Coupling GIS and LCA for biodiversity assessments of land use

Part 1: Inventory modeling

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Abstract

Purpose Geospatial details about land use are necessary to assess its potential impacts on biodiversity. Geographic information systems (GIS) are adept at modeling land use in a spatially explicit manner, while life cycle assessment (LCA) does not conventionally utilize geospatial information. This study presents a proof-of-concept approach for coupling GIS and LCA for biodiversity assessments of land use and applies it to a case study of ethanol production from agricultural crops in California.

Materials and methods GIS modeling was used to generate crop production scenarios for corn and sugar beets that met a range of ethanol production targets. The selected study area was a four-county region in the southern San Joaquin Valley of California, USA. The resulting land use maps were translated into maps of habitat types. From these maps, vectors were created that contained the total areas for each habitat type in the study region. These habitat compositions are treated as elementary input flows and used to calculate different biodiversity impact indicators in a second paper (Geyer et al., submitted).

Results and discussion Ten ethanol production scenarios were developed with GIS modeling. Current land use is added as baseline scenario. The parcels selected for corn and sugar beet production were generally in different locations. Moreover, corn and sugar beets are classified as different habitat types. Consequently, the scenarios differed in both the habitat types converted and in the habitat types expanded. Importantly, land use increased nonlinearly with increasing ethanol production targets. The GIS modeling for this study used spatial data that are commonly available in most developed countries and only required functions that are provided in virtually any commercial or open-source GIS software package.

Conclusions This study has demonstrated that GIS-based inventory modeling of land use allows important refinements in LCA theory and practice. Using GIS, land use can be modeled as a geospatial and nonlinear function of output. For each spatially explicit process, land use can be expressed within the conventional structure of LCA methodology as a set of elementary input flows of habitat types.

Keywords Biodiversity · Bioethanol · Geographic information systems (GIS) · Habitats · Land use · Spatially explicit inventory modeling

Preamble The present paper is the first in a series of two that demonstrate the potential of coupling geographic information system (GIS) technology with LCA for assessing biodiversity impacts of land use. This first paper demonstrates the use of GIS-based inventory modeling to generate elementary input flows of habitat types. The second paper presents four different characterization models that are applied to the habitat flows to calculate biodiversity impact indicators.

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1 Introduction and background

LCA methodology is intended to yield a comprehensive environmental profile of product systems (ISO 2006). Standard LCA practice, however, does not assess land use

impacts such as impacts on biodiversity, which remains an active research topic. Assessing land use impacts basically requires two main additions to the conventional methodology. First, it must introduce new elementary flows that appropriately reflect and quantify land use, and second, it requires appropriate characterization models in order to calculate indicator results from the new elementary flows. Needless to say, the two tasks cannot be strictly separated from one another.

Many production processes, such as resource extraction or agricultural production, transform and/or occupy substantial amounts of land. This poses specific problems for LCA that are not encountered with other processes. One challenge is that the potential output from the use of land, the land productivity, varies geographically with biophysical characteristics such as soil and climate. LCA is structured around the use of average values such as fixed production yields. An increase in output to meet increased demand will typically require a nonlinear increase in land area as use expands to less productive lands. Consequently, the first adaptation necessary for LCA to accommodate spatial dependence is to permit nonlinear relationships in the inventory models. Whereas these spatially explicit aspects of varying land use productivity are problematic for standard LCA, they are quite straightforward with geographic information system (GIS) technology. GIS can store observed data for specific locations (e.g., soil types, climate factors), and it can model new information from these data (e.g., potential crop yield) through empirical statistical analysis, mechanistic process models, or rule-based logic methods. GIS can also calculate regional summaries, such as total potential yield and total area of each land type.

During the last 10 years, efforts have been made to model land occupation and transformation as environmental interventions in LCA studies, to develop practical ways to model the impacts of land use on ecosystem health and biodiversity, and to calculate indicators that are understandable, responsive to land use changes, and ecologically relevant (Koellner 2000; Schenck 2001; Brentrup et al. 2002; Koellner and Scholz 2007). There are three serious challenges to assessing impacts on biodiversity.

First, biodiversity is an extremely complex concept that is difficult to summarize in a single indicator as other environmental concerns are. The dilemma of how to quantify biodiversity is not just specific to LCA but to conservation assessment, monitoring, and planning in general (e.g., Noss 1990; Sanderson et al. 2002; Scholes and Biggs 2005). Biodiversity is by definition a general concept encapsulating the full range of life, including diversity within species, between species, and of ecosystems (Convention on Biological Diversity 1992, Rio de Janeiro). Enormous variation in species assemblages and

ecosystems makes it difficult to compare biodiversity impacts between similar ecosystems at different locations (e.g., tidal wetlands in Chesapeake Bay vs. the Gulf of Mexico) or between different ecosystem types (e.g., wetland vs. grassland). Scientists have attempted to develop universal impact indicators to make such comparisons feasible. One class of indicators uses data on species richness to measure the loss of species or populations compared to a reference condition (Lindeijer 2000; Koellner 2000; Scholes and Biggs 2005). Researchers have also attempted to develop indicators of land use based on ecosystem characteristics such as naturalness or wildness (Brentrup et al. 2002; Sanderson et al. 2002), exergy (Wagendorp et al. 2006), or emergy (Hau and Bakshi 2004). Climate change impacts are summarized by applying physical laws to convert a relatively small number of greenhouse gases (GHG) into a standardized measure of their effect on radiative forcing, called global warming potential and expressed as kilograms CO_2 equivalents. Impacts on biodiversity, on the other hand, are much more complex. Comparable approaches to standardize the relative importance of a myriad of species are controversial and value-based. In addition, species respond uniquely to land use, so it is challenging to infer overall impacts on biodiversity directly from measures of land use change.

The second challenge is to reflect the spatial aspects of biodiversity. Even with similar climatic conditions, the evolutionary history of North American grasslands leads to different assemblages of species and different species richness than in grasslands on other continents. Furthermore, species assemblages are dynamic in time. At a local scale, past land use changes determine which species are present and could be impacted by further land use transformations. Whereas GHG emissions ultimately mix in the atmosphere so that their point of origin is immaterial to quantifying their impacts on climate, impacts on biodiversity require that we consider the location where the land use occurs. The impacts will also depend on the initial quality of habitat and its location within the landscape. All this requires the assessment tool to be spatially explicit.

The third challenge is the nonlinear relationship between land use and species viability. Depending on the absolute level of production, additional increases in fuel crop cultivation may cause either minor or dramatic impacts on biodiversity.

In summary, we require indicators that are meaningful for the biodiversity in any location, but accurately reflect the complex, spatially dependent and nonlinear manner in which land use impacts biodiversity. The challenge facing LCA is to balance a practical implementation within the conventional tools with a methodology that produces a meaningful measure of impacts on a multidimensional and multiscale environmental concern.

Responding to this challenge, we have developed a framework for loosely coupling conventional LCA with

GIS to provide the necessary geographic analysis for a spatially explicit form of LCA. In the inventory phase described in this paper, spatially explicit scenarios of land use are generated to meet agricultural production targets set in the scoping phase. These land use scenarios are summarized as elementary flows of habitat types within LCI. The next step, as summarized in the second paper (Geyer et al., submitted), associates wildlife species with habitats to calculate regional impact indicators for biodiversity. The framework links the ecological concept of "habitat" that can be mapped with remote sensing with knowledge of species–habitat preferences, which has been compiled for many taxonomic groups. Thus, the framework analyzes biodiversity at the level of the species composition and abundance in an ecoregion and yet operates at a level of abstraction that avoids collection of comprehensive field observations of all species or modeling their individual responses to changing conditions. This approach has been widely applied in conservation risk assessments such as the US Gap Analysis program (Scott et al. 1993; Jennings 2000).

We demonstrate the coupling of GIS and LCA for the assessment of biodiversity impacts from land use in the context of growing ethanol feedstock crops in California's San Joaquin Valley (Fig. 1). Many LCA studies of biofuel production and use have appeared in the last decade (e.g., Hanegraaf et al. 1998; van den Broek et al. 2001; Sheehan et al. 2003; Dornburg et al. 2003; Kim and Dale 2005b). A recent review found that these studies primarily focused on net energy balance and global warming potential of various feedstocks but that land use impacts had generally not been assessed (von Blottnitz and Curran 2007). Milà i Canals et al. (2006)) cited biofuels as an especially important product system for which land use impacts should be incorporated in LCA, given the potential significance of biofuels in energy policy. Before policy makers and business leaders commit heavily to large-scale production of biofuels, the discussion needs to be informed about the potential impacts on biodiversity (Hanegraaf et al. 1998; Chan et al. 2004; Semere and Slater 2007).

2 Materials and methods

2.1 The scope of the inventory model

For this study, we developed cradle-to-gate inventory models of ethanol production from corn (*Zea mays*) and sugar beet (*Beta vulgaris*) feedstocks. Corn-based ethanol can be produced from grain alone or grain and stover, which is the cellulosic residue of the stalks and leaves. To demonstrate the use of GIS for spatial, nonlinear crop production modeling, we described all process inventories

in terms of total rather than average or marginal ethanol output and used multiple reference flows of increasing sizes. The reference flows are 10%, 25%, 50%, 75%, and 100% of 2.76 MMT of ethanol, which is the ethanol contained in 3.5×10^9 l of reformulated gasoline containing 5.7% ethanol by volume, the estimated demand for gasoline in 2010 in California (California Biomass Collaborative 2006; Williams et al. 2007). We convert these ethanol production targets into metric tons of required annual crop harvest for each crop (Table 1). We refer to each target output–feedstock combination as a scenario since our crop production models are purely hypothetical and not meant to be predictions. All process models were obtained from the GaBi 4 database, except for the GIS-based crop production model (described in Section 2.3) and a dummy process in GaBi 4 which receives the GIS model results. The growing of biofuel crops is the only process in our product system for which we model and assess land use impacts. If one models the locations of new ethanol conversion plants (Voivontas et al. 2001), it would be possible to include those land use impacts as well, but they would generally be much smaller. There are likely to be processes upstream and downstream of biofuel crop production that have land use impacts. While these are outside the scope of this study, the ultimate aim would be to use GIS-based inventory modeling for all relevant processes of the product life cycle.

Our study area consists of the four southernmost counties of the San Joaquin Valley of California (Fig. 1). The San Joaquin Valley of California used to be semi-arid grassland before vast parts of it were converted to irrigated cropland in the nineteenth and twentieth centuries. These counties (Fresno, Tulare, Kings, and Kern) are among the most productive agricultural lands in the nation (US Department of Agriculture 2002). Today, roughly half of the land area is in farms with primary agricultural revenue generated from wine, dairy, fruit, tomatoes, and nuts (Umbach 2002). Irrigation water evaporates in the relatively dry climate, leaving salts on the surface. Some parts of the San Joaquin Valley are already unusable for crop production due to the raised salinity of the topsoil. However, small patches of native grassland, shrubland, and wetland remain. Native wildlife species use both pristine and cultivated land as habitat. The San Joaquin Valley is the region with the largest number of threatened or endangered species in the mainland United States (US Fish and Wildlife Service 1998). Native species are threatened mostly by habitat loss from conversion to cropland and urban development.

2.2 LCA-GIS coupling

GIS and LCA are fundamentally different and complementary. The former is specifically designed to organize and analyze spatial data, while the latter inventories and
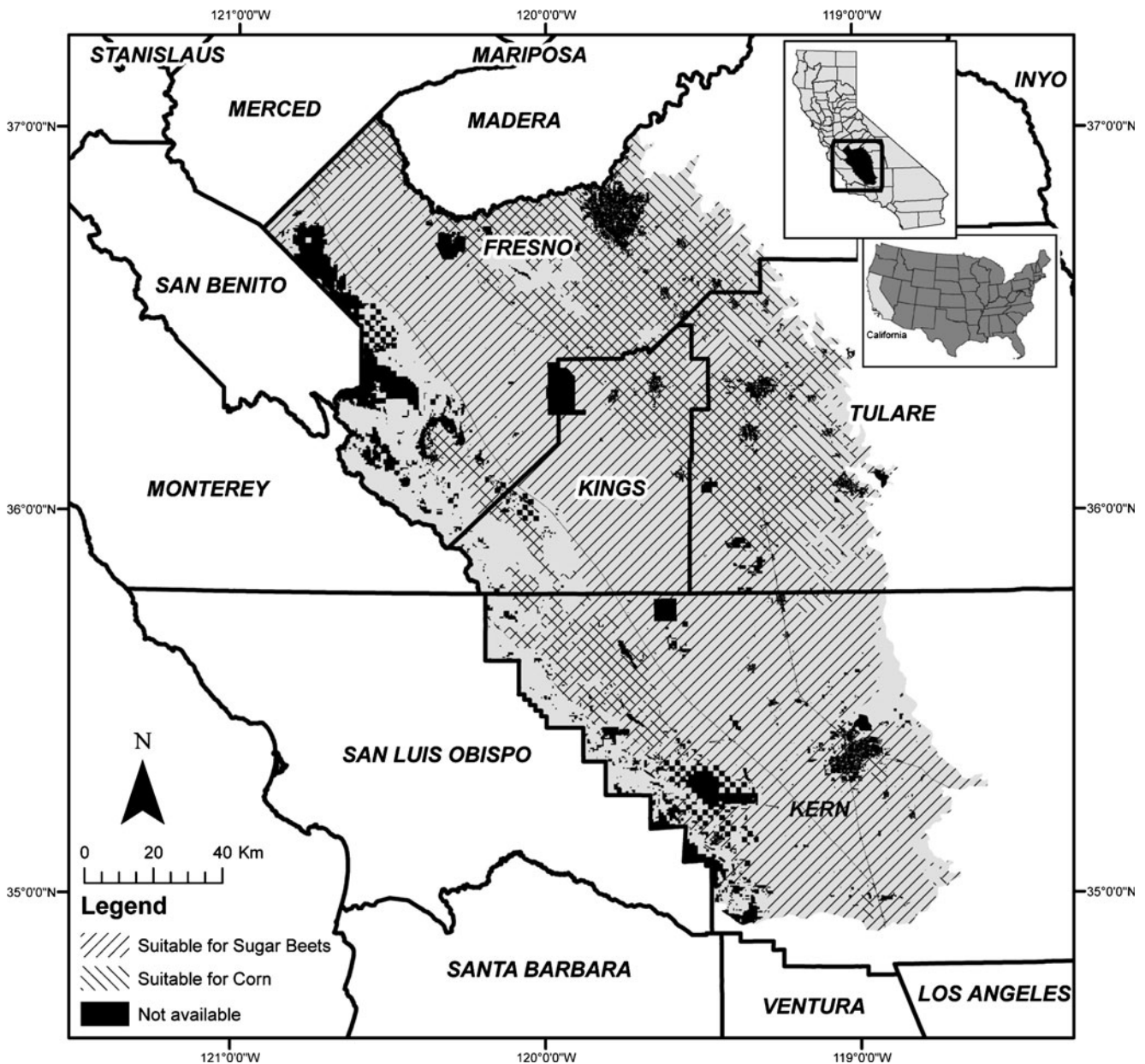
Fig. 1 Location map of study area showing lands suitable and available for growing corn or sugar beets. Areas labeled *not available* (e.g., publicly owned land, urban development) were excluded from the crop scenarios

analyzes data on product systems and typically does not operate on geospatial information. Although LCA's lack of spatial differentiation is frequently criticized, there is no consensus on how it should be integrated. A decade ago, it was suggested that GIS should be integrated with LCA (Bengtsson et al. 1998), but implementation has been slow. Azapagic et al. (2007) described a framework for linking LCA, GIS, and environmental models, although GIS would merely be used to provide locational information on pollution sources as input for other models and to display the spatial distribution of predicted impacts. Burke et al. (2008) used GIS to map biotopes before and after a single mining operation and to generate characterization factors.

Results were appended to the LCIA findings, but GIS data were not apparently passed to the LCA model for assessment. To assess desertification potential, Núñez et al. (2010) used GIS to calculate a score as an elementary flow along with ecoregion-specific characterization factors. Combining these values with the area of the process and the area of the ecoregion determined the impact.

The procedures developed for and applied in this work are shown in the flowchart in Fig. 2. In the LCA system, all conventional cradle-to-gate processes and flows of an agriculture-based end-product are shown (Kim and Dale 2005a). To incorporate land use, a crop production model is inserted (center of the LCA box in Fig. 2), which receives

Table 1 Fuel crop production targets (in kilograms of crop/year)

Percent of ethanol demand in CA in 2010	Ethanol source (kg ethanol/year)	Corn grain (CR, kg grain/year)	Corn grain and stover (CS)		Sugar beet (SB, kg sugar beet/year)
			(kg grain/year)	(kg stover/year)	
10	276,244,500	941,993,745	724,610,573	235,870,304	3,375,707,790
25	690,611,250	2,354,984,362	1,811,526,433	589,675,760	8,439,269,475
50	1,381,222,500	(4,709,968,725)	3,623,052,865	1,179,351,519	16,878,538,950
75	2,071,833,750	(7,064,953,087)	(5,434,579,298)	(1,769,027,279)	25,317,808,425
100	2,762,445,000	(9,419,937,450)	(7,246,105,731)	(2,358,703,038)	33,757,077,900

Annual ethanol demand for California in 2010 derived from Williams et al. (2007). Crop to ethanol conversion factors (in kilograms feedstock/kilogram ethanol): corn grains, 3.41; corn stover, 3.7; sugar beet, 12.22. We assumed that 30% of stover could be harvested to produce ethanol such that 23% of the grain target could be offset by stover. Targets in parentheses are not feasible within study area (2,538,482 ha)

its intermediate inputs from an upstream cradle-to-gate LCI model and feeds its crop outputs to a downstream gate-to-gate LCI model of ethanol conversion. In the goal and scope phase, scenarios are defined with target demand for ethanol production, which are transformed into crop demand based on conversion factors (Table 1). A GIS land use model calculates the amount and location of crop land needed to meet the target (Section 2.3). A land use map is thus generated for each scenario, which is then converted into a map of habitats (Section 2.4). In principle, GIS could be used to model the land use of all processes with significant land requirements, such as resource extraction, transportation infrastructure, and industrial sites. GIS-based inventory models can be regarded as a spatially explicit component within a traditional life cycle inventory model. Such LCA–GIS coupling facilitates spatially explicit, nonlinear input–output modeling of intermediate and elementary flows. In the present study, the coupling is limited to calculating elementary flows of habitat-type areas as functions of fuel crop type and production level. The habitat-type areas and all other inventory data are used to generate a crop production process in the LCA model (Fig. 2). Inputs such as irrigation water, fertilizer, pesticides, and fossil fuel and outputs such as greenhouse gases and nitrates are based on averages in our study. They likely will vary with locations and could also be modeled explicitly in GIS, given that the relevant data are available. In the impact assessment phase, the habitat-type areas are used to calculate indicator results for potential biodiversity impacts (Geyer et al., submitted).

2.3 GIS-based crop production scenario model

Crop scenario models can be extremely sophisticated to capture all relevant influences such as land productivity, climate, farmer behavior, market forces, land use policies,

Fig. 2 Flowchart of LCA and GIS coupling. The LCA model converts ethanol demand into crop demand and reports it to the GIS model, which in turn derives a land use / habitat scenario from the crop demand. The data from the land use / habitat scenario are used to generate crop production inventory data (**a**) and characterization factors for biodiversity impact assessment (**b**). *Bold arrows* indicate linkages between LCA and GIS
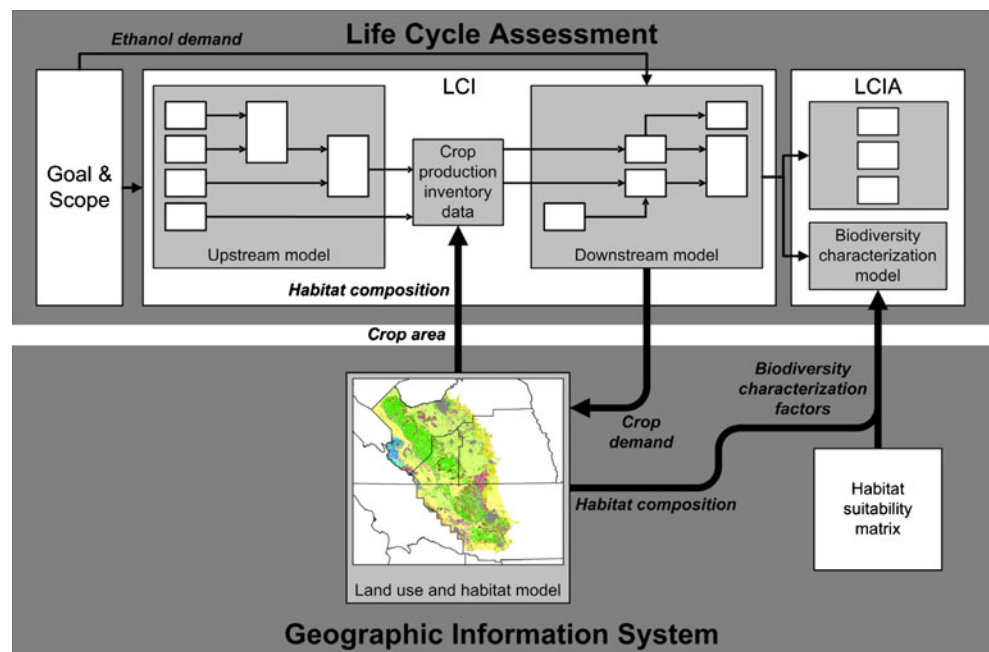
infrastructure, and economic incentives. As our purpose in this study was to demonstrate the coupling of LCA and GIS in order to assess impacts on biodiversity, we opted to develop a relatively modest scenario model. This model also neglects land use associated with upstream and downstream activities such as resource extraction and siting of biorefineries. There is nothing in this framework, however, that would preclude use of a more sophisticated scenario model or the inclusion of ancillary land use changes if appropriate data were available.

Our crop production model maps each annual fuel crop production target onto a set of land parcels while accounting for land productivity, basic production economics, and different land use policies. For each crop type and production target in Table 1, the GIS model returns a list of land parcels that, if used for fuel crop production, would collectively achieve the required annual output. To achieve this, we roughly follow the GIS-based modeling approach suggested by Bryan et al. (2008) that integrates soil productivity for each biofuel crop type with the potential revenues and costs of production. The resulting spatially explicit land use scenarios are intended to be feasible and plausible, but not meant as predictions of actual land use changes due to given fuel crop demand.

For this demonstration, corn and sugar beets were selected as exemplary fuel crops because the San Joaquin Valley is suitable for growing them, the technologies for converting feedstocks to ethanol are known, and the necessary spatial data were available. The crops differ in the conversion technology as corn grain generates starch-based ethanol, corn stover produces cellulosic ethanol, and sugar beets can be converted to a sugar-based ethanol. The GIS modeling, implemented in ArcGIS 9.2 (ESRI 2009), consisted of the following four steps.

The first step was mapping the production potential for each feedstock (Noon and Daly 1996; Voivontas et al. 2001; Price et al. 2004; Hughes and Mackes 2006; Bryan et al. 2008; Hellmann and Verburg 2010). The production potential for corn and sugar beets was based on estimates by soil types and expressed as spatially varying crop yields (Soil Conservation Service 1994). On suitable soils, the corn grain yield ranges from 4,400 to 9,400 kg ha^{-1}year^{-1}. In the first set of corn-based ethanol scenarios, we assumed that the corn stover would be left in the field as residue to conserve topsoil under best management practices. In additional scenarios, we assumed that 30% of the corn stover would also be used for cellulosic ethanol, with the remaining 70% left in the field. Sugar beet yields range from 45,000 to 78,000 kg ha^{-1}year^{-1} on soils that are suitable, which differ from those suitable for corn (Fig. 1). Commercial biofuel crops cannot be grown in certain areas because of land management or prior commitments of land use. Therefore, potential yields on lands owned by public

agencies or conservation groups and on existing urban development were set to zero based on GIS layers of land ownership and land use (Lovett et al. 2009). These unavailable lands are depicted in black in Fig. 1. Using all the spatial data from above, 1-ha grid cell maps of production yields in kilograms per hectare per year were derived for corn (with and without stover) and sugar beets.

The second step utilized economic data for these crops specific to the San Joaquin Valley or similar regions to derive a map of potential economic net returns (University of California Davis 2004). Establishment, production, and some harvest costs are fixed per unit area, while other harvest costs and gross revenue are related to volume of harvest. Maps of potential net return (gross revenues from the crop yield minus fixed and variable production costs) in dollars per hectare per year were produced for each crop type by subtracting fixed and variable costs from potential revenue for each 1-ha cell. Potential net return (dollars per year) and crop yield (MT per year) for each land parcel in the study area were calculated by summing over all 1-ha cells in each parcel. Parcel size, ranging from 5 to 15,000 ha, was also computed by the GIS software.

The third step employed a simple ranking and selection algorithm to generate parcel sets that efficiently produce the annual target level of the crop for each scenario (Table 1). It is necessary to make assumptions about agricultural markets and about individual landowner decisions when developing crop production scenarios (Sheehan et al. 2003; Santelmann et al. 2004). Our approach was to generate a list of all parcels ranked by their potential net return per hectare under current conditions, i.e., with the parcel having the highest return on top and the one with the lowest return on the bottom. The parcel with the highest net return was selected, its potential output was added to the cumulative total output, and its area added to the cumulative area. Parcels were then selected in descending order of returns until the cumulative output met the target level. The result of this procedure is an economically plausible set of parcels which collectively meet the annual target level.

The final step was to calculate the types and amounts of (intermediate) inputs, such as irrigation water, fertilizers, pesticides, and use of agricultural machinery required for each land use scenario (set of selected parcels). There was no spatially differentiated data on input requirements available for our case study. Average values are used instead, which are independent of parcel location and therefore only functions of parcel area.

2.4 Habitat composition as elementary input flows

"Habitat" is the area or places inhabited by a species where its life history requirements for food, cover, and reproduction are met. Biologists often categorize sets of places into a

finite set of mutually exclusive habitat types based on their shared attributes of vegetative cover and structure as they relate to those life history requirements of wildlife species (Mayer and Laudenslayer 1988). Each of these habitat types can be characterized by its degree of suitability for each species in a wildlife–habitat relationships database. A habitat type is typically suitable for many different species, and many species will have more than one suitable habitat type. Each species thus has its own potential geographical distribution depending on which habitat types it finds suitable for its needs. Combining geographic information on habitat distribution with knowledge of species–habitat relationships provides a means of mapping potential species distributions, with approaches ranging from relatively simple relational models to more complex models that account for species dispersal and population dynamics (Guisan et al. 2006). At a minimum, we suggest basing characterization models for biodiversity indicators on inventory results that contain pertinent habitat information. More specifically, we suggest that inventory models should contain elementary input flows that represent habitat types associated with land cover and use. In California, experts have defined a set of mutually exclusive and collectively exhaustive standard habitat types, including eight for agricultural landscapes, as the basis for modeling species' geographical distributions (Mayer and Laudenslayer 1988). Nearly half of the terrestrial vertebrate species in California utilize the state's agricultural lands, particularly those that are more mobile such as birds and bats (Brosi et al. 2006). For most of these species, agricultural land is more valuable for feeding and cover than for reproduction. The continuing importance of the San Joaquin Valley as a major flyway for migratory birds illustrates this point. Even some threatened or endangered species can persist with modest set-asides in the working landscape. For instance, the San Joaquin kit fox can survive in farmland if its prey base is maintained and there are sufficient patches of untilled land for denning sites (US Fish and Wildlife Service 1998). Corn is a member of the habitat-type irrigated grain (IGR) crops, whereas sugar beets are irrigated row and field (IRF) crops. Thus, these feedstocks not only differ in their location and conversion processing but also in the habitat they provide for wildlife.

We compiled a baseline habitat map from multiple sources. The Multisource Land Cover layer (California Department of Forestry and Fire Protection 2002) was the best available geospatial data for native or naturalized habitats but had lumped all farmland into a single map class. Therefore, we merged this information with maps of specific crop types of the study area (California Department of Water Resources 2010) and reclassified the crops to their corresponding habitat type. The resulting baseline layer comprised 29 habitat types, including eight agricultural

habitats. For each scenario, baseline habitat types in the selected parcels were replaced with the habitat type associated with the fuel crop of the scenario in the GIS habitat model (Fig. 2) to generate a new wildlife habitat-type layer. The area of each of the 29 habitat types was then derived for the entire study area. For each scenario, the sum of the 29 habitat areas equals the total study area, which reconfirms that the 29 habitat types are mutually exclusive and collectively exhaustive.

In addition to all other input and output flows, the GIS-based crop production model thus also generates 29 elementary input flows, the habitat composition, containing habitat-type areas in hectares. The inventory model characterizes each considered amount of annual fuel crop output with a habitat composition, which can be used for attributional analysis. For consequential analysis, the inventory model relates land use changes (in this case to meet increasing fuel crop production targets) to the resulting changes in habitat composition. It should be noted that inventory modeling based on total inputs and outputs is a digression from standard LCA, which uses average process inputs and outputs for attributional analysis and marginal changes in inputs and outputs for consequential analysis. Average and marginal data can be readily derived from total input and output data, but not vice versa. Part 2 of this paper series (Geyer et al., submitted) demonstrates how the elementary input flows of the habitat composition can be used to calculate potential biodiversity impacts.

3 Results

Our GIS-based inventory model uses land and other inputs to grow the amount of fuel crop required to meet the increasing annual ethanol production targets. Total area is the simplest and most basic indicator of land use. For agricultural processes, such as biofuel feedstock production, crop yield varies spatially as a function of soil properties and other factors. Therefore, the area requirement for meeting a given ethanol target depends on the locations where the crops would be grown. Large differences were found in the land area to be transformed to meet the increasing annual ethanol targets of the scenarios (Fig. 3). Corn required several times as much land as sugar beets. There is only sufficient suitable land in the study area to meet the 10% and 25% targets using corn grain without stover. If 30% of the corn stover were to be used for cellulosic ethanol, the area requirements would decrease proportionally and the 50% target could be reached. Sugar beets are far more productive than corn such that the full 100% target could be met, but this would transform almost one million hectares (or 36% of the study area). For a given ethanol target, sugar beets require less than half the land

Fig. 3 Area requirements to
meet crop production scenario
targets from Table 1

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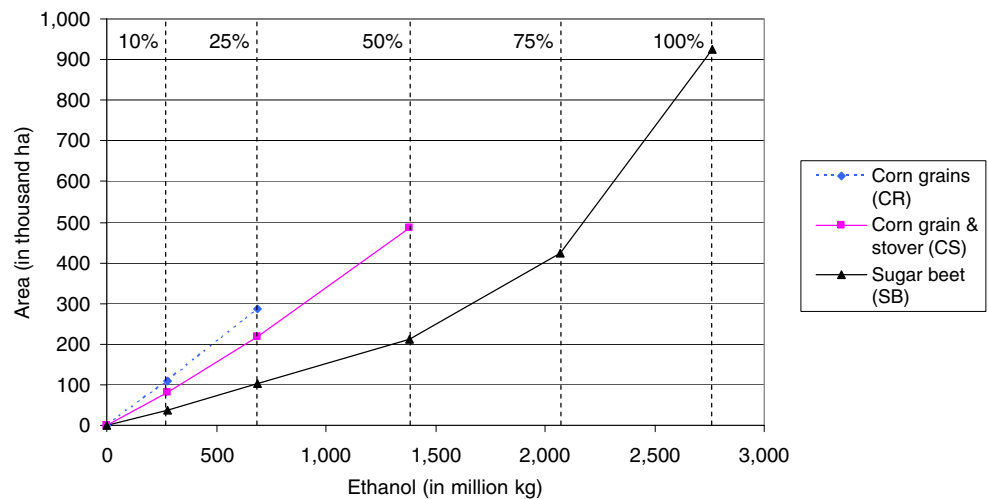
area needed by the corn with stover scenarios and roughly a third of the corn only scenarios. Above the 50% target level, the land area required for sugar beets becomes a very nonlinear function of the ethanol target as less productive land would be transformed.

Of the ten feasible scenarios, average crop production yields for sugar beets are a full order of magnitude larger than those for corn. That the difference in land area required to meet the ethanol targets is not as dramatic is due to the fact that corn has a significantly higher crop-to-ethanol conversion rate than sugar beet (see Table 1). The other insight from the scenario results is that yields are decreasing as total output increases. The decrease is modest for the first three ethanol production targets and more dramatic for the higher ones, which only sugar beet can achieve. This means that even the area–ethanol data that appear linear in Fig. 3 are, in fact, slightly convex. Typical, non-spatial process inventory models, assuming linear relationships between all inputs and outputs, would have to choose a fixed average or marginal yield and would thus not be able to reflect this important aspect of agricultural production processes.

Considerably more informative than total area requirements alone are the habitat compositions for each scenario shown in Tables 2 and 3. The fuel crop either displaces other crops within the same habitat type or crop production or other land uses with different habitat types. Only the latter leads to changes in habitat composition relative to the baseline. Analysis of Tables 2 and 3 shows that for scenarios CR-10, CR-25, CS-10, CS-25, SB-10, SB-25, and SB-50, 93% or more of the habitat composition changes relative to the baseline come from shifts between five agricultural habitat types: deciduous orchard (DOR), irrigated grain crops (IGR), irrigated row and field crops (IRF), irrigated hayfield (IRH), and vineyard (VIN). In the corn scenarios, IGR displaces DOR, IRF, IRH, and VIN in fairly equal proportions, while sugar beet has a proportion-

ally higher impact on VIN and lower impact on IRH. The scenarios CS-50, SB-75, and SB-100 increasingly rely on transforming annual grassland (AGS). For the 100% target with sugar beets, annual grassland, along with oak woodland and various shrub communities, would lose 50% or more of their current area. Figures 4, 5, and 6 show the absolute area changes for the seven most affected habitats, which are DOR, IGR, IRF, IRH, VIN, AGS, and EOR (evergreen orchard). In scenarios CR-10, CR-25, CS-10, CS-25, SB-10, SB-25, and SB-50, they account for around 99% of the habitat composition changes. For CS-50, SB-75, and SB-100, it is 97%, 96%, and 89%, respectively.

4 Discussion

Location is extremely important for addressing land use in LCA for several reasons. For agricultural land use or resource extraction, potential production output per unit area varies spatially with the biophysical characteristics of geographic locations or sites (Voivontas et al. 2001; Tuck et al. 2006). By modeling fuel crop production over a range of plausible target output levels, we have demonstrated that the average yield per hectare can vary significantly. Assuming linear input–output relationships for agricultural production processes is thus problematic. Varying yields combined with socioeconomic factors affect costs and net revenues of a production site (Bryan et al. 2008). Profitability of production, which impacts the likelihood of land use changes, is thus also a function of location. Moreover, the current habitat composition of a region is a historical legacy of both the biophysical environment and past land transformations. By coupling GIS to LCA, even loosely as we have done in this paper, it is possible to quantify habitat composition through a set of elementary input flows in the inventory phase of LCA. As we will show in Part 2 (Geyer et al., submitted), these flows are the

Table 2 Habitat compositions for corn production scenarios with area of habitat types in hectares *CR* corn grains only, *CS* grains and stover

All values are in hectares	Scenario name					
Habitat Type	Baseline	CR-10	CR-25	CS-10	CS-25	CS-50
Agricultural and urban habitats						
DOR	216,069	189,660	160,747	194,720	172,099	132,692
EOR	87,829	85,430	82,906	85,947	83,573	72,502
IGR	340,644	434,372	575,948	413,480	521,652	725,106
IRF	583,664	559,847	526,702	565,172	538,534	486,588
IRH	165,555	150,409	126,912	153,999	135,525	104,032
PAS	1,806	1,562	1,380	1,580	1,503	1,127
RIC	2,652	2,637	2,603	2,637	2,631	316
URB	128,971	128,574	128,206	128,630	128,330	126,754
VIN	184,364	162,186	113,847	167,804	133,579	92,938
Native habitats						
AGS	664,581	662,089	658,712	662,643	660,148	639,414
ASC	36,946	36,942	36,906	36,945	36,918	35,625
BAR	620	620	571	620	617	459
BOP	38,531	38,531	38,529	38,531	38,530	38,521
BOW	29,485	29,336	28,923	29,396	29,004	28,171
COW	137	134	134	134	134	134
CRC	7,668	7,668	7,668	7,668	7,668	7,668
CSC	13,709	13,709	13,709	13,709	13,709	13,709
DSC	16	16	16	16	16	16
EUC	507	499	477	499	491	459
FEW	8,102	7,918	7,718	7,961	7,787	7,239
JUN	933	933	933	933	933	933
LAC	269	226	208	226	208	158
MCH	20,523	20,500	20,468	20,513	20,494	20,350
MHW	1,741	1,651	1,422	1,679	1,472	945
PGS	584	584	584	584	584	584
RIV	626	626	626	626	626	621
SGB	331	331	331	331	331	331
VOW	259	259	254	259	254	252
VRI	1,360	1,235	1,045	1,242	1,135	841

DOR deciduous orchard, *EOR* evergreen orchard, *IGR* irrigated grain crops, *IRF* irrigated row and field crops, *IRH* irrigated hayfield, *PAS* pasture, *RIC* rice, *URB* urban, *VIN* vineyard, *AGS* annual grassland, *ASC* alkali desert scrub, *BAR* barren, *BOP* blue oak-foothill pine, *BOW* blue oak woodland, *COW* coastal oak woodland, *CRC* chamise-redshank chaparral, *CSC* coastal scrub, *DSC* desert scrub, *EUC* eucalyptus, *FEW* freshwater emergent wetland, *JUN* juniper, *LAC* lacustrine, *MCH* mixed chaparral, *MHW* montane hardwood, *PGS* perennial grassland, *RIV* riverine, *SGB* sagebrush, *VOW* valley oak woodland, *VRI* valley-foothill riparian

inventory results that serve as inputs to the characterization models of our four discussed biodiversity impact indicators. Our approach to integrating land use into LCA is to generate land use maps of production scenarios and then translate these land uses into habitat types.

Lack of appropriate spatially differentiated data is consistently mentioned as the single largest obstacle to the advancement of land use and biodiversity indicators in LCA (Guinée 2002). For agricultural processes, such as fuel crop production, land productivity, typically expressed as yield, is the most important property. Regulations, land ownership, and environmental constraints may also limit the locations that can be dedicated to fuel crops regardless of their intrinsic productive capacity. Following a general

GIS modeling approach suggested by Bryan et al. (2008), we found readily available spatial information for the San Joaquin Valley for potential yields, costs, and returns of feedstocks, current land use/land cover, and habitat types. At least for the USA, and probably most developed countries, such digital information is commonly available. For instance, land cover of Europe has been mapped by the CORINE program (European Environmental Agency 2000), while Tuck et al. (2006) have modeled the variation in bioenergy crop yields. Yield data for food crops that could be used as first-generation feedstocks are the most available. However, we were not able within the scope of this study to obtain adequate spatial data on yields of a second generation feedstock, e.g., Bermuda grass which has

Table 3 Habitat compositions for sugar beet (SB) production scenarios with area of habitat types in hectares

All values are in hectares	Scenario name					
Habitat type	Baseline	SB-10	SB-25	SB-50	SB-75	SB-100
Agricultural and urban habitats						
DOR	216,069	207,927	198,142	183,620	167,094	154,443
EOR	87,829	86,489	85,232	82,770	80,652	68,131
IGR	340,644	334,234	325,735	307,770	294,889	275,737
IRF	583,664	615,303	662,070	741,632	894,812	1,250,194
IRH	165,555	162,165	156,195	149,881	145,561	140,697
PAS	1,806	1,703	1,685	1,609	1,532	1,402
RIC	2,652	2,652	2,652	2,652	2,647	2,631
URB	128,971	128,882	128,579	128,239	126,757	114,329
VIN	184,364	172,577	152,100	115,975	100,870	88,392
Native habitats						
AGS	664,581	662,089	658,712	664,293	663,907	662,376
ASC	36,946	36,942	36,906	36,945	36,935	36,905
BAR	620	620	571	620	620	588
BOP	38,531	38,531	38,529	38,531	38,531	38,530
BOW	29,485	29,336	28,923	29,473	29,457	29,431
COW	137	134	134	134	134	134
CRC	7,668	7,668	7,668	7,668	7,668	7,668
CSC	13,709	13,709	13,709	13,709	13,709	13,709
DSC	16	16	16	16	16	16
EUC	507	499	477	499	499	477
FEW	8,102	7,918	7,718	8,092	8,091	8,082
JUN	933	933	933	933	933	933
LAC	269	226	208	227	227	214
MCH	20,523	20,500	20,468	20,513	20,503	20,451
MHW	1,741	1,651	1,422	1,737	1,702	1,660
PGS	584	584	584	584	584	584
RIV	626	626	626	626	626	626
SGB	331	331	331	331	331	331
VOW	259	259	254	259	259	259
VRI	1,360	1,235	1,045	1,360	1,360	1,360

DOR deciduous orchard, *EOR* evergreen orchard, *IGR* irrigated grain crops, *IRF* irrigated row and field crops, *IRH* irrigated hayfield, *PAS* pasture, *RIC* rice, *URB* urban, *VIN* vineyard, *AGS* annual grassland, *ASC* alkali desert scrub, *BAR* barren, *BOP* blue oak-foothill pine, *BOW* blue oak woodland, *COW* coastal oak woodland, *CRC* chamise-redshank chaparral, *CSC* coastal scrub, *DSC* desert scrub, *EUC* eucalyptus, *FEW* freshwater emergent wetland, *JUN* juniper, *LAC* lacustrine, *MCH* mixed chaparral, *MHW* montane hardwood, *PGS* perennial grassland, *RIV* riverine, *SGB* sagebrush, *VOW* valley oak woodland, *VRI* valley-foothill riparian

Fig. 4 The seven habitats in the corn grains (*CR*) production scenarios with the largest absolute changes in total area. Together, they account for 99% of the habitat composition changes due to ethanol production
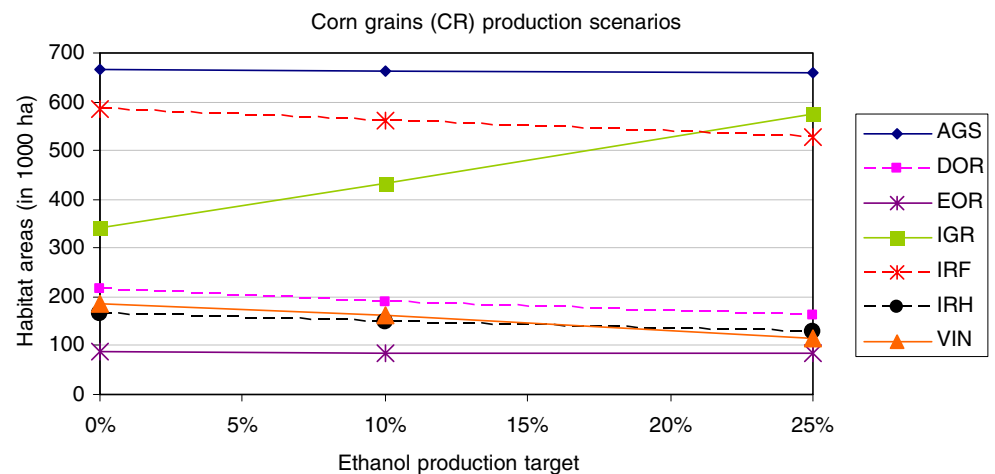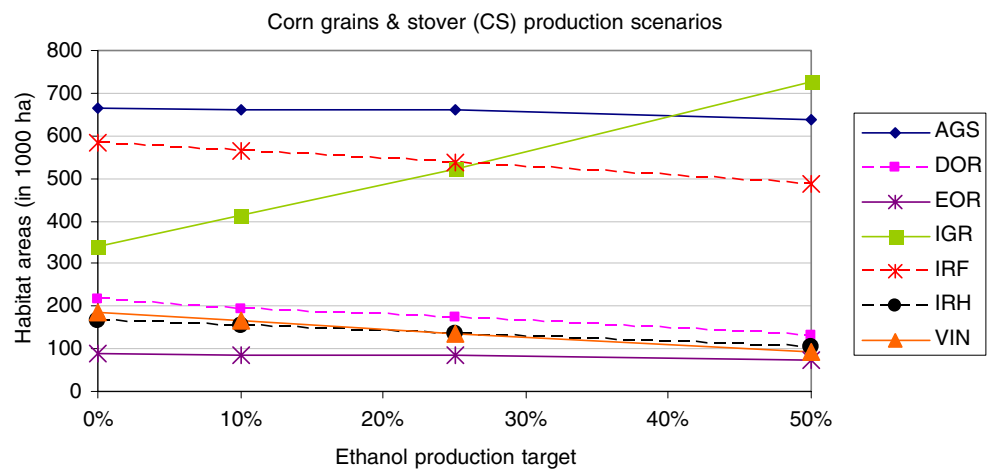
Fig. 5 The seven habitats in the corn grains and stover (*CS*) production scenarios with the largest absolute changes in total area. Together, they account for 97–99% of the habitat composition changes due to ethanol production

been proposed as a cellulosic feedstock on salt-degraded soils in the San Joaquin Valley (California Biomass Collaborative 2006).

An additional challenge is introduced if the aim is to assess not only current but also potential future land use. This study generated scenarios using an alternative futures approach (Santelmann et al. 2004) in which parcels were allocated to feedstock production by a rule-based algorithm to achieve production targets. Other more sophisticated scenario modeling could have been applied as well, such as an agricultural sector model (Walsh et al. 2003) that considers economic trade-offs among competing crops. We are not aware, however, of this class of model being used at a scale that can track site-specific habitat changes. Except for Chan et al. (2004), no one has looked systematically at impacts across a range of production levels, i.e., for different reference flow sizes.

Note that our study focuses on size and quality of land use changes and does not address their frequently discussed temporal dimension (Koellner and Scholz 2007; Milà i Canals et al. 2007). Each production scenario is characterized by a single transformation from one habitat composition to another. This approach would be less

satisfactory for land use changes such as timber harvest that initially transform a habitat type to a younger stage of the same type that gradually recovers over time, more or less, to its initial condition. We also do not model crop rotations that lead to periodical habitat-type switches, such as corn–soybean rotations. Continuous planting of a crop increases the likelihood of disease and declining yields over time. Recent experience in the USA suggests though that farmers producing corn ethanol feedstocks may be abandoning the rotation system because of the higher returns for biofuel feedstock than for food for humans or livestock. All these temporal aspects add another level of complexity to spatially explicit LCA by requiring temporal modeling of habitat recovery processes, habitat successions, and habitat–species relationships.

In principle, our approach could discriminate between alternative agricultural practices (Kim and Dale 2005b) or between farming for food vs. for energy (van den Broek et al. 2001), given that inventory data and habitat type information are available that distinguish between them. An example would be different levels of intensification such as increased fertilization or irrigation or improved cultivars with higher yields. The inventory models would

Fig. 6 The seven habitats in the sugar beet (*SB*) production scenarios with the largest absolute changes in total area. Together, they account for 89–99% of the habitat composition changes due to ethanol production
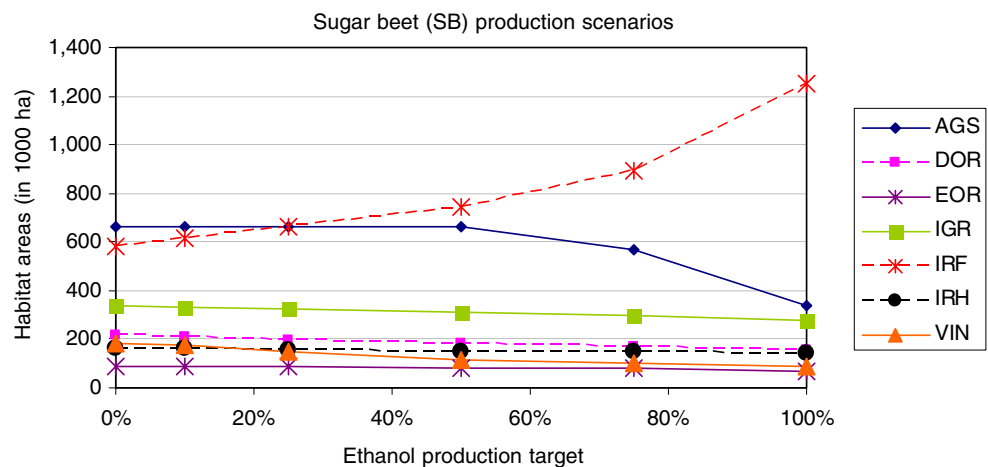
reflect that for a given amount of crop output, more inputs but less land is required. However, intensification may also impact the habitat value of the land, which might be difficult to quantify.

Total habitat area alone may not always be a good measure of biodiversity. The landscape configuration of habitat patches may also influence the suitability of habitats. Small isolated patches of habitat may not be sufficient to sustain a viable population or mating pair of a species. White et al. (1997) only ascribed habitat area to species in Pennsylvania if the patch exceeded a minimum size based on the requirement of each species. Thus, they included landscape context and fragmentation aspects. To do so in GIS-based inventory modeling would mean tracking flows of viable habitat for each species–habitat combination, which would be an unwieldy sized vector. We believe that our approach strikes a reasonable balance between scientific credibility and operational feasibility.

An open question is how our approach can be generalized to product systems that include land use in several ecoregions. For simplicity, we limited this study to a single ecoregion. In inventory modeling of product systems where inputs cause land use changes in different ecoregions, it would be beneficial to track habitat type and ecoregion, perhaps by appending the region name to the habitat name. This would be similar to the way in which the receiving environmental compartment is frequently added to emission flows. However, it will still be challenging to compare biodiversity impacts between competing products from different regions of the world. How do you compare the biodiversity impact of one hectare of Amazonian rainforest transformed to sugarcane to 1 ha of grassland in the San Joaquin Valley transformed to corn? The challenges of developing characterization models that are able to do this on a scientific basis will be discussed in Part 2 of this paper series.

Consequential assessments of land use will also need to account for indirect land use changes elsewhere in response to direct transformations of land from food to fuel crop (Kløverpris et al 2008). Searchinger et al. (2008) modeled greenhouse gas emissions from indirect land use changes with a global model of the agricultural sector to indicate which regions would likely replace the lost food sources and estimate the type of land cover that would be transformed. For a biodiversity impact assessment, accounting for indirect land use changes such as this would also require a scenario of parcel-level land use changes in these secondary regions in order to track the changes in habitats. Even though this would be the correct approach to estimating biodiversity impacts from large-scale changes in fuel crop production, lack of spatial data and local knowledge about the secondary regions combined with the large uncertainties surrounding indirect effects are likely to render this very challenging.

Besides developing spatially explicit crop production models, GIS can complement LCA in other ways as well. GIS modeling can identify locations for biorefineries within a "harvest shed" with an adequate biomass supply from which more precise estimates of transportation costs and distances can be made (Voivontas et al. 2001; Western Governors' Association 2008). The cost information could refine the crop production scenarios (Noon and Daly 1996), while transportation distances could refine the estimates of fossil fuel inputs associated with GHGs. Other inventory flows are also likely to be spatially varying and amenable to GIS modeling, such as soil carbon (Liebig et al 2008), soil organic matter (Sheehan et al. 2003), irrigation, or fertilization (Azapagic et al. 2007), and therefore, these may also respond nonlinearly to increases in references flows. Thus, the potential application of GIS in support of LCA has barely been tapped.

5 Conclusions

For processes that transform or occupy substantial land areas, the precision of LCA can be improved by accounting for spatial variation in their input–output relationships. GIS technology offers the combination of spatial data and analytical functions to quantify flows from specific locations. GIS-based inventory modeling of production processes that transform and/or occupy a substantial amount of land, such as agricultural production and resource extraction, allows several refinements in LCA:

1. Land use can be modeled as a nonlinear function of agricultural or resource output (Fig. 3).
2. Other inputs and outputs related to land use, such as irrigation water, fertilizer, nitrogen runoff, and soil carbon, can also be modeled more accurately.
3. Land use of processes can be described in detail and expressed as elementary input flows of habitat types.

Quantifying impacts on biodiversity from land-hungry processes, such as fuel crop production, requires spatially explicit representations of precisely how much land is used and where the use occurs. In consequential LCA, land use changes can be modeled through if-then type modeling, scenario analysis, or more predictive approaches. Predictive approaches, such as forecasts, would have to be based on agro-economic modeling that account for biophysical factors, market conditions (demand for and price of crops), and landowner behavior. No such forecasts for our study area exist, and developing this type of model was outside the scope of this project. To ensure plausibility of land use scenarios, basic drivers and constraints, such as profitability and land ownership, should be taken into account, as shown in this study.

In Part 2 (Geyer et al., submitted), the elementary input flows of habitat size and composition are combined with characterization models for potential biodiversity impact that account for species richness, abundance, and evenness. Species abundance and evenness are only meaningful in the context of an ecologically relevant spatial area, typically an ecoregion. The geographic scope of life cycle inventory modeling with spatially explicit land use should therefore be entire ecoregions. The elementary flows of habitat types should be tracked separately for each ecoregion if more than one is involved in production. Geographers have much to contribute to LCA. Kløverpris et al. (2008) noted that geography, along with other disciplines, can aid in modeling and assessing land use. We agree and specifically recommend that geospatial analysis be used for spatially explicit inventory modeling and impact assessment. Coupling LCA with GIS thus has the potential to significantly advance the theory and practice of life cycle assessment and improve its value as a decision support tool (Bengtsson et al. 1998).

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