 42° latitude (214 in total), none of the four villages could be mapped on the watershed.

228

229 **2.4. Sensitivity and uncertainty analyses**

230 A sensitivity analysis of the results of the discrete parameters as determined by scenarios presented

231 in [Table 1](#) (Section 2.1) was conducted by comparing impact scores without any internal

232 normalization. For continuous parameters, sensitivity of impact scores was quantified by computing

233 normalized sensitivity coefficients (eq 1), based on Ryberg et al., (2015):

$$234 \quad X_{IS,k} = \frac{\Delta IS / IS}{\Delta a_k / a_k} \quad (\text{eq 1})$$

235 where $X_{IS,k}$ is the dimensionless normalized sensitivity coefficient of impact score (IS) for

236 perturbation of continuous parameter k , a_k is the k th parameter value, Δa_k is the perturbation of

237 parameter a_k , IS is the calculated impact score, and ΔIS is the change of the impact score that

238 resulted from the perturbation of parameter a_k . Baseline parameter values were used as default in all
 239 scenarios listed in [Table 1](#). They originate from measurements and are described in [Section 2.2](#).
 240 Perturbed parameter values representing lower and higher ranges of parameters were defined based
 241 on variations reported earlier in other experimental studies on biochar in developing and middle-
 242 income countries ([Table 3](#)). A parameter is considered important if $X_{IS,k} \geq 0.3$, corresponding to a
 243 medium sensitivity (Cohen et al., 2013). Uncertainties in those parameters which were found
 244 important in the perturbation analysis ([see SI, Section S6.5](#) for results of the sensitivity analysis)
 245 were assigned either normal, or triangular, or uniform distributions based on the distribution of
 246 measured values ([SI, Section S4](#)).

247 In addition to parameter uncertainties, uncertainties in the life cycle inventories were also
 248 considered. For the foreground processes (e.g. in material inputs or emissions) they were estimated
 249 using the Pedigree matrix approach, as illustrated in [Ciroth et al., \(2013\)](#) assuming that the data was
 250 log-normally distributed ([Huijbregts et al., 2003](#)). Uncertainties in the background processes were
 251 based on geometric standard deviations already assigned to flows in theecoinvent processes used.
 252 Uncertainties in characterization factors are not provided for the majority of the methods, and were
 253 therefore not considered. Monte Carlo simulations (1000 iterations) were carried out for pairwise
 254 comparison between scenarios listed in [Table 1](#) while keeping track of the correlations between
 255 pairs of systems. Comparisons were considered statistically significant if at least 95% of all 1000
 256 Monte Carlo runs were favourable for one scenario.

257 [Table 3](#). Uncertain, continuous model parameters for processes associated with biochar systems.
 258 Values referred to as default apply to all relevant scenarios listed in [Table 1](#). Perturbation analysis
 259 was carried out to test the influence of a parameter value on the results for selected scenarios.

Parameter	Parameter values		Unit	Source
	Default	Perturbation		

		s (min-max)		
Biochar yield (flame curtain and earth-mound kilns)	22	17-27	%	Measured in Cornelissen et al., (2016) Error of 5.0% as measured by Sparrevik et al., (2015)
Biochar yield (Adam retort)	32	27.4-36.6	%	Measured in Sparrevik et al., (2015) Error of 4.6% as measured by Sparrevik et al., (2015)
Biochar application rate (per village) ^a	NT: 1200	1140-1260	kg/ha	Measured in Sparrevik et al., (2014) Error of 5% assumed, expected to be in realistic range of values
	N: 4000	3800-4200		
	LS: 5000	4750-5250		
	LJ: 4000	3800-4200		
Crop yield without biochar addition (per village) ^a	NT: 6500	5655-7345	%	Measured in Sparrevik et al., (2014) (NT) and in this study (for the other locations). Error of 13% based on values reported in Zambia by Sparrevik et al., (2013)
	N: 2000	1740-2260		
	LS: 6000	5220-6780		
	LJ: 8000	6960-9040		
Crop yield change when biochar is used (per village)	NT: 10	7.1-11.6	%	Measured in Sparrevik et al., (2014) (NT), in this study (N and LS) or assumed (LJ) equal to 10%, which is a conservative estimate (Jeffery et al., 2017, 2011). Perturbation ranges based on measurements in Napu (N) were scaled to other villages assuming equal variance
	N: 248	176-287		
	LS: 100	71-116		
	LJ: 10	7.1-11.6		
Mineralization rate constant for the recalcitrant pool	8.58E-04	9.2E-06 - 6.1E-03	yr ⁻¹	Measured in Zimmerman and Gao, (2013) for six different biochars. Default (geometric mean), minimum, and maximum values were used
Priming effect	45	30-60	%	Modelled in Woolf and Lehmann, (2012) Increase in soil organic carbon stock in the long-term (100 years) was used. Perturbation

				values are ranges reported (Woolf and Lehmann, 2012)
Water use for irrigation (per village) ^a	NT: 0.155	0.11-0.20	m ³ /kg output	Measured in this study. Perturbation values assumed 30% increased and decrease, which is in realistic range of values
	N: 0	0-0		
	LS: 0.155	0.11-0.20		
	LJ: 0.155	0.11-0.20		
Fraction of PM smaller than 2.5 μm	0.92	0.73-0.95	kg/kg	Measured for residential wood combustion as reported in Humbert et al., (2011) Value of 0.73 is for low-stack emissions, value of 0.95 is in higher range of measured values for various sources (Humbert et al., 2011)

260 ^a NT: Ngata Toro; N: Napu; LS; Lampung, Sumatra; LJ: Lamongan, Java

261 **3. Results**

262 **3.1. Comparison between generic and spatially differentiated impacts**

263 [Figure 2](#) shows the comparison between generic and spatially differentiated impacts from biochar
264 produced using a flame curtain kiln and used in agriculture, as influenced by geographic location of
265 the field and fertilizer type (scenarios 1-4 and 13-15 in [Table 1](#)). Impact scores for individual
266 impact categories either increased or decreased compared with generic scores, depending on the
267 impact category (see also [SI, Section S6.1](#)). The largest consistent increase (by ca. 2 orders of
268 magnitude) was observed at all locations for the *human health impacts from water use* (except
269 Napu). Spatially differentiated characterization factors for human health impacts in the watersheds
270 are equal to 0 DALY/m³ for all sites except Napu where the characterization factor is higher and
271 reflects water scarcity problems on Sumba. However, current agricultural practice does not rely on
272 irrigation in this village. This explains why there are no apparent benefits in terms of water used
273 impacts when the system is credited for increasing crop yields in Napu for both spatially
274 differentiated and generic assessments. The comparison between spatially differentiated and generic
275 impacts also shows that there is some reduction in human health impacts stemming from emissions
276 of PM_{2.5} (difference up to factor of 2), mainly because the site-specific intake of PM_{2.5} resulting
277 from emissions are smaller at the site-specific level at these rural sites, than the default value used
278 in global-generic assessment.

279 The largest consistent decrease when spatial differentiation was used (by ca. 1 order of
280 magnitude) was observed at all locations for *land use impacts on birds and mammals*. Indonesian
281 ecoregions are among the most biodiverse globally, and characterization factors are generally one
282 order of magnitude higher in all villages when compared to global-generic values (Chaudhary et al.,
283 2015). Changes in impact scores for other impact categories ranged from small (below 10%) to
284 large (up to a factor of 5) when spatial differentiation was considered, but these differences were

285 largely non-conspicuous as the contribution of these impacts categories to total damage was often
286 very small (less than 1% of total damage). Statistically significant differences between regionalized
287 and generic impacts were found in nearly all impact categories, except for freshwater
288 eutrophication. Similar trends were observed for other kilns (see [SI, Section S6.2](#)). The major
289 differences between spatially differentiated and generic impacts were, again, due to significantly
290 smaller (but not equal to zero) contributions from water use impacts on the terrestrial ecosystem
291 ([Fig. 2b](#)). Here, the very high resolution of watersheds used in the method of Pfister et al., (2009)
292 which includes relevant minor watersheds, allowed each village and its corresponding watershed to
293 be mapped. In addition, there was an increase in impact scores for terrestrial acidification due to a
294 small alkaline buffering capacity of the soils, making them more vulnerable to acidic emissions.
295 [Figure 2b](#) also shows that there is some reduction in ecotoxicological impacts stemming from using
296 soil-specific characterization factors for metallic elements (like Cd or Zn) emitted together with
297 fertilizer as co-contaminants. Terrestrial ecotoxicity characterization factors for these elements are
298 generally higher (approximately twice as high) compared to generic values because acidic soils
299 have a higher bioavailable metal concentration and thus a higher toxicity potentials in soils
300 (Owsianiak et al., 2017; Owsianiak et al., 2015).

301 When aggregating impacts at the human health and ecosystem level, the impact of spatial
302 differentiation was less pronounced. The spatially differentiated damage to human health was
303 approximately 3 to 5 times higher when compared to generic scores, except for Napu where total
304 damage was comparable between approaches ([Fig. 2a](#)). For aggregated potential impacts on
305 ecosystems, the effect of spatial differentiation was not significant ([Fig. 2b](#)), although impact scores
306 varied by up to one order of magnitude for the individual impact categories. This is mainly caused
307 by the small absolute numbers for the impact categories mostly influenced by spatial differentiation
308 (such as marine eutrophication or ozone formation) (see [SI, Section S6.1](#)), as well as trade-offs

309 between categories, where an increase in impact scores for some categories was compensated by a
310 decrease in others. For example, the increase in impact from water use and acidification in the
311 regionalized assessment was compensated by increased benefits from land use impacts on plants.
312 These benefits roughly doubled when compared with the global-generic assessment.

313 [Fig. 2.](#)

314

315 **4. Discussion**

316 **4.1 Relevance of spatial differentiation for decision support**

317 Results presented in [Fig. 2](#) and in [Section S6.1 of the SI](#) show that spatially differentiated impact
318 assessments resulted in more accurate and realistic results than generic assessments. This finding is
319 consistent with earlier regionalized LCA studies demonstrating the use of spatially differentiated
320 LCIA methods. Mutel et al., (2011) already showed that spatially differentiated ecosystem damage
321 and human health scores of coal-based power generation in America were 30% higher and 38%
322 lower, respectively, compared to generic scores. Anton et al., (2014) reported that regionalized
323 human toxicity impacts of tomato agriculture in Spain were one order of magnitude higher than
324 those determined from generic assessment. More recently, Henderson et al., (2017) demonstrated
325 that spatial differentiation resulted in a nearly double water stress for American food production
326 when compared to a generic assessment.

327 This is the first regionalized comparative LCA study where influence of spatial
328 differentiation on decision support was investigated. While this study corroborates earlier
329 regionalized LCA studies in terms of influence of spatial differentiation on impact scores, it
330 demonstrates that the benefits of spatial differentiation for decision-support are closely connected to

331 the goal of the LCA. The discussion below therefore relates to various aspects in a decision support
332 context, using the application of biochar technology as the example.

333 *4.1.1 Evaluation at an absolute scale*

334 In order to make decisions about the implementation of a new biowaste management strategy,
335 information about overall environmental performance of the technology is needed. In this study,
336 impact scores were negative in most (but not all) of the individual impact categories, and the total
337 damages were all negative (Fig. 2). Thus, environmental benefits from increased crop productivity
338 outweighed the environmental burden of biochar production, which can include human health
339 impacts from particulate matter and emission of toxic carcinogenic compounds. This holds true for
340 all of the geographic locations, biochar production techniques, and fertilizers compared, suggesting
341 that spatial differentiation does not influence decisions about implementing biochar systems in
342 Indonesia. This study showed that a crop productivity increase as low as 10%, such as in Lampung
343 and Ngata Toro (and lower than 25% as reported in a recent meta-analysis for tropical soils (Jeffery
344 et al., 2017), is sufficient to make spatial differentiation irrelevant with regards to making decisions
345 about the implementation of biochar-based management strategy for biowaste in Indonesia. Burden
346 and benefits can also be determined by the current waste management practice that is replaced by
347 the new biowaste management strategy (Owsianiak et al., 2016). In the biochar context, spatial
348 differentiation is therefore expected to be less relevant in cases where the replaced waste
349 management system is based on the polluting methods composting or landfilling, which emit the
350 potent greenhouse gas methane (Laurent et al., 2014).

351 The increase in crop productivity of 10% may, however, be sufficient to make spatial
352 differentiation relevant for certain chars where production and/or transportation to the field are
353 important contributors to total impacts, as has been shown to be the case for hydrochars (Owsianiak
354 et al., 2017). This may also hold true for biochars made on an industrial scale (and thus off-site). It

355 is therefore important to see spatial differentiation in connection to the quality of the inventory,
356 which for most relevant processes in this study used site-specific data.

357 ***4.1.2 Relative ranking***

358 One plausible management decision from the LCA would be a relative feasibility ranking of
359 villages to assess the benefit of implementing biochar technology in that specific region. For human
360 health damage, both generic and spatially differentiated assessments identified Lampung as the
361 village performing best, while Napu and Ngata Toro/Lamongan were identified as least optimal in
362 both the generic and site-specific assessments (Fig. 3 and SI, Section 6.3). This difference is due to
363 different quantities of water used for irrigation. Further, different villages were identified as best in
364 scenarios with alternative fertilization strategies. This makes spatial differentiation relevant to
365 consider in cases where detailed rank information is desirable. For total ecosystem damage
366 however, Lampung and Lamongan performed best in both generic and spatially differentiated
367 assessments, with no statistically significant difference between them. This was mainly due
368 relatively large geographic differences in life cycle inventories between villages, which were larger
369 than geographic differences in characterization factors. Indeed, the good performance of Napu
370 (relative to the other villages) is explained by the very high productivity increase when biochar is
371 amended to soils (250% increase compared to the control; Table 2). The relatively good
372 performance of Lampung is explained by the high productivity increase (100% increase compared
373 to the control; Table 2) which in turn reduces the need for inorganic fertilizers, combined with the
374 fact that the absolute yield was relatively high for agricultural practices without biochar.

375 To isolate the effects of variability in life cycle inventories from spatial differences in
376 characterization factors, inventory flows in all villages were set to be the same, and equal to that of
377 Ngata Toro. Spatially differentiated LCA carried out showed that a different village performed best

378 when considering total damage to human health (Lamongan, against Lampung for site-specific
379 inventories) (Table S36). This further emphasizes that differences in ranking between villages were
380 mainly caused by variability in life cycle inventories between villages. Henderson et al., (2017) also
381 showed that in addition to spatial differences in characterization factors, variability in inventories of
382 water used for irrigation explained a large part of the differences in water deprivation impacts from
383 corn production and from milk production between different geographic locations within the U.S.

384 ***4.1.3. Process contribution***

385 Finally, decision makers are interested in identifying improvement options in the biochar life cycle.
386 At the total damage level, spatial differentiation was generally not important in determining which
387 processes contributed most to overall benefits (here, agricultural benefits from increasing yields or
388 sequestration and storage of carbon). Only in one case (scenario 1) were the largest benefits
389 attributed to increases in crop productivity in the generic assessment, while both the productivity
390 increase and biochar production (specifically, sequestration of carbon) contributed nearly equally to
391 human health benefits in regionalized assessment (SI, Section 6.4). However, spatial differentiation
392 did influence the identification of processes with the largest environmental burdens in some
393 individual impact categories. For example, it identified biochar use as a major driver of freshwater
394 eutrophication (due to direct emissions of phosphorus together with the biochar added to soil) in the
395 generic assessment, while in the spatially differentiated assessment the contribution of this process
396 was smaller and comparable to that of biochar production. Thus, spatial differentiation could still be
397 relevant to support decision about improving environmental performance of a given biochar system
398 by suggesting changes in processes which decision-makers have influence on (foreground
399 processes). In this particular case, the decision-maker could focus on reducing P emissions by using
400 biochar with smaller content of P, but more accurate and realistic assessment of environmental

401 impacts as offered by spatially differentiated impact assessment is needed to determine whether
402 such improvement is valuable.

403 [Fig. 3.](#)

404 **4.2. Practical implications**

405 This study corroborates earlier studies showing that spatial differentiation is particularly relevant in
406 cases where geographic variability in characterization factors is large (e.g., land or water use), and
407 where total impact is dominated by one or few flows contributing to that impact category (e.g.
408 irrigation or land occupation) (Chaudhary et al., 2016; Henderson et al., 2017b). As product life
409 cycles are global, emissions in the life cycles can occur anywhere, making spatially differentiated
410 LCA the preferred option if accuracy and realism of impacts are important for the goal of the LCA.
411 This includes cases where the intended application is identification of weak points in the product
412 system as a basis for environmental optimization. In this case, different conclusions were drawn
413 related to potential improvement options in the biochar system to address eutrophication impacts on
414 freshwater ecosystems.

415 Due to trade-offs between burden and benefits spatial differentiation had no relevance for
416 decisions related to whether a new biochar-based waste management strategy should be
417 implemented. Thus, in this aspect of the goal definition, spatial differentiation in LCIA did not lead
418 to better decision support. This conclusion is expected to hold for systems where environmental
419 benefits largely outweigh burdens, including the use of other chars in agriculture (Owsianiak et al.,
420 2017) or technologies which replace inefficient waste management systems or allow reducing food
421 losses (Fabbri et al., 2018).

422 Large geographic variability in life cycle inventories, combined with trade-offs between
423 impact categories, resulted in spatial differentiation having a limited relevance for decisions about

424 identification of best biochar production techniques and agricultural use conditions for ecosystem
425 damage. Heidari et al., (2017) also showed that for pasta production in Iran the impact of ozone
426 formation was up to a factor two larger than the generic determined impact, while impacts for land
427 use and acidification were up to a factor of three smaller. Trade-offs between impact categories like
428 those presented in this study and earlier in Heidari et al., (2017) are expected to occur for other
429 product systems if they are located in dry and not very biodiverse regions (e.g. Iran), or in water-
430 rich and biodiverse areas (like the majority of the Indonesian islands). However, in less extreme
431 conditions with regard to water availability and biodiversity status (e.g. in Europe), similar trade-
432 offs may not occur, and other impact categories may become dominant contributors (e.g. marine
433 eutrophication impacts in Baltic Sea are expected to be higher compared with the Indonesian Sea
434 marine ecosystems) (Cosme et al., 2017). Further, tradeoffs between impact categories were less
435 relevant for total damage to human health. In addition, species can be weighted differently in LCIA,
436 influencing trade-offs between impact categories (Verones et al., 2015). Thus, spatial differentiation
437 is recommended to be considered as a default approach in comparative LCA studies.

438 **4.3. Limitations of the study**

439 Execution of this case study required implementation of regionalized characterization factors for
440 most impact categories into the modelling software employed (SimaPro) and a subsequent matching
441 of them with regionalized input and output flows. This practice, although perhaps the most
442 straightforward from the LCA practitioner's perspective, has some limitations.

443 Uncertainties in characterization factors were not considered due to incomplete knowledge
444 related to them and the limited ability of the modelling software to consider them. If these
445 uncertainties had been considered, the number of pairwise comparisons with statistically significant
446 differences between regionalized and generic assessments is expected to be smaller. It is a challenge
447 for LCA practitioners to determine whether uncertainties in characterization factors combined with

448 inventory and parameter uncertainties are larger than geographic variability in life cycle inventories.
449 Henderson et al., (2017) showed that for water use impacts, spatial variability may be larger than
450 uncertainty.

451 The second limitation is that the selection of the spatial scale for the impact assessment was
452 based on a simple method of matching regionalized inventories with available respective
453 characterization factors at the smallest scale possible. This limitation is not expected to influence
454 conclusions because geographic locations of each village are accurate and because locations of
455 respective ecoregions, watersheds and agricultural fields corresponding to each village were known.
456 This allowed for both accurate and precise quantification of impacts for relevant impact categories,
457 including water use, land use, and ecotoxicity emissions. Thus, aggregating grid-specific
458 characterization factors in these categories, as proposed by Mutel et al., (2011) is not expected to
459 reduce uncertainty in this case study. Selection of appropriate spatial scale of impact assessment
460 could be relevant however, for some regional impact categories such as freshwater eutrophication.
461 In this case eutrophication relied on the use of country-specific characterization factors, but this
462 impact category was not important contributor to total damage.

463

464 **5. Conclusions**

465 This first regionalized LCA study where spatially differentiated LCIA methods were consistently
466 applied to all relevant impact categories at damage level level showed that although spatial
467 differentiation improved accuracy and realism of environmental impacts, it did not necessarily lead
468 to better decisions. This finding was unexpected considering that conditions in Indonesia with
469 regard to biodiversity are very different compared to generic conditions. Geographic variability in
470 life cycle inventories, combined with small contribution of some impact categories to total damage

471 and tradeoffs between impact categories influenced the role of spatial differentiation for decision-
472 support in this case study.

473 Although extrapolation of these findings to other cases is not straightforward, this study may
474 suggest that depending on the goal of the LCA, practitioners should consider potential benefits of
475 implementing spatially differentiated LCIA methods as opposed to potential benefits from
476 collecting site-specific inventories. This study indicates that the former should be the priority in
477 studies where accuracy and realism are required (e.g. in weak point analyses and eco-design LCA
478 studies), but also in comparative LCA studies, while the latter should be the priority in studies
479 where environmental performance of a system is expected to be mainly determined by trade-offs
480 between burden and benefits.

481 The findings presented in this study raise several additional questions. First, it is unknown
482 whether environmental benefits from implementation of biochar systems are larger than
483 environmental burdens in other regions of the World. Second, it is unknown whether the findings
484 generally apply to other comparative LCA case studies. Third, an intelligent approach needs to be
485 developed to determine which of the flows in the foreground system are relevant to consider for
486 spatially differentiated impact assessments, and which can be omitted. Forth, in this study, spatial
487 differentiation was considered for all flows in the foreground system, but this can be challenging if
488 more complex systems are modelled. Finally, the use of spatially differentiated LCIA methods
489 depends on the ability of LCA modelling software to consider them, and solutions are needed to
490 enable easy and consistent use of spatially differentiated LCIA methods in LCA of products and
491 systems in the future.

492

493

494 **Supplementary material**

495 Details of case studies, model parameters, unit processes, details of uncertainty analysis, details of
496 LCIA methods, and additional results.

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Fig. 1. System boundaries for treatment of biogenic carbon with use of biochar as soil conditioner to support crop productivity. The functional unit was defined as “treatment of 1 kg of biogenic carbon from biomass residues in rural areas in Indonesia”. Dashed lines indicate avoided processes.

Fig. 2. Generic and spatially differentiated damage to human health **(a)** and ecosystems **(b)** from biochar production using flame curtain kiln and its use for improving agriculture in Indonesia, as influenced by geographic location and fertilizer type (scenarios 1-4 and 13-16 in [Table 1](#)). Absolute uncertainties are too large to be shown, but comparison taking into account correlations revealed statistically significant differences between generic and regionalized damage (see [the SI, Section S6.2](#)). Scores for biochar production using Adam retort and earth-mound kilns are presented in the [SI, Section S6.1](#).

Fig. 3. Ranking of biochar systems (all scenarios) in terms of total damage to human health **(a)** and ecosystems **(b)** as influenced by switching from generic to regionalized LCA. Values presented in each cell represent to median impact score from 1000 iterations, in DALY/functional unit **(a)** and species.yr/functional unit **(b)**. A colour scaling system was applied, where colours are determined by values in each cell, where increasing shades of green correspond to biochar systems performing better, respectively. Details of the comparison between systems taking into account uncertainties are presented in [SI, Section S6.3](#).

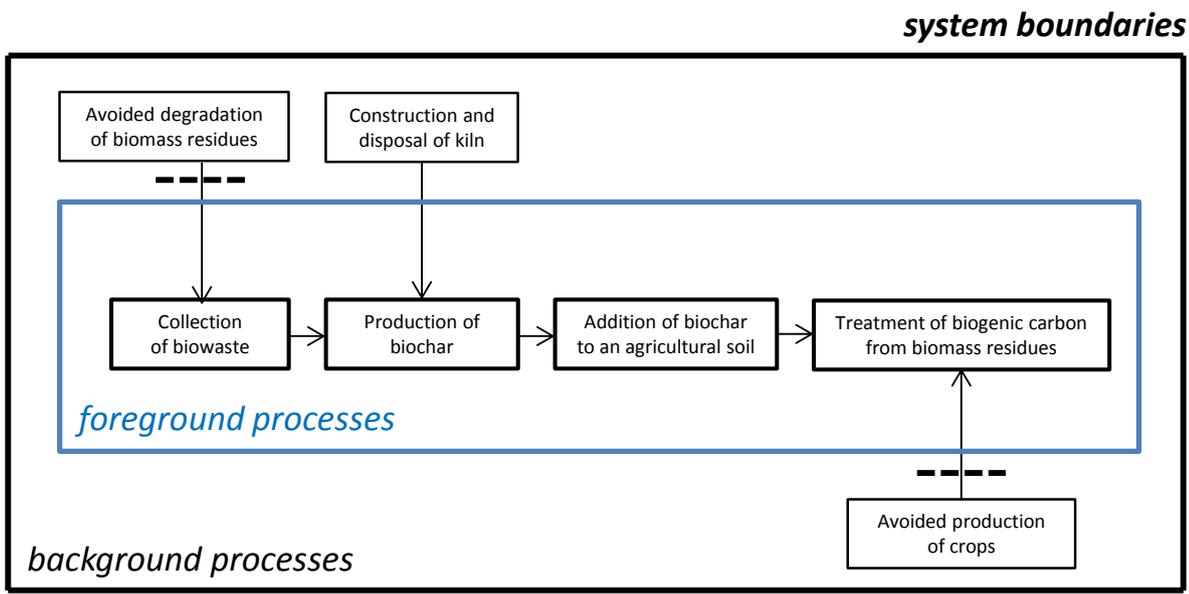


Fig. 1 (in color)

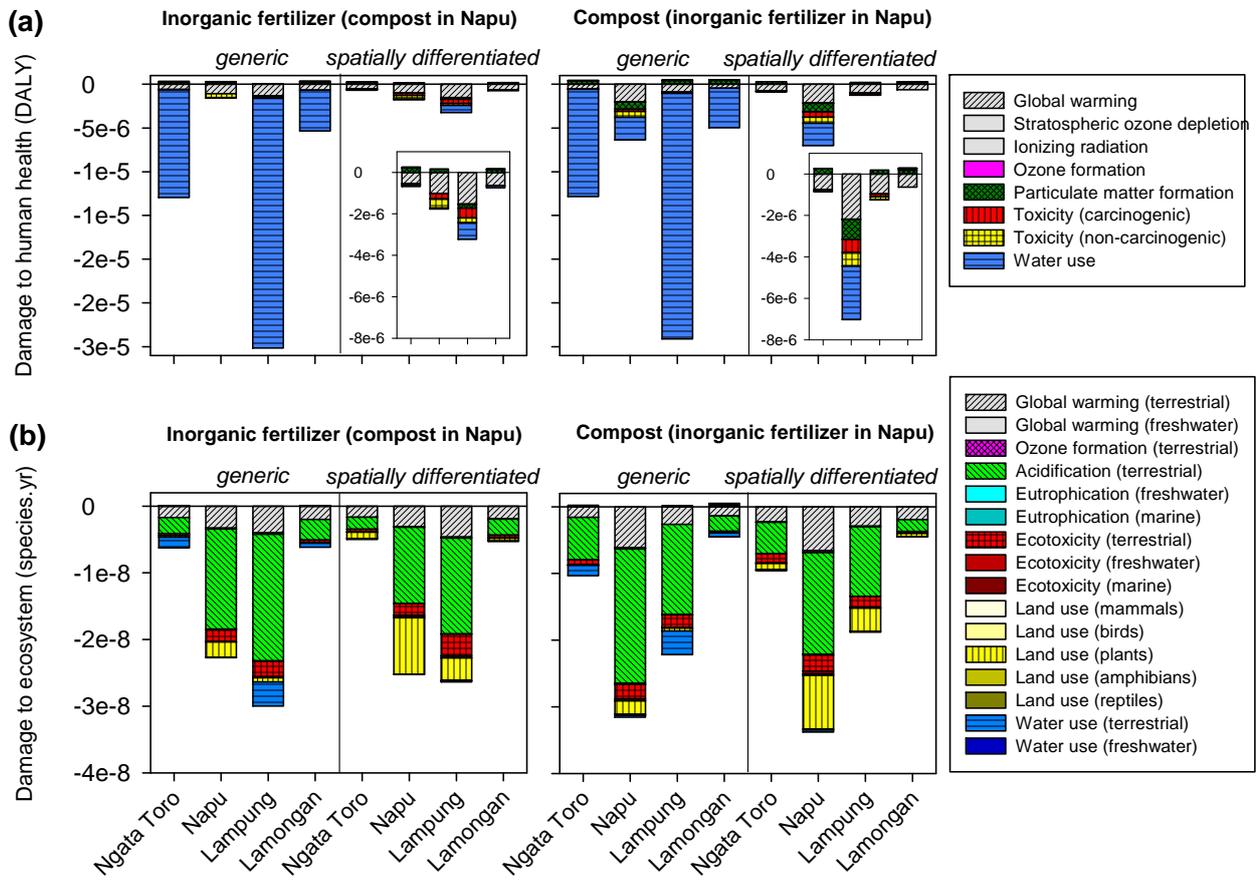


Fig.2 (in color)

(a)

		generic				spatially differentiated			
Inorganic fertilizer (compost in Napu)	flame-curtain	-13E-05	-13E-06	-3.0E-05	-5.1E-06	-4.4E-07	-18E-06	-3.2E-06	-5.7E-07
	Adam retort	-13E-05	-13E-06	-3.0E-05	-4.8E-06	-3.8E-07	-18E-06	-2.8E-06	-1.0E-07
	earth-mound	-13E-05	-1.0E-06	-2.8E-05	-4.6E-06	-1.8E-07	-1.6E-06	-3.0E-06	-3.6E-07
Compost (inorganic fertilizer in Napu)	flame-curtain	-12E-05	-6.5E-06	-2.9E-05	-4.7E-06	-7.1E-07	-7.1E-06	-1.1E-06	-3.7E-07
	Adam retort	-13E-05	-6.3E-06	-2.9E-05	-4.9E-06	-4.2E-07	-7.0E-06	-1.2E-06	-8.2E-08
	earth-mound	-12E-05	-6.4E-06	-2.6E-05	-2.4E-07	-2.4E-07	-7.1E-06	-9.4E-07	7.5E-08
		Ngata Toro	Napu	Lampung	Lamongan	Ngata Toro	Napu	Lampung	Lamongan

(b)

		generic				spatially differentiated			
Inorganic fertilizer (compost in Napu)	flame-curtain	-6.5E-09	-2.4E-08	-3.1E-08	-6.4E-09	-5.4E-09	-2.7E-08	-2.7E-08	-5.6E-09
	Adam retort	-5.5E-09	-2.4E-08	-3.1E-08	-4.8E-09	-4.1E-09	-2.6E-08	-2.4E-08	-2.3E-09
	earth-mound	-4.7E-09	-2.2E-08	-2.9E-08	-4.3E-09	-4.4E-09	-2.6E-08	-2.6E-08	-4.8E-09
Compost (inorganic fertilizer in Napu)	flame-curtain	-1.1E-08	-3.4E-08	-2.3E-08	-4.1E-09	-1.0E-08	-3.6E-08	-2.0E-08	-4.7E-09
	Adam retort	-1.2E-08	-3.4E-08	-2.5E-08	-5.4E-09	-8.7E-09	-3.6E-08	-1.9E-08	-1.5E-09
	earth-mound	-9.1E-09	-3.3E-08	-2.2E-08	-3.3E-09	-8.7E-09	-3.6E-08	-2.0E-08	-3.2E-09
		Ngata Toro	Napu	Lampung	Lamongan	Ngata Toro	Napu	Lampung	Lamongan

Fig. 3 (in color)