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Policy Analysis

Effects of Spatial Scale on Life Cycle Inventory Results

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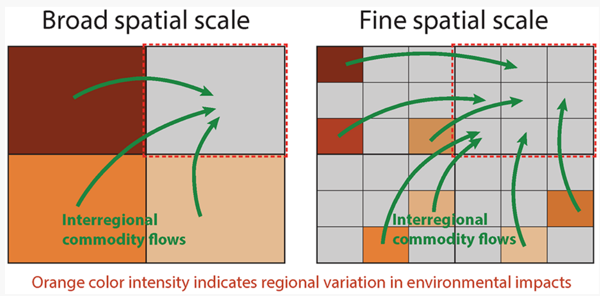
ABSTRACT: Efforts to compile life cycle inventory (LCI) data at more geographically refined scales or resolutions are growing. However, it remains poorly understood as to how the choice of spatial scale may affect LCI results. Here, we examine this question using U.S. corn as a case study. We compile corn production data at two spatial scales, state and county, and compare how their LCI results may differ for state and national level analyses. For greenhouse gas (GHG) emissions, estimates at the two scales are similar (<20% of difference) for most state-level analyses and are basically the same (<5%) for national level analysis. For blue water consumption, estimates at the two scales differ more. Our results suggest that state-level analyses may be an adequate spatial scale for national level GHG analysis and for most state-level GHG analyses of U.S. corn, but may fall short for water consumption, because of its large spatial variability. On the other hand, although county-based LCIs may be considered more accurate, they require substantially more effort to compile. Overall, our study suggests that the goal of a study, data requirements, and spatial variability are important factors to consider when deciding the appropriate spatial scale or pursuing more refined scales.



1. INTRODUCTION

With the world economic system so heavily integrated, most products produced today are a result of complex linkages in and between subnational and international supply chains, with few products, if any, that are completely locally made. Suppliers, producers, distributors, retailers, and consumers from around the world are becoming part of this increasingly interwoven web of global supply chains.[1] This is obvious for complicated products such as personal electronics,[2] but also true for seemingly simple and local products such as fresh produce.[3] In other words, the goods and services we consume have global environmental implications.

Life cycle assessment (LCA) is an approach of growing influence for evaluating such global impacts.[4] At the core of LCA is the quantification of inputs (e.g., energy and materials) and outputs (e.g., waste and emissions) at each stage of a product's life cycle from resource extraction to disposal.[5] This is known as life cycle inventory (LCI) analysis. Ideally, an LCI should be based on primary data collected directly from processes or facilities. Consider a cotton T-shirt. We need, first, to know where it was knitted and finished, what inputs were used, and what pollutants were released. The same goes for dying, weaving, yarning, and cotton production. Collecting data for all these processes would entail a large effort and is complicated by data gaps. The global garment industry has grown so complex[6] that it is difficult to trace back to the farms where cotton was grown.[7] However, life cycle thinking encourages accounting for not only processes directly associated with the T-shirt, but also their upstream suppliers (e.g., electricity generation and dye production) and so on and so forth. As the supply chain web expands, the challenges to collect information at the facility level multiply.

In practice, therefore, LCA practitioners work mainly with secondary data that are typically averages representative of certain spatial scales. The term "spatial scale" can mean different things to different people.[8,9] Here, we define it in the same way Montello defines analysis of scale in geography, i.e., "the size of the units in which phenomena are measured and the size of the units into which measurement are aggregated for data analysis and mapping."[9] Thus, scale in our study is synonymous with resolution, and the two terms may be used interchangeably throughout the text. For example, if an LCA study for a given country has a single average life cycle inventory for the entire country, its spatial scale or resolution is country-scale, and if it has state-specific life cycle inventories, its spatial resolution is state-scale. An increase in resolution means that the spatial scale becomes smaller, for example, from a low-resolution country scale to a higher-resolution state scale. Perhaps the most common spatial scale used in LCA is country-scale, as partly reflected in the country-specific data sets compiled in process LCA databases frequently used in LCA studies[10−13] and partly reflected in the large number of national input−output LCA models developed worldwide.[14−18] Average country-level data, however, may poorly

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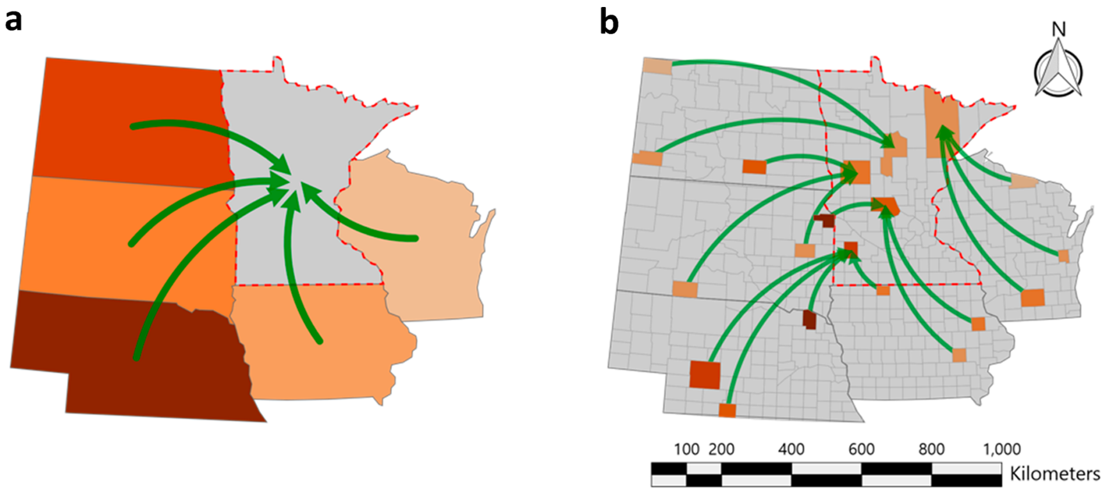

Figure 1. An illustration of life cycle modeling at the two different spatial scales (state (a) and county (b)), using Minnesota (dashed red line) purchasing corn from neighboring states as an example (see text). In the state-based (county-based) model, emission factors for production are estimated at the state (county) level and capture state-to-state (county-to-county) variation as indicated by the differences in color intensity, and this requires interstate (intercounty) commodity flows to be estimated for quantifying the life cycle emissions of a product consumed in a given region.

reflect regional or local situations, especially for countries with high spatial variability in geographic factors, such as climate and soil, and/or in energy and economic structures. For example, marginal SO_2 emission intensity of electricity generation in the United States ranges from 0.2−3.3 kg per MWh across regions,[19] with a mean of 1.3 kg per MWh, which, if used, would significantly mispresent both low- and high-intensity regions.

Recognizing the limitations of national average data to address regional questions, there have been growing efforts to compile LCIs at more geographically refined scales, such as state, county, and city. This is also driven by environmental policies, strategies, and legislations being increasingly implemented at the regional level, such as the state-level renewable electricity policies in the United States and worldwide regional and city-level climate action commitments.[20−22] Notably, a growing number of subnational input−output LCA models have been built, for example, in Australia,[23] China,[24] Japan,[25] Spain,[26] Canada,[27] and the United States.[28,29] Similarly, many process-based regional inventories have been compiled, for instance, for electricity generation,[30−32] biofuels,[33−36] foods,[37−39] and textiles.[40]

As interest in regionalizing LCA at subnational levels continues to expand, an important question that remains poorly understood is the choice of spatial scale.[29,41,42] A highly refined small scale, as discussed above, is theoretically sound but practically challenging, while a national scale is likely unrepresentative at smaller scales. A proper spatial scale should yield relatively accurate results by adequately capturing regional heterogeneity and meanwhile balance high data intensity.[43] The question of spatial scale also depends on the goal and geographic scope of a study. For example, estimating the life cycle emissions of total food consumption by the entire Chinese population may be satisfied by inventory data at a relatively coarse spatial scale compared to estimating the emissions for individual provinces or counties. Further, the question of spatial scale depends on how geographically variable the product system is in terms of its input requirements and environmental outputs. If the variability is small, all else being equal, results accuracy may increase only marginally with further spatial differentiation (e.g., from state to county).[43] All things considered, there may not be "one scale fits all", and the question of a proper spatial scale needs to be investigated on a case-by-case basis.

Previous studies have examined the question of spatial scale in LCA in the context of impact assessment, such as that by Mutel et al.,[41] which used a case study of electricity generation. Here, we study how the choice of spatial scale may affect life cycle inventory (LCI) results, using corn production and consumption in the United States as a case study. Corn is one of the most widely grown crops in the United States, with a total planted area of ∼36 million hectares and a total production of 371 million metric tons in 2017.[44] Historically, livestock feed was the primary use of U.S. corn, but over the past two decades corn used for ethanol has increased substantially.[45] The two sectors now consume ∼80% of total corn production.[38] Relying on intensive use of agrochemicals and farm machinery, corn production causes various environmental releases both directly (e.g., from fertilizer application on site) and indirectly (e.g., from fertilizer production and distribution). As a result, corn production contributes to a wide range of environmental problems, including global warming, nutrient pollution, smog formation, and ecological toxicity.[46] Given differences in soil, climate, and management practices, the stress corn production puts on the environment varies considerably across space.[38] A better understanding of the variability is important for determining the life cycle impacts of corn-derived products, such as ethanol and meat, and identifying improvement opportunities along their supply chains.[38]

In our analysis, we ask how life cycle emissions per average kg of corn consumed by ethanol plants and livestock farms in a given state or across the entire country may differ based on emission factors and interregional commodity flows estimated at two different spatial scales, state and county. This question is relevant to, for example, environmental policy makers of a given state interested in whether corn ethanol consumed in the state meets their renewable fuels standard. It is also relevant to national food companies that purchase commodities from farmers across the country and seek to "green" their supply

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chains by identifying and engaging with large impact contributors (i.e., hotspots). In the following section, we describe the methods used for estimating the life cycle inventory of corn across the United States based on two different spatial scales and for estimating interregional corn flows. Our results focus on GHG emissions and consumptive water per kg of corn produced and consumed due to data availability and corporate interest in tracking and managing these supply chain impacts.[38] We close with a discussion of the implications of the study.

2. METHODS AND DATA

Why does spatial scale matter? We explore this question with first a conceptual example (Figure 1). Suppose we are interested in the carbon footprint of corn consumed by Minnesota ethanol facilities. To answer the question requires estimating (1) where corn is sourced from (or interregional corn flows), and (2) how it is produced and affects the environment (or region-specific emission factors).[47] A state-based model (Figure 1a) would derive interstate corn flows and state-specific emission factors reflecting state-average corn practices and emissions. The problem with a model at this scale is that it could mask potential heterogeneity at the substate level: the corn supplied to Minnesota ethanol plants may be produced in particular locations whose emission factors may be substantially different from the state average. In this case, improving the geographic resolution of the model—for example, to the county-scale with intercounty corn flows and county-specific emission factors (Figure 1b)—can improve the accuracy of life cycle results, assuming that county average production practices and flows are able to be adequately captured. For clarity, a county is a political subdivision of a state; for example, the state of Minnesota has 87 counties, as shown in Figure 1. However, to what extent the accuracy can be improved with increased resolution depends partly on the supply chain connections between production and consumption, and partly on the degree of variation in production practices across states and counties.

Our analysis thus consists of three steps. First, we estimate the cradle-to-farm gate GHG emissions and blue water consumption of corn production at two scales, county and state (section 2.1). We focus on blue, instead of green, water consumption because blue water represents the portion of total water consumption that is directly influenced by farm management practices, while green water consumption occurs as a result of natural precipitation, where such water loss would largely occur regardless of the crop being grown. Although our estimates are cradle-to-gate, including emissions and water consumption embedded in inputs, only the process of corn production is regionalized in our analysis. This is partly because of the challenges in regionalizing all background processes, which not only require additional spatial characterization of upstream inputs but also data on the interregional flows of such inputs, thus significantly increasing data requirements and modeling complexity.[48] However, more importantly, focusing on corn production may be sufficient to capture the overall spatial variability of the corn life cycle (and derived products).

Corn production is likely the most spatially variable process and has also been shown to be the major contributor to corn (or derived products) life cycle environmental impacts.[35,38,49] Second, we estimate the mobility of corn within the United States based on demand in the receiving regions and the total impedance or difficulty of transporting commodities between regions (section 2.2). Finally, we calculate the cradle-to-gate GHG emissions and water consumption per average kg of corn *consumed* by ethanol plants and cattle, hog, and poultry farms at the state and the national level (see Figure S1 in Supporting Information 1 (SI-1) for the differences between production versus consumption-based impact characterization at county, state, and national scales of analysis). In other words, our final results reflect cumulative cradle-to-gate GHG emissions and water consumption embedded in an average unit of corn at the point of consumption by ethanol plants and livestock farms in a particular state and in the country as a whole.

We further compare the state-based results against the county-based results. If the former agrees well with the latter, this could mean that corn GHG emissions and water consumption in the counties that actually supply corn to a particular sector do not differ much from the state averages. This could also mean that they do differ; e.g., some counties have much higher emission rates and some lower, but the weighted average, with weights being the amounts of corn supplied, is close to the state average. In either case, state could be a sufficient spatial scale. However, if state-based results do not agree with county-based results, this suggests it may be necessary to compile county-level life cycle inventories. Final results and all estimates of cradle-to-gate GHG and water consumption estimates and interregional corn flows can be found in the SI-2.

2.1. GHG Emissions and Water Consumption at State and County Scales.

The primary goal of this part of the study is to investigate how characterizing LCIs at two different spatial scales affects emission results, so our intent is to maintain methodological consistency between state and county characterizations. Emission factors for county corn production are based on a streamlined spatial life cycle assessment provided by Pelton,[49] whereas this study provides estimates at the state-scale, following the county-scale estimation procedures as closely as possible when appropriate. The streamlined assessment focuses on key inputs and outputs of corn production that have both a high degree of spatial variation across corn producing regions and a significant contribution to total corn life cycle emissions relative to other inputs/outputs. Nitrogen (N) fertilization contributes over 50% of total corn impacts, on average, due to the embedded emissions of fertilizer production and the on-field nitrous oxide (N_2O) emissions from nitrogen application.[50] The embedded emissions from N fertilizer and associated N_2O emissions are also highly variable across the production landscape due to differences in the type of fertilizers applied, the quantity of N fertilizer applied, and the biogeochemical characteristics of the land affecting direct and indirect emissions of N_2O.

In addition to the spatial variability of N fertilizer related emissions, emissions associated with irrigation are also highly variable across production locations. Although irrigation's average contribution is small, accounting for ∼5% of corn life cycle emissions,[50] there is substantial variation in (1) the locations and methods in which irrigation is applied and (2) the corresponding fuel mixes used to power the irrigation systems. These spatial differences in N fertilization and irrigation practices and emissions are captured in the streamlined spatial LCA and combined with national average emissions associated with the other inputs to corn production, such as other fertilizers (e.g., potassium, phosphate, lime, etc.), fuel use, and pesticides (approximately 450 kg CO_2e/acre).[50]

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Environ. Sci. Technol. 2020, 54, 1293−1303

While potassium, phosphate, and pesticides together contribute less than 5% of average total cradle-to-farm gate emissions, lime application and fuels used in machinery make up about 40% of total emissions.

Lime application rates are expected to be variable across production regions, but regionalizing these inputs is limited by data availability. We expect fuel use from farm machinery to have minimal variation as most farms are conventionally tilled and require similar planting and harvesting practices. As such, with the exception of lime inputs, focusing on the nitrogen fertilizer, N_2O emissions, and irrigation captures the majority of spatial variation. The average emissions estimates per acre representing embedded impacts from these other inputs to production are then combined with state- and county-specific yields (bushels/acre) to estimate emissions per bushel of harvested corn, providing an additional small degree of spatial differentiation (see Table S5 in SI-1 for details). Harvested bushel estimates are based on the 2007 and 2012 average corn production, which helps smooth out the variation from year to year, and is based on the most recently available census estimates compiled only every five years. The data used for the assessments include a combination of census and survey compiled by the U.S. Department of Agriculture (USDA), among several other data sources described herein and in detail in Pelton.[49]

To estimate embedded fertilizer emissions, this study diverges slightly from the methods used for county-level estimation in order to take advantage of the existing USDA state-level survey data providing N application rates by crop. The survey data represent the best methodologically consistent data set available, to our knowledge, that matches the scale of inquiry and would be the primary data set of choice to develop a state-scale LCI for fertilizer inputs. This data set can be used to understand differences in N application rates across surveyed corn producing states and does not exist in a publicly available format at the county-level, thus requiring the full estimation conducted in Pelton. For those states with no primary survey data available, fertilizer application rates are estimated in accordance with the method provided in Pelton, which maintains the methodological consistency for estimating data gaps to better compare results across the two geographical scales of assessment (county versus state). Specifically, fertilizer application rates are estimated using state-level total annual synthetic N fertilizer quantities applied across all types of agricultural crops,[51] and subtracting the amount of fertilizer expected for wheat, cotton, and soybean production, which take into account the relative differences in application rates between the most commonly produced crops in the United States, accounting for 75% of total agricultural crop production. The remaining quantity of N is then multiplied by the proportion of corn acres to all other crop acres (less the acres from soybean, wheat, and cotton). The resulting total estimated quantity of N applied to state corn acres is then divided by the state total harvested corn acres to determine an estimated application rate. Whether from the USDA or estimated, state N fertilizer application rates are combined with the distribution of N fertilizer types used across each state (e.g., urea, ammonium nitrate, etc.) and their respective embedded manufacturing emissions, which range from 1.6 to 16 kg CO_2e/kg N applied.[13,49,52]

State N_2O emission rates are derived using USDA data providing corn N_2O emission rates by soil type (fine, medium, coarse) and land resource region, which are based on outputs from two biogeochemical models (Daycent and DNDC) to capture the interactions of temperature, precipitation, and soil type, among others that affect N_2O emission rates. We estimate a state-level N_2O emission factor, capturing emissions from both background processes and N application, using geographic information systems (GIS) to first characterize the portion of corn grown on each soil class in each LRR for a weighted average emission rate per LRR, and then estimate the portion of each LRR growing corn in each state for a state weighted average. This method aligns with the weighted average at the county level presented in Pelton.[49]

For irrigation, state-level metrics on the type of application method (gravity or sprinkler), the source of water (groundwater or surface water) and the energy source for sprinkler powered systems are used and combined with average state-level irrigation rates (L/acre) to estimate the total energy used for pumping irrigation water to corn acres.[49,53,54] The ANL water model provides blue water consumption for irrigated corn production at the county scale, which we average for a state-scale estimate.[53] We then combine these with state-scale estimates of the consumption to withdrawal ratios to calculate the total irrigation water withdrawn, which is used for estimating greenhouse gas emissions from powered irrigation systems. For sprinkler systems powered by electricity, state-level electricity emission factors are estimated based on the weighted average portion of irrigated corn acres in each eGRID subregion (22 regions) intersecting each state and the corresponding energy mixes,[13,55] allowing for a full accounting of life cycle energy emissions (including material extraction, combustion, and transmission/distribution losses across fossil and renewable energy generation portfolios). This method aligns with the county-scale assessment where counties are also partitioned to eGRID subregions. Similarly, for other fuel powered systems (e.g., diesel, natural gas, propane, etc.), both upstream production and combustion related emissions are included.[13] All emission factors are available in the SI (Tables S1−S5 in SI-1 and also SI-2). For water consumption, we combine the respective county and state average irrigation water consumption with the embedded water consumption associated with all other inputs to corn production, including embedded water associated with nitrogen fertilizers.[13,50]

While most U.S. corn consumption is domestically produced (>99%), a portion of U.S. consumed corn comes from foreign imports. USDA feed yearbooks indicate almost 40% of U.S. corn imports come from Canada. As such, we apply an average corn production emission factor for Canadian corn,[56] and a global average emission factor for all other imports.[57] For water consumption, on the other hand, we apply the average U.S. water consumption intensity due to data limitations for characterizing global average and Canadian water consumption (Table S6 in SI-1).

2.2. Interregional Corn Flows. We estimate how corn moves between counties within the United States using the FoodS[3] model developed by Smith et al.[38] and intermodal county-to-county impedance factors provided by the Center for Transportation Analysis (CTA) at the Oak Ridge National Laboratory.[58] The impedance factors are based on consideration of costs of transporting commodities between counties—in the form of total distance, speed limits, traffic congestion, tolls, and other impedances—of multiple modes including truck, rail, and barge and are estimated by multiplying the modal distance from county to county and adjustment factors for different modes.[58]

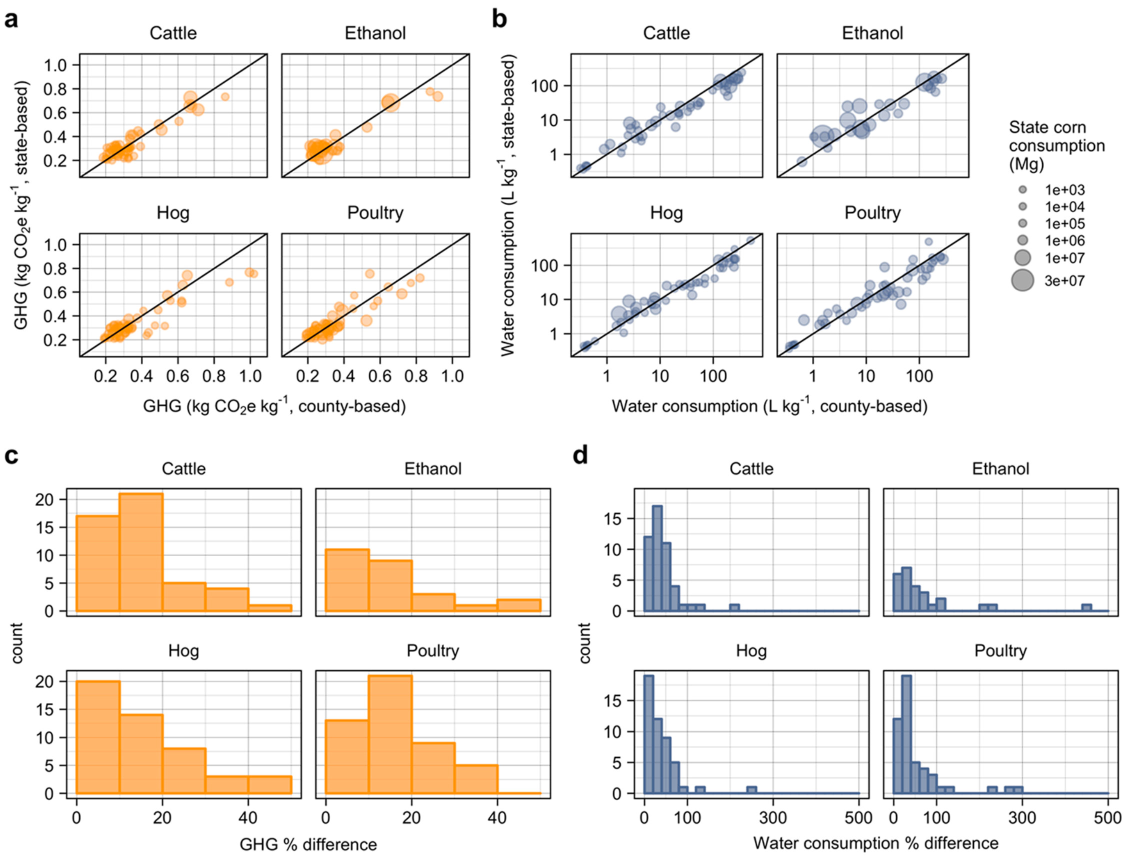

Figure 2. Comparison between state-based and county-based results for greenhouse gas (GHG) emissions and water consumption (a, b) and in terms of absolute percentage difference (c, d). *(a, b) Circles indicate the cradle-to-gate GHG emissions and water consumption per average kg of corn consumed in different states (see the SI-2 excel file, tab *Results-State*); circle size indicates the total amount of corn consumed in each state; the 1:1 line indicates equivalence between state-based results (*y*-axis) and county-based results (*x*-axis). (c, d) The absolute percentage difference of state-based results from county-based results.

The mobility modeling is formulated as a linear programming problem, where the total system impedance of moving corn supplies to the destination locations of consumption is minimized, subject to several constraints, as described below:

$$\text{Minimize: } \sum_{(r=1)}^{R}\sum_{(i=1)}^{n}\sum_{(j=1)}^{n} IC_{(i,j)} \times FC_{(r,i,j)}$$

Subject to

$$\sum_{i=1}^{n} FC_{r,i,j} = D_{r,j}, \text{ for } r = 1, \ldots, R \text{ and } j = 1, \ldots, n$$

$$\sum_{r=1}^{R}\sum_{j=1}^{n} FC_{(r,i,j)} \leq S_i, \text{ for } i = 1, \ldots, n$$

$$FCr,\ i,\ j \geq 0, \text{ for } r = 1, \ldots, R,\ i = 1, \ldots, n \text{ and } j = 1, \ldots, n$$

where $IC_{i,j}$ is the intermodal impedance from the origin county i to the destination county j. $FC_{r,i,j}$ is the quantity of corn transported from the origin county i to the destination county j in sector r. $D_{r,j}$ is the quantity of corn demanded by sector r at the destination county j, and S_i is the quantity of corn supply at the origin county i. There are 11 sectors in the model including animal feeds (broiler, hog, pullet, turkey, dairy cattle, layer, beef cattle), wet-mill, ethanol, export, and all other use. For our results, we consider only domestic corn consumption by major sectors, which account for ~80% of domestic corn production, including demand from ethanol producers, cattle (sum of meat cows and dairy cows), hogs, and poultry (sum of broilers, pullets, layers, and turkeys).

The mobility model yields intercounty corn flows for different sectors in 2012 (see SI-2). The intercounty flows are coupled with county-based GHG and water consumption intensities to calculate the cradle-to-gate GHG emissions and water consumption per average kg of corn consumed by a particular sector in a given state or in the country (hence, county-based results). We perform a similar analysis for the state-scale, where state-based corn flows are coupled with state-based GHG emission and water intensities, yielding state-based results. Instead of using state-based impedance factors, however, which would require additional estimation and would introduce additional sources of uncertainty, we instead estimate state-level corn flows by summing the intercounty flows, which maintains consistency in the interregional corn flows across the county and state levels, and facilitates better comparison of county versus state-based impact results, allowing us to better examine the issue of spatial scale in LCI analysis. Code for the transport model, together with a simple fictitious example for illustration, can be found in the SI-1.

2.3. Sensitivity Analysis. In our analysis, county- and state-based estimates of GHG emissions and water con-

Table 1. Detailed Comparison between the State- and County-Based Production Inventories for State-Level Consumption Estimates, Using Corn Consumed by Arizona Cattle Farms As an Example (Figure 3a)[a]

			state-based		county-based	
	supplying states	ratio (%)	production	consumption	production	consumption
GHG emissions (kg CO_2e/kg corn)	Arizona	8	0.50	0.38	0.42	0.33
	Colorado	38	0.30		0.30	
	New Mexico	4	0.71		0.82	
	Texas	51	0.40		0.31	
water consumption (L/kg corn)	Arizona	8	560	158	476	298
	Colorado	38	86		136	
	New Mexico	4	694		720	
	Texas	51	108		359	

[a]Corn is estimated to come from Colorado (38%), New Mexico (4%), Texas (51%), and in state (8%). For comparison, county-based production estimates are aggregated to the state level based on the counties within a state that are estimated to supply corn to Arizona cattle farms, as opposed to state-based production estimates reflecting state averages (see text).

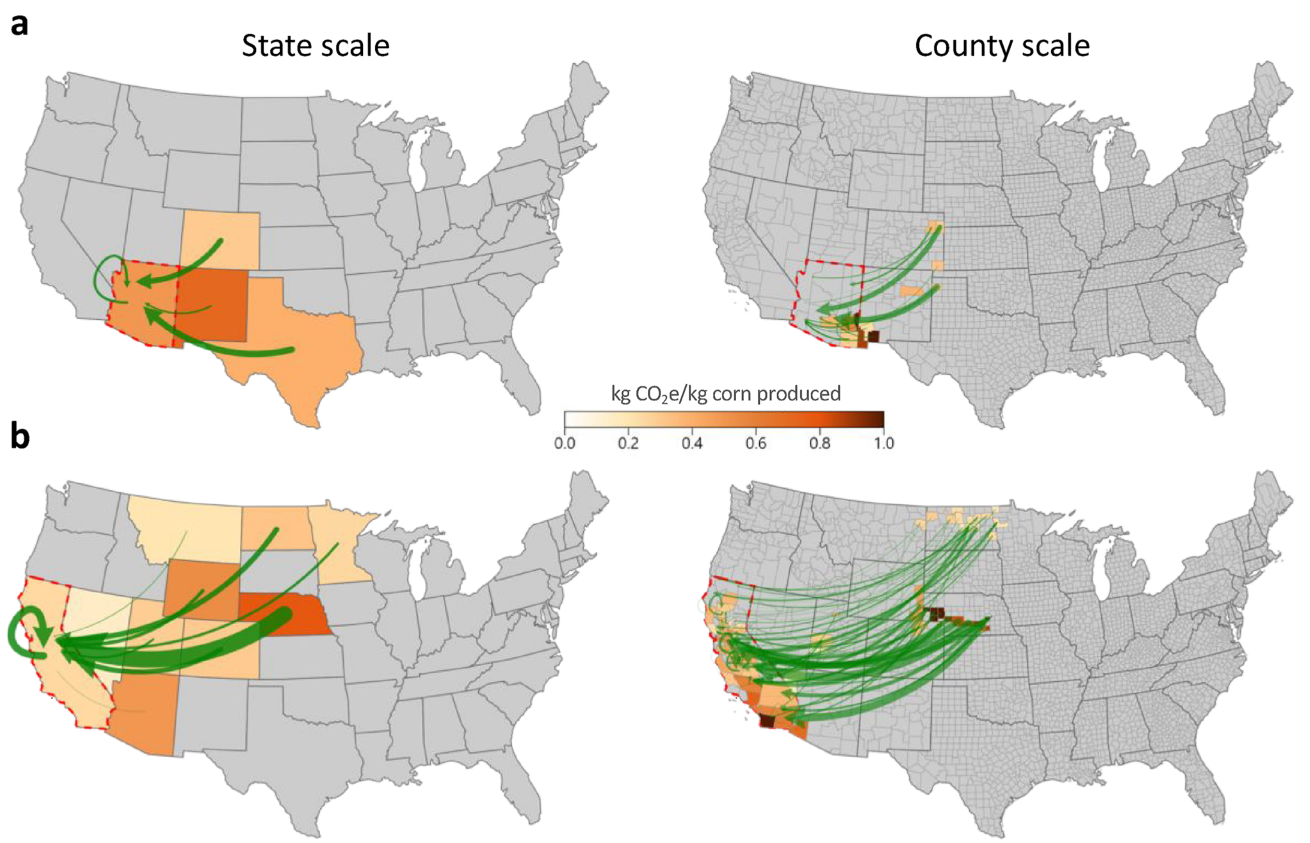

Figure 3. Two contrasting cases of corn sourcing at state and county scales. (a) Arizona cattle farms, which are estimated to source corn from a small number of counties in neighboring states and also from counties in state. (b) California cattle farms, which are estimated to source corn from a large number of counties in the Midwest over long distances and also from counties in state. Supply counties or states are color coded, with colors indicating life-cycle GHG emissions per kg of corn produced.

sumption associated with corn production have a similar level of uncertainty given the methodological consistency maintained between the two (section 2.1). The most uncertain component of the results is likely interregional corn flows. Compared with international imports and exports, commodities travel freely within a country,[29] making it difficult to keep track of their movement. In the United States, the best data source of this sort is the Commodity Flow Survey (CFS), compiled by the Bureau of Transportation Statistics, which includes data on shipments between states and city clusters for certain business establishments.[59] However, commodities covered in CFS are differentiated into ∼30 broad categories, a level of aggregation that is of little use for LCA studies of individual commodities (e.g., corn, soybean, nitrogen fertilizer). That is to say, interregional commodity flows in LCA have to rely on modeling and are likely highly uncertain.[25,38]

Interregional corn flows can also affect the question of spatial scale. For example, if corn consumed by a sector is purchased mainly from top-producing counties, then life cycle inventories compiled at the state scale, which to a large extent reflect the impacts of top-producing counties, may be sufficient. However, if the corn is purchased from small counties with quite different impacts from the average, a state scale may not capture the substate variability and thus falls

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short. To test to what extent our comparative results are affected by the modeling of corn mobility, we apply another set of intercounty corn flows estimated based on cost minimization[38] as opposed to our minimization of impedance (see SI-3).

3. RESULTS AND DISCUSSION

3.1. Differences at the State Level. Overall, we find that for state-level GHG analysis (i.e., cradle-to-gate GHG emissions per average unit of corn consumed in a given state), state-based inventories of corn production give roughly similar results as the county-based analysis (Figure 2a,c). In 2012, livestock farms operated in 48 states, while ethanol plants operated in 26 states. The state- and county-based GHG results are within 10% of difference for 37−42% of states across the four sectors, within 20% of difference for 71−79% of states, and within 40% of difference for >90% of states (Figure 2c). In other words, for the majority of states (71−79%), using state-based life cycle inventories of corn production would give similar results (within 20% of difference) as using detailed county-based corn life cycle inventories.

By contrast, for state-level water consumption analysis (i.e., cradle-to-gate water consumption per average unit of corn consumed in a given state), results at the two scales differ more substantially (Figure 2b,d). The state- and county-based water results are within 10% of difference for 15−25% of states, within 20% of difference for 23−40% of states, within 40% of difference for 50−65% of states, and within 60% of difference for 65−83% of states. In other words, for 17−35% of states, using state-based life cycle inventories of corn production would give quite different results (by >60%) than using detailed county-based corn life cycle inventories. A concordance correlation analysis,[60] which quantifies agreement between two variables, shows that the correlation coefficient is 0.90 (0.87−0.92; confidence interval at 95%) for GHG emissions and 0.83 (0.78−0.87) for water consumption. This confirms that estimates given by the two scales agree more on GHG emissions than on water consumption.

To further illustrate the differences, consider a couple of examples. The cradle-to-gate GHG emissions and water consumption per average kg of corn consumed by cattle farms in Maine are estimated at 0.33 kg CO_2e and 1.9 L using county-based inventories, compared with 0.22 kg CO_2e and 1.1 L using state-based inventories. In Nebraska, the cradle-to-gate GHG emissions and water consumption per average kg of corn consumed by poultry farms are estimated at 0.54 kg CO_2e and 76 L using county-based inventories, compared with 0.76 kg CO_2e and 147 L and using state-based inventories.

To explain the differences between the two scales, let us take a detailed look at Arizona cattle farms, which are estimated to purchase corn from Colorado (8%), New Mexico (38%), Texas (51%), and in state (8%) (Table 1; Figure 3a). The cradle-to-gate GHG emissions and water consumption per kg of corn consumed by Arizona cattle farms are estimated at 0.38 kg CO_2e and 158 L using state-based inventories. These inventories reflect average GHG emissions and water consumption of corn production in Colorado (0.30 kg CO_2e/kg and 86 L/kg), New Mexico (0.71 kg CO_2e/kg and 694 L/kg), Texas (0.40 kg CO_2e/kg and 108 L/kg), and Arizona (0.50 kg CO_2e/kg and 560 L/kg). However, on the basis of county-level inventories and counties (22 of them) estimated to have supplied corn to Arizona cattle farms, the aggregated state-level GHG emissions and water consumption of corn production associated with Arizona cattle farms are estimated at 0.30 kg CO_2e/kg and 136 L/kg in Colorado, 0.82 kg CO_2e/kg and 720 L/kg in New Mexico, 0.31 kg CO_2e/kg and 359 L/kg in Texas, and 0.42 kg CO_2e/kg and 476 L/kg in Arizona (see Table S5 in SI). These, coupled with each state's supplying ratio, give the cradle-to-gate GHG emissions and water consumption per kg of corn consumed by Arizona cattle farms at 0.33 kg CO_2e/kg and 298 L, as opposed to 0.38 kg CO_2e and 158 L using state-based inventories. Figure 3b shows a more complicated case, California cattle farms, which are estimated to source corn from dozens of counties in the Midwest over long distances.

3.2. Differences at the National Level. For national level GHG analysis (i.e., cradle-to-gate GHG emissions per average kg of corn consumed by a given sector in the United States), the results of which are relevant for industry associations, national level policy making, and connecting U.S. exports and impacts to global supply chains, we find that state-based inventories of corn production give very similar estimates to county-based inventories, with differences smaller than 5% across all sectors (Figure 4a). For national-level water consumption analysis, however, results at the two scales differ from 5% to 34% (Figure 4b). The largest discrepancy appears for cattle (34%), where the county-based estimate is 127 L per kg of corn consumed, and the state-based estimate is 84 L per

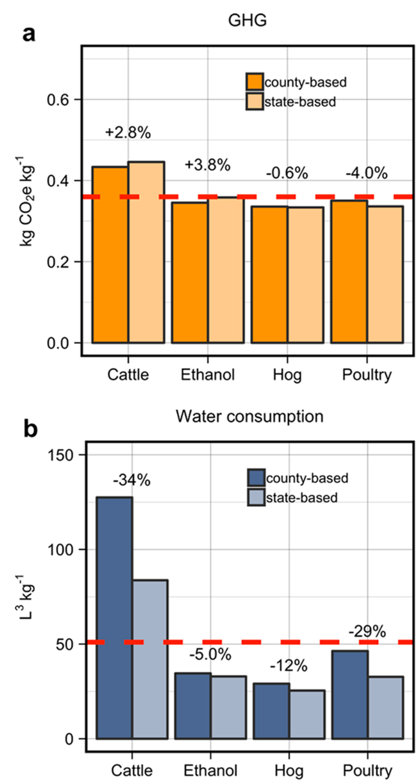

Figure 4. Cradle-to-gate GHG emissions (a) and water consumption (b) per average kg of corn consumed by cattle, ethanol plants, hogs, and poultry in the United States using state-based inventories and county-based inventories. The number above each bar indicates the percentage difference of the state-based estimate from the county-based estimates. Red dashed lines indicate estimates for an average kg of corn produced in the United States (weighted average of county-based results, weights being production shares), reflecting the impact of producing a kg of "generic" corn at the national level without considering its destination and user.

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Environ. Sci. Technol. 2020, 54, 1293−1303

kg. The second largest discrepancy appears for poultry (29%), where the county-based estimate is 46 L per kg, and the state-based estimate is 33 L per kg. We also calculate GHG emissions and water consumption for a kg of "generic" corn in the United States (red dashed lines in Figure 4) based on production data. Such estimates are commonly provided in LCA databases, but if they are applied without considering the downstream sector, it could be problematic. As Figure 4b demonstrates, corn supplied to different sectors can have substantially different embedded water consumption, because of the large spatial variation in water consumption and where each sector sources corn from.

3.3. Results of Sensitivity Analysis. Replacing our default intercounty corn flows based on minimization of total impedance (section 2.2) with those based on minimization of total cost[38] does not change the main findings for either the state-level or national-level analysis (see Figures S4 and S5 in SI-1). Using cost minimized corn flows, state- and county-based inventories of corn production also yield similar results for state-level GHG emissions and even greater differences in the results for state-level water consumption compared to use of the impedance model (Figure S4 in SI-1). For example, state-based and county-based GHG results are within 20% of the difference for 65−73% of states and within 40% of the difference for >90% of states. And state- and county-based water consumption results are within 40% of the difference for 38−54% of states and >60% of the difference for 38−46% of states. For national level GHG analysis, state- and county-based results are also within 5% of the difference, and for national-level water consumption analysis, the two differ by 4−34% (Figure S5 in SI-1). While our interregional corn flows are undoubtedly uncertain, and data to empirically validate the model are limited, the outputs of the impedance minimization model are similar to the outputs of the cost-minimization model (see Figure S9 in SI-1 and also SI-2 for distance comparison). This similarity provides at least some level of model validation, because the cost-minimization model has been shown to agree with broad level commodity flows provided in the Freight Analysis Framework which use Commodity Flow Survey data, as is indicated in Smith et al.[38]

4. DISCUSSION AND IMPLICATIONS

In this study, we explore how inventories of corn production compiled at the county- and state-scale affect estimates of cradle-to-gate GHG emissions and blue water consumption by major sectors of corn demand in the United States. In national-level sectoral analysis (e.g., emissions per average kg of corn consumed by hog farms in the country), estimates at the state and county scales are close to each other across all sectors (<5% of difference) for GHG emissions, but can differ by up to 30% for water consumption. In state-level analysis (e.g., per average kg of corn consumed by ethanol plants in Ohio), estimates at the two scales are roughly similar for the majority of states for GHG emissions (e.g., ≤ 20% of difference for 71−79% of states and ≤40% of difference for >90% of states), but have greater differences for water consumption (e.g., ≤ 40% of difference for 50−65% of states and >60% of difference for 15−35% of states). These results suggest that state-based corn production inventories may suffice for broad national-level analysis as well as many state-level analyses of corn GHG emissions. Such state-scale LCIs, however, may fall short for corn production related to blue water consumption, and a substate spatial scale, like county, may be needed.

The discrepancy between GHG emissions and water consumption as revealed by the two models is due in part to the fact that water consumption from corn production is much more spatially variable than GHG emissions. Using county-based inventory results, the coefficient of variation is 78% for GHG emissions and >370% for water consumption. This large difference in variability is caused by the fact that there is a relatively common set of inputs required for corn production that contribute more consistently toward GHG emissions compared to the highly variable use of irrigation water, given that green water (i.e., precipitation) often can satisfy water requirements, supplanting localized needs for blue water irrigation. Another factor that contributes to the discrepancy is the variability in interregional links. The county-based model intuitively has more nodes (counties) and links (trade connections) than the state-based model (see SI-2). However, for each individual node, it has an average of just 2−3 outside county suppliers, as compared to 10−12 different state suppliers for each node (state) in the state-based model. This means that, because of the number of counties in each state, the number of connections going to each state will be amplified with the county-to-county characterization. The variation between county-level consumption-based LCI results will thus be higher than the variation between state-level consumption-based LCI results, because the greater number of state connections can average out the variation between the high- and low-impact supply regions, whereas the county level, with only 2−3 counties suppling the demand, is more influenced by the high- or low-impact supply regions.

Our results also indicate that even if it is the same product (e.g., corn), life cycle emissions can vary depending on the sector that uses it (e.g., ethanol plants or cattle ranches). Fundamentally, this is because such a product has a high system variability across regions, and different sectors may purchase it from different regions depending on their locations, logistical cost, and supply chain management. In life cycle modeling, it is common to rely on LCA databases, especially for modeling background processes. However, most of these databases provide only generic, or country-level, inventory data without regional differentiation at subnational levels, let alone interregional commodity flows. Our results provide a cautionary note on extracting LCA databases for products or processes that are likely to be highly spatially variable.

While a county scale can increase accuracy, there is a trade-off in the costs of producing these increasingly spatially refined LCI estimates. We examine such costs in terms of the volume of input data and computational time and efforts required to produce county versus state scale LCIs. On the basis of the perceived cost of gathering data sets, building models for estimation, and computation time, we estimate that the state-scale LCI is ∼90% less costly to develop than the county-scale LCI (see SI-2 excel file tab *DataCost* for details). As such, LCI development costs must be balanced against any expected gains in accuracy that may result by increasing spatial resolution, where for example, due to the similarity in corn production GHG emissions between the two scales, it may not be worth the added costs of LCI development to increase spatial resolution to the county scale.

The recent broad efforts to capture state-level LCIs and interstate commodity flows, such as those provided by surveys or input−output models, may in some cases provide sufficient levels of detail for estimating intermediate consumption-based impacts across consuming sectors. However, such level of

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Environ. Sci. Technol. 2020, 54, 1293−1303

spatial resolution may fall short in other cases where there is considerable system variability across space, as our results on blue water consumption indicate. Overall, our study suggests several aspects to consider, in addition to cost, for choosing a proper spatial scale or deciding to improve existing spatial scale for LCI analysis.

First, the choice of a proper spatial scale depends largely on the scope of the assessment and the type of product under study, as has also been noted by others.[61,62] Broader scale assessments (e.g., national and state level) may be sufficient for informing national or state policy and industry association decisions and for impact categories with low spatial variability, as increased data granularity may result in small improvements that may not justify the additional costs. Substate characterizations, however, may be better suited for informing state or local consumption-based policy-making and for impact categories with high spatial variability. Where impact variability is likely to be high, increasing the spatial resolution of LCI assessments will be vital for informing company-level supply chain assessments and targeting engagements. This is because highly variable impacts are aggregated in unique ways based on individual facility locations and demand, and can result in substantially different impacts and hotspots across facilities and companies.[37] The relative uncertainties of characterizing inventories at lower and higher spatial resolutions and estimating commodity flows at different spatial scales, however, must also be considered.

Furthermore, the question of whether a coarse scale (e.g., state in our case) is satisfactory or to pursue more spatially refined scales depends on the application of LCA and the question being studied. Consider the following example. A state mandates that ethanol consumed in the state has 20% lower life-cycle GHG emissions than gasoline. Suppose gasoline emissions are 100 g CO_2e MJ^{-1} with high certainty (as most come from gasoline burning) and corn ethanol emissions using state-based corn inventories are 50% lower or 50 g CO_2e MJ^{-1}. Also, suppose this GHG estimate for corn ethanol is likely within 20% of error as compared with that using county-based inventories. In this case, it is not worth pursuing county-based inventories as that would not change the result that corn ethanol meets the state mandate. However, if the state-based corn ethanol had GHG emissions of 75 g CO_2e MJ^{-1}, on the verge of the 20% threshold, it may justify the additional effort to compile county-based inventories. Overall, how we interpret LCA results and determine acceptable levels of uncertainty depends largely on the purpose of the study, such as to identify areas of improvements or to promote ecofriendlier alternatives in comparative analyses. The challenge is in establishing what the likely uncertainty bounds are, a priori, for state versus county LCA results within a given impact category to justify a higher resolution assessment. The challenges presented by the cutoff rules for streamlining LCA are similar in this regard. In streamlined LCA, inputs and outputs may be excluded from the inventory if they make up less than 5% of the mass, energy, or contribution to total impacts, but such an examination also requires an a priori assessment to achieve the intent of the streamlining efforts. If future research can establish these a priori assumptions defining the uncertainty bounds of broad versus fine scale LCA results, policy makers could then use these to establish thresholds of uncertainty to support particular policy decisions and/or certifications.

In summary, the choice of a proper spatial scale thus may be, at least initially, subjectively reached by an optimization of these criteria. Future research may continue to examine these linkages in other agricultural and nonagricultural products and on other impacted categories not explored here, such as water scarcity, eutrophication, and ecological toxicity, whose impact characterization factors themselves have spatially explicit implications to consider for future regionalization efforts. These efforts will help provide additional clarity for determining the criteria on which different spatial scales may be appropriate for informing sourcing and supply chain management decisions and, potentially, quantitatively examine the optimization of such criteria.

A limitation of our analysis is the omission of land management change and its effects on soil organic carbon (SOC) in the long term.[63−65] Our analysis spans a relatively short time frame, is retrospective in nature, and reflects the status quo of management practices, thus assuming no change in SOC. SOC is a key component in the life cycle emissions of crops and crop-derived products, and is also highly variable across space.[66] Future studies on spatial scale of crop systems may incorporate long-term changes in land management and SOC.[63] Also, our cradle-to-gate inventories do not capture all variability. Emissions from fuel and lime use are also likely to vary, but due to data limitations, these are not spatially differentiated. The purpose of our study, however, is not to fully spatialize the emission estimates, but to compare how spatializing the same, major, and likely most variable inputs using different scales of analysis can lead to different results and potentially different decisions. Further, our study only qualitatively examines uncertainty, identifying (1) similar uncertainty for the cradle-to-gate inventories of corn production at the spatial scales due to methodological consistencies and (2) that estimates of interregional corn flows are likely the most uncertain component due to the inherent modeling requirements. It has been pointed out, however, that spatial differentiation could increase aggregate uncertainty in LCI.[67] Future studies incorporating full uncertainty analysis should confirm whether this is the case for deriving county-level life cycle inventories versus state-level inventories and under what circumstances.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.9b03441.

SI-1: Various supporting figures and tables (PDF)

SI-2: Results of GHG emissions and water consumption based on interregional corn flows estimated using the impedance minimization method, and other Supporting Information such as network analysis and data cost of LCI compilation (XLSX)

SI-3: Results of GHG emissions and water consumption, and interregional corn flows using the cost minimization method for comparison (XLSX)

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Notes

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