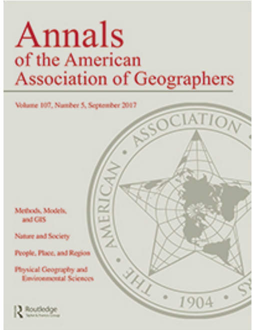

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Estimating Available Abandoned Cropland in the United States: Possibilities for Energy Crop Production

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Abandoned cropland (ACL) is often cited as a land resource on which to produce energy crops while reducing the negative impacts of broad-scale energy crop production; for example, carbon emissions from land-cover change and competition with food production. In contrast to marginal land, which refers to a set of biophysical and economic criteria usually imposed by experts or policymakers, the designation of ACL refers to a land-use decision by a land owner. As such, ACL is argued to be a more appropriate indication of land availability for dedicated energy crop production. Prevailing estimates of ACL in the United States vary widely due to inconsistent treatment of land-use conversions away from cropland and overreliance on remote sensing methods that measure land cover, even though ACL is a category of land use. This article develops and applies a replicable and flexible methodology to estimate available abandoned cropland (AACL) at the county level in the United States, which accounts for conversion of ACL to forest cover, urban development, or permanent pasture. Estimates of AACL are derived for two scenarios: (1) land abandoned between 1978 and 2012, which excludes lands with meaningful forest regrowth, and (2) land abandoned between 2007 and 2012, which corresponds to land-use constraints imposed by the Renewable Fuel Standard. Results show that 15.0 and 4.9 Mha of AACL exist in the United States in the two scenarios, respectively, amounting to between only 3 and 8 percent of total light-duty gasoline consumption in the United States. The policy implications of these findings and the need for future research are discussed. *Key Words: abandoned cropland, agriculture, biofuel, energy, land use.*

废弃农地 (ACL) 经常被引用作为生产能源作物同时降低大规模能源作物生产的负面冲击的土地资源; 例如土地覆盖变迁的碳排放和其与粮食生产的竞争。与经常由专家和政策制定者定义的生物物理及经济范畴的边际土地相反的是, ACL 是由土地所有者指派的土地使用决定。ACL 因此被认为是评估可用来生产能源作物的土地的更合适指标。尽管 ACL 是土地使用的分类, 但由于从农地转为其他用途的土地使用变更之测量方法不一致, 以及过度依赖测量土地覆盖的遥感方法, 使得美国盛行的 ACL 评估存在高度歧义。本文发展并应用一个可复製且具弹性的方法, 评估美国在郡县层级可利用的废弃农地 (AACL), 其中包含了从 ACL 变更为森林覆盖, 城市发展或是永久牧场。本研究为两个方案取得 AACL 之评估: (1) 在 1978 年与 2012 年间弃置的土地, 并排除有意义的森林再生土地; 以及 (2) 2007 年至 2012 年间弃置的土地, 并与由再生能源标准所施加的土地使用限制相符。研究结果显示, 在美国的两个方案中, 分别存在十五百万公顷与四点九百万公顷的 AACL, 等同于仅佔美国轻型石油总消耗的百分之三与百分之八。本文讨论这些研究发现的政策意涵以及未来研究的必要性。 *关键词: 废弃农地, 农业, 生质燃料, 能源, 土地使用。*

La tierra de cultivo abandonada (ACL) es a menudo referida como un recurso de la tierra en la cual producir cosechas energéticas, reduciendo al propio tiempo los impactos negativos de la producción de energía de origen agrícola a gran escala; por ejemplo, las emisiones de carbono generadas por el cambio de cobertura de la tierra y la competencia con la producción de alimentos. En contraste con la tierra marginal, que se refiere a un conjunto de criterios biofísicos y económicos usualmente impuestos por expertos o por legisladores, la designación ACL se refiere a una decisión sobre uso del suelo tomada por un propietario de tierras. Caracterizada de esa manera, la ACL es sustentada como una más apropiada indicación de la disponibilidad de tierra para la producción especializada de energía de origen agrícola. Los actuales estimativos de ACL en los Estados Unidos varían ampliamente debido al trato inconsistente de las conversiones de uso del suelo fuera de los campos de cultivo y por la excesiva dependencia en métodos de percepción remota para medir la cobertura del suelo, a pesar de que ACL es una categoría de uso del suelo. Este artículo desarrolla y aplica una metodología replicable y flexible para calcular la tierra de cultivo abandonada disponible (AACL) en los Estados Unidos a nivel de condado, que toma en cuenta la conversión de ACL a cobertura boscosa, desarrollo urbano, o pasturas permanentes. Los estimativos de AACL

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se derivan para dos escenarios: (1) tierra abandonada entre 1978 y 2012, que excluye tierras que exhiban una repoblación significativa con bosque, y (2) tierra abandonada entre 2007 y 2012, que corresponde a restricciones impuestas por el Estándar de Combustibles Renovables. Los resultados muestran que en los Estados Unidos hay 15.0 y 4.9 Mha de AACL en los dos escenarios, respectivamente, lo que equivale apenas a entre el 3 y 8 por ciento del total del consumo de gasolina para trabajo ligero en Estados Unidos. Se discuten las implicaciones políticas de estos descubrimientos y las necesidades adicionales de investigación. *Palabras clave: tierra de cultivo abandonada, agricultura, biocombustible, energía, uso del suelo.*

Concerns about the amount of land area that is required to produce a meaningful quantity of biomass for energy or fuel production (hereafter *energy crops*) underpin debates about whether bioenergy or biofuel systems are sustainable (Lynd et al. 2007; Tilman et al. 2009). Broadly speaking, these debates feature two issues: (1) environmental impacts such as habitat change and carbon sequestration as land is converted into energy crop production (Fargione et al. 2008) and (2) social impacts such as competition with food prices and large-scale land transfers from local subsistence to multinational corporations (i.e., land grabbing), most relevant to cases outside the United States (Nalepa and Bauer 2012). Further complicating the sustainability and acceptance of energy crop production is the potential for indirect land-use change, where land might be converted elsewhere to compensate for food crop production that was displaced by energy crop production (Searchinger et al. 2008). Yet, biomass is the only renewable resource that can provide base-load heat or electricity without complex storage systems; the only renewable resource from which to produce nonenergy products that are currently derived from petroleum (e.g., plastics); and the resource that is most likely to directly substitute for liquid fossil fuels in heavy-duty vehicles, shipping, and aviation in the near term. In this light, it is critical to locate and quantify land that might support energy crop production with minimal undesirable biophysical and social impacts (Calvert 2011).

It is widely believed that the impacts of energy crop production on land use and food systems can be mitigated if energy crops are produced on abandoned cropland (ACL; Kang et al. 2013; Milbrandt et al. 2014). Here, ACL is defined as land area that was once used for, or declared as, agricultural cropland but is no longer (considered to be) performing that function. In this sense, ACL is land that was once included within agricultural surveys, such as the U.S. Department of Agriculture (USDA) Census of Agriculture, and is no longer counted. Defined thusly, it is possible to estimate ACL using historical census data.

This article contributes to the conceptual, methodological, and empirical foundations of estimating land potential for dedicated energy crop production, using the United States as a case study. The article has four parts. First, the relationship between ACL and the concept of marginal land is discussed. Second, a review of existing estimates of ACL is undertaken. Building from this work, the article then develops a methodology for calculating the quantity of available abandoned cropland (AACL) at the county level in the United States. By AACL we refer to ACL that has not been converted to another active use such as urban development, forest cover, or permanent pasture. Before concluding, the implications for decision making on how results are visualized cartographically are discussed. In sum, the article argues that AACL is a more appropriate category than marginal agricultural land for quantifying and locating land that might support dedicated energy crop production with minimal social and ecological impacts. The United States is shown to have a small amount of AACL relative to the area of land required to supply meaningful amounts of biomass, although regional opportunities exist.

Distinguishing Abandoned Cropland from Marginal Land

It is widely believed that the impacts on land use and food systems from energy crop production can be mitigated if the latter are grown on marginal land (Gopalakrishnan, Negri, and Snyder 2011). Use of the label *marginal* to identify potential land areas for energy crop production has been criticized for several reasons. First, it lacks a standard, unambiguous definition. Richards et al. (2014) performed a review of fifty-one articles written between 2008 and 2012 that use the term marginal and found that only 53 percent of these articles provide an explicit definition, 31 percent provide an implicit definition that could be inferred from context, and 16 percent provide no definition at all. Ambiguity is further compounded by the fact that multiple terms are sometimes used interchangeably with marginal, including unproductive, waste, underutilized, idle, abandoned, degraded, unused, suitable, free, spare, set aside, fallow, additional, and appropriate (Kang et al. 2013; Shortall 2013).

Second, the conceptual and methodological ambiguity just reviewed leads to scientific deficiencies. Conclusions drawn by studies that attempt to locate and quantify marginal land differ significantly depending on how marginal is defined. Lewis and Kelly (2014) performed a study of twenty-one articles from 2008 to 2013 that illustrates the impact of such variability on estimates of marginal land. Their results include five examples from China where differences in definitions produced marginal land estimates ranging from 2.80 to 22.26 percent of China's total land area. Two of the most methodologically similar studies reviewed by Lewis and Kelly (2014) produced estimates of marginal land from 19.9 to 43.75 Mha. Most startling about this example is the fact that each study relied on nearly identical input data. In other words, assessments of marginal land do not provide a strong basis on which to make evidence-based policy.

The third issue with assessments of marginal land is the sociopolitical dimension. Politically, the lack of consensus around what defines land as marginal underpins actions by dominant actors (e.g., governments or corporations), who often allege that land being used for biofuel production is marginal without being transparent about the criteria used to classify land as such (Nalepa, Gianotti, and Bauer 2016). Even where criteria are stated, the classification of marginal is often imposed on a given plot of land from a distance for the purpose of implementing new land-use policies or attracting foreign investment as a way of (re)enrolling land into a formalized economy, without consideration of how local people actually use the land (Baka 2014; Nalepa and Bauer 2012). This might lead to social injustices such as the displacement and further marginalization of people who were using those so-called marginal lands for subsistence lifestyles (Nalepa and Bauer 2012; Baka 2014; Nalepa, Gianotti, and Bauer 2016).

In contrast to the more common category of marginal land, the ACL implies a temporal change in land use, not a static characteristic of land cover or productivity (Munroe et al. 2013). Although the classification of marginal is often imposed on land by expert analysts or governments (e.g., see Baka 2014; Milbrandt et al. 2014), ACL categorizes land according to a land-use decision by a land owner (i.e., to remove from formal agricultural production). Indeed, ACL is defined as land that was once used for, or declared as, agricultural cropland but is no longer supporting that function (see also Zaragozi et al. 2012; Milbrandt et al. 2014). In other words, our definition of abandoned is made in relation to formal agricultural practices and to agricultural census data. Furthermore, ACL does not imply unused land. It is likely that land removed from crop production is under a new active land use, such as pasture or urban development. As such, Zaragozi et al. (2012) argued that a dynamic approach is more appropriate by considering land to be abandoned "if there is no current land use despite a recent history of farmland use, normally declining, over [the] last 10 years" (125).

Although ACL is a more empirically straightforward land-use category, we do not mean to suggest that it is apolitical. On the contrary, the category ACL is wrapped up into the politics and political economy of land use, in the process of deciding to remove land from agricultural used, and in terms of the political motivations and implications of measuring ACL and how the results of such an assessment might influence land-based policy decisions such as the development of energy crops. In some spatiotemporal contexts, for example, ACL might emerge due to social conflict and fundamental political–economic reforms that lead to mass outmigration (Pazur et al. 2014). Researchers interested in locating and quantifying ACL for dedicated energy crop production should consider excluding ACL that has been abandoned for these reasons, because it is likely that under a peaceful set of conditions said land would be used for food production. Furthermore, key drivers of ACL are often socioeconomic in nature, including farmer demographics and emigration to urban areas by rural farmers (Rey Benayas et al. 2007). We reflect further on the upstream and downstream political implications of ACL in the conclusion of this article.

Given the challenges and implications of the use of marginal as the underlying concept to identify land for energy crops, this study proposes ACL as a more appropriate indication of land availability for dedicated energy crop production. Per Richards et al. (2014), ACL includes economic and biophysical factors shaping land cover and land use (see Figure 1). Abandoned agricultural land is in almost all cases economically marginal because it is no longer in production, which might relate to the fact that it is also biophysically disadvantaged relative to surrounding land but also to political–economic factors such as changing commodity markets, international competition, or the demographics of the land owner(s). As

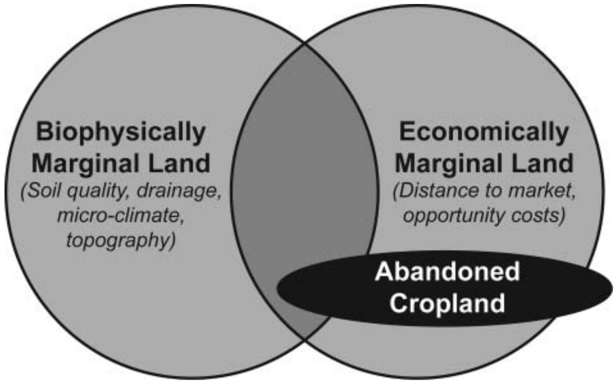

Figure 1. The definition of abandoned cropland within the biophysical and economic dimensions of marginal land.

indicated in Figure 1, ACL can be considered a subset of marginal land if one assumes that areas removed from active crop production are of a poorer quality than the lands remaining in production (see Pazur et al. 2014). Unlike the category of marginal, however, ACL relies on fewer imposed and ambiguous standards for measurement.

Literature Review: Estimating Abandoned Cropland

The process of identifying abandoned land is based on a temporal analysis of changes in agricultural activity in a given area or for a specific plot of land. There are two predominant approaches to estimating ACL: (1) remote sensing based and (2) land owner data based, derived from interviews and surveys. Although recent work has relied on a combination of these two, the distinction between remote sensing–based work and survey-based research is determined by the data used to generate historical timelines and maps of agricultural land use.

Ramankutty and Foley (1999a, 1999b) conducted studies of cropland change at both global and continental extents. Their map of cropland abandonment in North America is most pertinent to the study presented in this article. The authors built a hybrid approach to estimating ACL, combining remote sensing and agricultural survey data to produce a time series of cropland distribution. Historical cropland maps are produced by hindcasting from a baseline map for 1992. *Hindcasting* is the technique of extrapolating historical data patterns based on observations in a recent time period. The 1992 map was derived from the DISCover 1-km resolution land cover data set, and the results were aggregated at the five-minute (approximately 10-km) resolution (Loveland and Belward 1997). Agricultural land cover was represented as a fraction of each pixel. Linear interpolation was used to develop annual values of cropland from Census of Agriculture data that are collected every five to ten years. These values were used to adjust pixel fractions (Ramankutty and Foley 1999b). Using this method, Ramankutty and Foley (1999b) found that 81 Mha of cropland were abandoned in North America between 1850 and 1992.

Understanding historic land-use patterns by inference from current observations presumes the continuation of spatial patterns of cropland production and precludes capture of actual changes in land use that might occur beyond the extent of the 1992 cropland. In other words, the method would not be valid if it were replicated to generate estimates for present-day ACL. Second, and perhaps most important, 81 Mha is a gross total rather than a net total. This study does not explicitly account for conversions of ACL to developed, forested, or pasture land uses and is therefore an inadequate estimate of ACL that might be available for energy crop production.

Similarly, Campbell et al. (2008) developed a global map of abandoned agricultural land at the five-minute pixel resolution. The map was produced by calculating the change in agricultural areas between 1700 and 2000 using the HYDE land cover database. HYDE compiles estimates of agricultural acreage for counties and other regions from various sources and spatially allocates agricultural land cover by conforming to patterns of population density (Goldewijk 2001). To eliminate areas of agricultural abandonment that have converted to urban development or forest, Campbell et al. (2008) overlaid MODIS satellite imagery and removed pixels classified as urban or forest. The authors acknowledged that there is inherent uncertainty in this approach, specifically due to HYDE's use of population distribution to infer locations of agricultural activity and the potential bias that creates when using MODIS to exclude urban expansion.

A recent study by Lark, Salmon, and Gibbs (2015) exemplifies a remote sensing methodology for assessing cropland change in the United States. In this study, the Cropland Data Layer (CDL), a 30-m resolution land cover data set (U.S. Department of Agriculture National Agricultural Statistics Service [USDA NASS] 2015a), is used to classify land as crop or noncrop. Lark, Salmon, and Gibbs (2015) aggregated 107 unique cropland classes into a single crop class and twenty-seven unique noncropland classes into a single noncrop class. National-level CDL data sets from 2008 to 2012 were compared to measure the expansion or contraction of cropland over time.

Lark, Salmon, and Gibbs (2015) emphasized the difference between gross change and net change over the four-year period. *Gross change* is the sum of pixels that have changed to cropland plus the sum of pixels converting from cropland, whereas *net change* is the difference in the aggregated total cropland area between the two time periods. Recognition of the difference between these two measurements is important because the calculation of net change might undercount cropland abandonment in cases where land is abandoned in some areas but expands in different locations; for example, an area's net change might be zero when viewed in the aggregate (offsetting locations of cropland gain and loss), but its gross abandonment of cropland might be positive when viewed as the sum of individual pixels. Lark, Salmon, and Gibbs's results show a net increase of cropland area of 1.2 Mha from 2008 to 2012 and a gross abandonment of cropland of 1.76 Mha over the same period.

As a remote sensing–based study, the results from Lark, Salmon, and Gibbs (2015) have two shortcomings. First, remote sensing platforms do not unambiguously distinguish between natural grassland, pastureland, and certain forage crops (Nalepa and Bauer 2012), whereas this distinction would be explicitly documented in a census or survey. For this reason, Lark, Salmon, and Gibbs (2015) aggregated the classes grassland/pasture, pasture/hay, and other hay/nonalfalfa into their noncrop land class, despite the fact that some of those areas are most certainly cropland. This limitation might overestimate the amount of grassland that is being displaced for corn production (because pasture land is often converted to corn production due to market conditions, and this conversion might be mistakenly interpreted as grassland-to-corn). Second, remotely sensed data sets currently lack time series adequate to conduct historical trend analyses. Although they enable a calculation of gross change in recent years, they are unable to capture long-term trends that are observed by the U.S. Census of Agriculture over decades. To make assessments for earlier time periods would require the use of proxy data or extrapolations that could introduce error and uncertainty.

In contrast to remote sensing–based methodologies, survey- and questionnaire-based approaches rely primarily on data directly from land owners, who directly provide data regarding their use of land. The analysis by Zumkehr and Campbell (2013) exemplifies such an approach. Zumkehr and Campbell collected historical cropland data from Waisanen and Bliss (2002), which includes county-level values of total cropland in production for every five to ten years dating back to 1850; this data source is based on information from surveys such as the U.S. Census of Agriculture and the U.S. Census of Population and Housing. Zumkehr and Campbell calculated a gross estimate of ACL based on the difference between the current land in crop production in a given county (where current refers to the year 2000 for the purpose of their study) and the maximum amount of land in crop production in any year since 1850. A map of cropland distribution as of 2000, based on the remote sensing–derived land cover classification from Ramankutty et al. (2008), is used to represent the spatial distribution of cropland, which is assumed to represent historical patterns as well. County-level cropland data are downscaled to a grid of five-minute (approximately 10-km) pixels and then allocated to the land-cover map using the hindcasting methodology from Ramankutty and Foley (1999b). To account for forest regrowth and urban expansion, MODIS satellite imagery are used to remove areas (at the five-minute grid cell level) that are classified as forest or developed. This approach estimates that, as of the year 2000, 45 Mha of ACL in the United States are available for energy crop production.

Although Zumkehr and Campbell (2013) began their assessment with survey data, their final results are strongly dependent on the spatial overlay of remote sensing data with historical cropland. Any inconsistencies or errors in classification or spatial allocation of cropland will affect the accuracy of these calculations. Furthermore, this study does not account for conversion of pasture to cropland, and vice versa, even though land often converts between these two categories. Across the United States, for example, between 1997 and 2012 the total national area of cropland decreased by 22 Mha and the area of permanent pasture increased by 7 Mha (USDA NASS 2015b). It is likely that most or even all of the pasture increase is due to a direct conversion from cropland rather than the conversion of another land use such as forest, grassland, or developed. Accordingly, to make a conservative estimate of the amount of usable ACL, the amount of increase in pasture should be removed from the estimate of ACL.

The preceding discussion illustrates that methodological choices have a profound impact on results. Key choices to consider are (1) determining the timescale across which to consider changes in land use, (2) accounting for the regrowth of vegetation and storage of carbon on lands that have been abandoned from active agricultural production, (3) accounting for the conversion of agricultural land to developed urban land uses, and (4) accounting for the conversion of cropland to and from pasture. The remainder of this article presents a new methodology and results for the estimation of AACL in the United States. This methodology builds on the distinction between gross and net abandonment established in Lark, Salmon, and Gibbs (2015) introduces greater flexibility in the timescale that can be considered and how vegetation regrowth is estimated; and accounts for the conversion of cropland to pastureland.[1]

Data and Methods

Two scenarios were constructed in this study to guide estimates of ACL. The scenarios differ temporally. In the first scenario, we limit our time period to thirty-four years prior to the present day to avoid including abandoned agricultural land that would have had time to develop a mature forest cover. This is referred to as our *carbon constraint* scenario, because the final estimates of available ACL are constrained by an attempt to limit the carbon debt that would be incurred due to large-scale conversion of forest to energy crops (Fargione et al. 2008). In the second scenario, we include only those lands that have been abandoned since 2007, to be consistent with rules set out in the Renewable Fuels Standard (RFS2). This is referred to as our *regulatory constraint* scenario. In both scenarios, data on agricultural land use are collected from land owners in agricultural surveys executed and published by the USDA, and remote sensing data are used to locate and exclude areas that have converted to urban development and permanent pasture to arrive at a value of AACL. Estimates are provided at the county level for the contiguous United States.

To estimate AACL, we follow the logic set out by Equation 1:

$$AACL_i = \max_{(pd-x)\leq t\leq pd}\left(TCL_{i,t}\right) - TCL_{i,pd} - UC_i - PC_i, \quad (1)$$

where $AACL_i$ represents the calculated AACL for each county (i), and $\max TCL_{i,t}$ represents the maximum total cropland in production for county i in any year t that occurs between present day and a historical limit of year x. The historical limit is set at 1978 for our carbon constraint scenario and 2007 for our regulatory constraint scenario. $TCL_{i,pd}$ represents the total cropland area in production for county i in the present day pd, which is set at the date of the most recent agricultural census (in this case, 2012). UC and PC represent the quantity of ACL estimated to have been converted into urban development and permanent pasture, respectively. These are derived at the county level (not the pixel level based on interpretations of satellite imagery).

The sequence of subtractions described in Equation 1 can be subdivided into incremental equations describing each step. The first step calculates the total abandoned cropland ($TACL$) by subtracting the current cropland area from the historical maximum cropland area (Equation 2).

$$TACL_i = \max_{(pd-x)\leq t\leq pd}\left(TCL_{i,t}\right) - TCL_{i,pd}. \quad (2)$$

The primary data source to estimate total cropland over time is the U.S. Census of Agriculture. Historical cropland area data are derived from Waisanen and Bliss (2002), who produced a county-level compilation of population and agricultural data from 1790 to 1997. These data are updated using U.S. Census of Agriculture reports for the years 1997, 2002, 2007, and 2012 (USDA NASS 2015b), by extracting only total cropland and permanent pasture values. Total cropland is represented by the entire circle labeled cropland in Figure 2 and contains the subcategories of harvested cropland, cropland used for pasture, and other cropland. Our definition of permanent pasture excludes pastured woodland, most notably cropland used for pasture, which would be double-counted if included. Because historical data on pastureland are not included in the Waisanen and Bliss data set, a digital archive of the 1978 Census of Agriculture was obtained from the Cornell Institute for Social and Economic Research (CISER; U.S Census Bureau 1978).[2]

To avoid counting cropland that has been reforested for our carbon constraint scenario, this study sets the historical limit of analysis to thirty-four years (1978–2012), which is a generic national estimate and does not reflect region-specific growth rates, thus presenting an opportunity for future research. The thirty-four-year time frame applied in this research is chosen based on general forest growth rates found in the literature. Observed patterns of net primary production

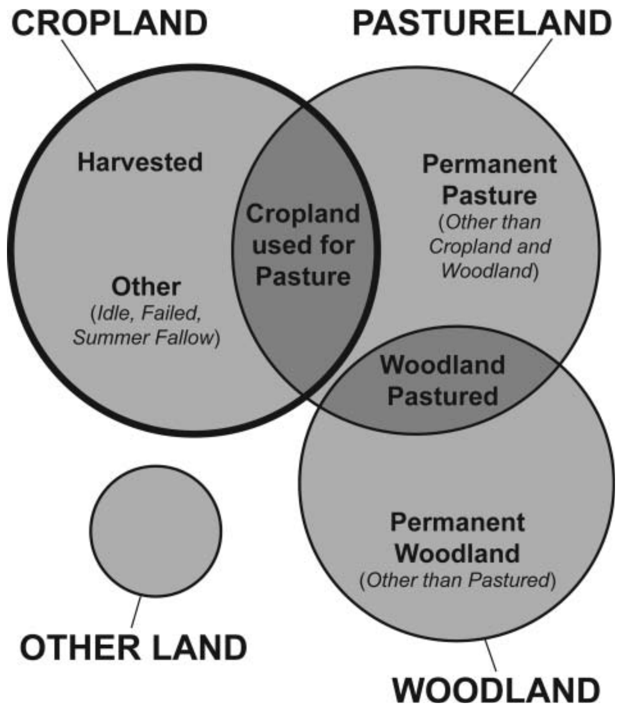

Figure 2. The intersections of variables defined in the U.S. Census of Agriculture. The dark outlined circle labeled *CROPLAND* is the primary data category used in this study to assess cropland abandonment.

and carbon accumulation of vegetation regrowth after a disturbance or deforestation generally show trees as the dominant vegetation type after thirty or forty years (D. P. Turner et al. 1995; Chapin, Matson, and Vitousek 2002). These generalized patterns of forest regrowth, although certainly not accurate for every species, region, and local condition, provide guidance for developing a single value to apply at the county level across the United States that presumably results in a conservative estimate of forest regrowth. The specific thirty-four-year window is chosen because it represents a year of Agricultural Census data collection and falls squarely within the previously mentioned time frame, at which trees start to become the dominant vegetation type. Developing region- or locality-specific vegetation growth rates is beyond the scope of this article and challenging due to the "interactions among multiple mechanisms," including the variability in intensity of a disturbance or land-cover change and the variability or the abiotic conditions and composition of the developing plant community, factors that are variable across much smaller spatial extents than the county-level scale of this article (M. G. Turner et al. 1998).

Our second scenario sets the historical limit of analysis to 2007 to derive an estimate that is in compliance with the RFS. Rules set out under the RFS preclude the issuance of credits for biofuels derived from crops that were grown on land not in agricultural production as of 2007 (Environmental Protection Agency 2010). In other words, biofuels generated from biomass grown on land that was abandoned prior to this date would not be eligible for production credits. These rules are trying to limit the conversion of land to energy crops to only those areas that were in agricultural production sometime since 19 December 2007 to avoid undesirable land-use change consequences that could negate the benefit of the intended energy crops.

To account for immutable land-use conversions postabandonment, such as to urban development and barren wasteland (e.g., quarries), the National Land Cover Database (NLCD) is utilized (Homer et al. 2015). The NLCD is unique in that it is a 30-m resolution land cover data set for the entire United States and contains the specific classes of agriculture and urban development required for this analysis. This permits the spatially explicit identification of locations that convert specifically from cropland to urban development or to other uses. More specifically, agriculture is represented by two classes, cultivated crops and pasture/hay. Based on the definitions of these two classes, it is determined that the pasture/hay class more closely aligns with the Census of Agriculture category of cropland than permanent pasture. As pointed out by Laingen (2015), a class called hay might be considered grassland if viewed as a land cover but would be viewed as cropland if viewed as a land use. Laingen's results also show that the combined NLCD classes of cultivated crops and pasture/hay are comparable to total cropland in the Census of Agriculture, which is the primary data value used in this study. Consequently, cultivated crops and pasture/hay are both combined and treated as cropland.

The quantity of land converting to an urban land use (UC) is calculated by observing changes between the raster data sets of the 2001 and 2011 NLCD.[3] First, a new data set is created by selecting all pixels that transitioned from cultivated crops or pasture/hay to developed or barren classes. Second, a new data set is created by selecting all pixels that transitioned from cultivated crops or pasture/hay to any class. A zonal statistics function is applied to the new raster data sets to aggregate all selected pixels within each county and populate two new county attributes, which contain the number of pixels transitioning from agriculture to developed or barren ($pixels_{AGtoDEV}$) and the number of pixels transitioning from agriculture to anything

($pixels_{AGtoANY}$). The attributes are divided to derive for each county (i) the fraction of its ACL that converts to an urban or barren land use versus any land use, setting any undefined values to zero (Equation 3).

$$UC_i = pixels_{AGtoDEV,i} \div pixels_{AGtoANY,i}. \tag{3}$$

These fractions are multiplied against TACL to derive the quantity of ACL that is estimated to have converted to a developed land use, and that area is then subtracted from TACL. The assumption is made that the fraction of urban conversion calculated for the time period of 2001 to 2011 is representative of the time period of the entire study, 1978 to 2012. We discuss the validity of this assumption in the Results section.

The final step is to remove ACL areas estimated to have converted to a permanent pasture land use, thereby accounting for the interaction between pasture and cropland that previous studies have ignored. Agricultural census data are used to calculate county-level changes in pastureland area rather than land cover data sets, which are based on the interpretation of remote sensing images and have notoriously poor accuracy in the differentiation between pastureland and cropland and other grasslands. The assumption is made that an increase in permanent pastureland in a given county will occur at the expense of cropland. Accordingly, an observed increase in permanent pastureland over the time period of analysis, 1978 to 2012, is deducted from the estimate of ACL. This generates a more conservative estimate of AACL, as some new pastureland likely comes from noncropland areas. The total area of permanent pastureland (TPP) in 1978 is subtracted from the permanent pasture figures reported in the 2012 NASS (USDA NASS 2012) data tables to calculate PC for each county (Equation 4).

$$PC_i = TPP_{i,2012} - TPP_{i,1978}. \tag{4}$$

The value for PC is then subtracted from each county's TACL to derive the quantity of ACL that is ultimately available for the production of energy crops. Conversion of cropland to pasture is assumed to be indicated by the total increase in permanent pastureland during the study period.

Results and Discussion

Estimates of AACL

The scenarios constructed in this study evaluated land change over the time periods from 1978 to 2012 and from 2007 to 2012, respectively. The results show 15 Mha of AACL in the United States under the first scenario and 4.9 Mha under the second scenario. These estimates differ from those in other similar studies (see Table 1). Disagreement with Ramankutty and Foley (1999b) is likely due predominantly to the fact that Ramankutty and Foley incorporated cropland area figures dating back to 1850, when much more land was in production, and including all of North America. Furthermore, the Ramankutty and Foley methodology does not adjust for potential conversion of cropland to developed, forested, or pasture uses. The study by Lark, Salmon, and Gibbs (2015), on the other hand, presents a much smaller estimate of AACL of 1.76 Mha in the United States. Again, much of the disagreement with this study's estimate is due to differences in the time period under consideration. Lark and colleagues only included the years between 2008 and 2012, which corresponds better with this study's regulatory constraint scenario. A second significant difference between these two studies is

Table 1. Liquid fuel production from switchgrass grown on different estimates of abandoned cropland and the percentage of the total U.S. demand for various fuel sectors each would offset

	Time frame	Area (Mha)	Millions liters	% Total	% LDV	% Aviation	% Ethylene
Baxter and Calvert, Scenario 1	1978–2012	15	38,648	6	8	81	39
Baxter and Calvert, Scenario 2	2007–2012	4.9	12,834	2	3	27	13
Ramankutty and Foley (1999b)	1850–1992	81[a]	170,100	25	36	358	174
Lark, Salmon, and Gibbs (2015)	2008–2012	1.76	3,696	1	1	8	4
Zumkehr and Campbell (2013)	1850–2000	45	94,500	14	20	200	96

Note: Total = total liquid transportation fuel; LDV = light duty vehicles; Aviation = aviation fuel; Ethylene = chemical production.
[a]Estimate for North America; all other estimates for the United States.

the reliance on agricultural census data versus remote sensing land cover data as the primary data source.

In contrast, the source data for historical cropland used in both Zumkehr and Campbell (2013) and this study are the same. Yet estimates of the national quantity of ACL differ significantly. Disagreement is due to three primary factors. First, Zumhehr and Campbell extended their historical view to 1850, relative to this study's limit of thirty-four years. Second, Zumhehr and Campbell accounted for forest regrowth by overlaying a spatially explicit map of ACL, at a five-minute resolution, with current land cover map derived from satellite imagery. This introduces two sources of error: first, the process of downscaling of county-level cropland totals to five-minute grid cells and, second, the interpretation of satellite imagery to delineate forest areas and the assumption that said areas can confidently be overlaid with the downscaled cropland areas. Finally, Zumkehr and Campbell did not account for pasture conversion in their calculations, which likely results in higher estimates of ACL availability.

This study is both a complement to Zumkehr and Campbell (2013) and, we argue, an improvement. The studies are complementary because, on one hand, both use the same record of historical cropland production and, on the other hand, Zumkehr and Campbell relied on remote sensing to develop initial cropland distribution maps, and this study relies on survey data to develop spatial distributions. This addresses the fundamental methodological contrast between remote sensing approaches and surveys to investigate land use and the pros and cons of each. The remote sensing approach allows for a higher spatial resolution (five-minute pixels) than the survey approach (counties); however, arguably the survey approach results in more accurate data because it directly measures land use, whereas the remote sensing approach measures land cover, from which land use must be inferred. This study improves on Zumkehr and Campbell (2013) fundamentally because of their reliance on remote sensing data sets for several purposes: to (1) initially classify a map of current cropland areas; (2) spatially distribute current and historical cropland areas, making the assumption that historical patterns of agricultural land use are the same as those today; and (3) exclude areas that are forested or developed. This study uses remote sensing data to adjust for urban expansion in a novel manner, but the core data and spatial distributions of cropland are based directly on surveys of agricultural land use, which avoids the inherent uncertainties of remote sensing and its derived classifications. Consequently, this study is a methodological improvement of the assessment of cropland abandonment by relying directly on local knowledge of land use rather than a more technocentric approach of relying on inference from remote sensing platforms.

Energy Crop Production Potential on AACL

To what extent might AACL in the United States contribute to growing energy needs? To answer this question, energy crop production potential on AACL is estimated using average county-level switchgrass yields, calculated using the Wullschleger et al. (2010) model. The Wullschleger model is based on a compilation of observations from field trials across the United States and defines yield as a function of annual average temperature, growing season precipitation, and nitrogen fertilization. A continuous 800-m resolution raster data set of temperature and precipitation was obtained from the PRISM Climate Group (2015). Two rasters were extracted containing thirty-year average annual temperature and thirty-year average growing season precipitation (April–September). For each pixel, the temperature and precipitation values were supplied as inputs to the switchgrass model to calculate yield. A zonal statistics function was applied to aggregate the pixel-level values into county-level yield averages. Multiplying each county's average switchgrass yield by its area of AACL generated a county-level map of potential switchgrass production.

The results from this study indicate that under the regulatory constraint scenario, only 2 percent of U.S. transportation fuel demand could be replaced by cellulosic ethanol produced from switchgrass on AACL (Table 1). Values in Table 1 are estimated using generic estimates of 10 Mg of switchgrass per hectare and 210 liters of fuel per dry ton of switchgrass. This figure increases to 6 percent under the carbon constraint scenario. Although insignificant relative to total fuel consumption in the United States, AACL might provide a basis for specific sectors. For example, energy produced on this ACL could account for 81 percent of the aviation fuel consumed in the United States. This indicates that decision makers might want to look not only at the total production numbers but also at how they relate to different downstream uses that might be perceived as more appealing, feasible, and meaningful.

Urban and Pasture Conversion

The distribution of pasture increase between 1978 and 2012 is shown in Figure 3. The highest concentrations of pasture land expansion are found in Texas and extending northeast into Missouri. Additionally, individual counties with high densities of pasture land are scattered across the Western plains. Low densities of pasture expansion occur in the Cotton Belt, the Dakotas, and south of the Platte River and correspond to areas of high ACL density. This suggests that such areas are losing cropland and lack the incentives to replace the crop production with pasture operations.

Estimates of AACL in this study are conservative in part because of the assumption that any increase in pasture is a result of decreasing cropland. It is possible that some new pasture production occurs on land not previously in crop production by, for example, converting grassland or forest land. It is difficult to determine from available data, however, the fraction of pasture increase that is responsible for decreases in other specific land types, and this study assumes that the most common land interaction with pasture is the conversion to and from cropland.

Furthermore, pasture area totals are subject to changes in definitions of pastureland in the Census of Agriculture over time (particularly prior to 1978, which is outside the scope of this study's analysis) as well as privacy issues. For example, 99 percent of the land area in Kenedy County, Texas, is reported as permanent pastureland in the 2012 Census of Agriculture, but no value is reported in the 1978 Census. This results in the calculation 369,188 ha of pasture increase between 1978 and 2012. It is very likely, though, that there was pasture in production in 1978, but due to the requirements to protect respondent confidentiality the value was suppressed in the 1978 Census report.

Estimates of cropland conversion to urban development are shown in Figure 4. Values of UC vary from county to county, ranging from zero in some areas to 100 percent in others, where urban and suburban expansion rates are high. A simple average of county-level fractions of ACL transitioning to a developed land use is approximately 38 percent across the entire United States, and when weighting the values by each county's area, the national average is 30 percent. Areas of high fractions of conversion from cropland to development are, not surprisingly, found in regions of high population—the Northeast, Pacific Coast, and Rust Belt—in addition to isolated pockets around urban centers, such as Salt Lake City, Denver, and Houston. Prominently low fractions of conversion are visible in the Cotton Belt region in the southeastern United States, which likely helps to explain why there is a relative abundance of AACL in that area.

The calculated fractions of conversion of cropland to urban development play a significant role in the estimates of AACL. Accordingly, these numbers were

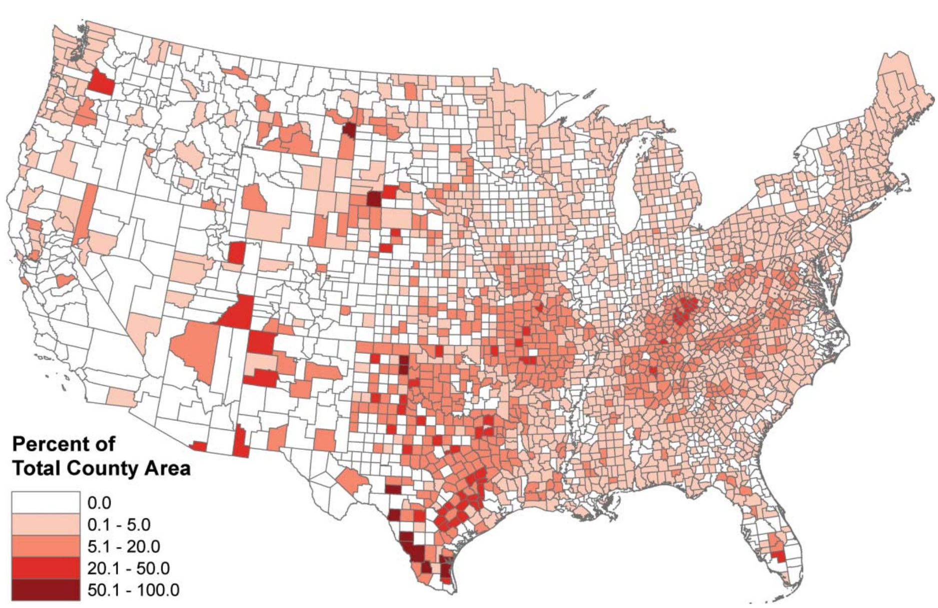

Figure 3. Pasture area increase between 1978 and 2012 presented as a density of total county area. (Color figure available online.)

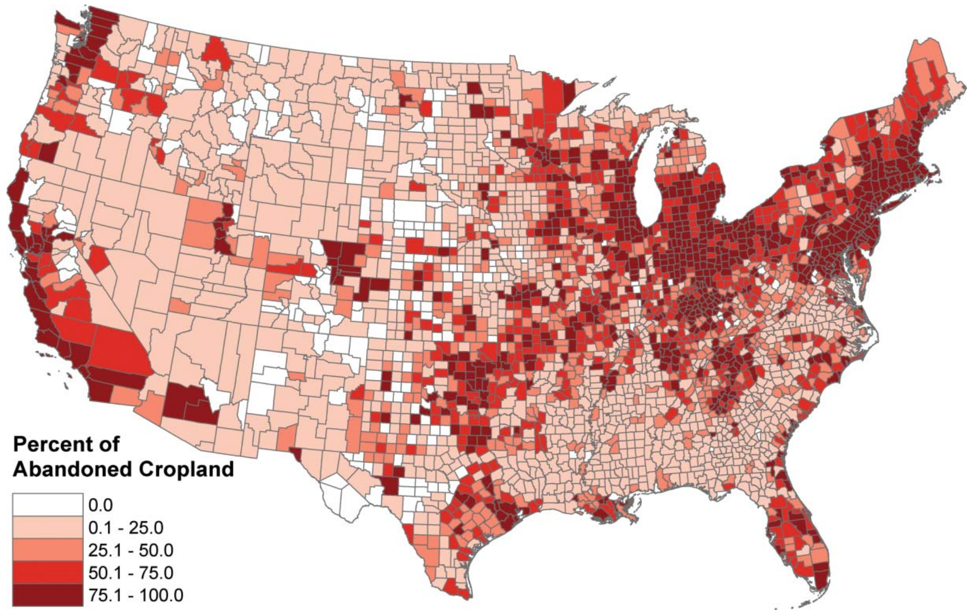

Figure 4. Fraction of abandoned cropland area that transitioned into a developed or barren land use between 2001 and 2011. The national average weighted by county area is 30 percent. (Color figure available online.)

validated against other data sources to assess confidence in the results. Validating this result is challenging primarily because county-level data for agricultural conversion to urban development do not exist nationwide. The USDA National Resources Inventory (NRI; USDA 2013) provides the best data source available to validate the calculations of urban conversion. The NRI is a survey of sampled locations nationally that is administered primarily every five years. Land cover and land use classes are identified by the NRI survey, including cropland, CRP land, pastureland, rangeland, forest land, other rural land, developed land and water areas, and federal land. To most closely align with the classification scheme used in the NLCD and the Census of Agriculture, the NRI classes of cropland, CRP land, and pastureland are combined and treated as cropland. Urban conversion fractions are calculated from the NRI data by summing the area converting from cropland, CRP land, and pastureland to developed land and dividing it by the sum of cropland, CRP land, and pastureland converting to anything (Table 2). These numbers illustrate a reasonable agreement with the urban conversion fraction calculated from the NLCD. Differences could be due to the different methods used to classify land as cropland versus pastureland, the fact that NRI is a sampled data set, the fact that the NLCD is based on the interpretation of satellite imagery, or the manner by which data are aggregated into a national average.

Spatial Patterns of AACL

Figure 5 illustrates the spatial distribution of the AACL in both the 1978 to 2012 and 2007 to 2012 scenarios. The regulatory constraint results present a subtle spatial pattern; AACL is distributed relatively evenly across the country, with counties of higher concentrations scattered across the middle of the country in a band spanning from the Canadian border to Texas. The carbon constraint scenario, on the other hand, reveals a distinct spatial pattern

Table 2. Estimates of the fraction of cropland converting to urban development based on analyses of the National Land Cover Database and National Resources Inventory over different time periods

	NLCD 2001–2011	NRI 1997–2002	NRI 2002–2007	NRI 2007–2010	NRI 1982–2010
Fraction of cropland converting to development	0.30	0.22	0.26	0.24	0.27

Note: NLCD = National Land Cover Database; NRI = National Resources Inventory.

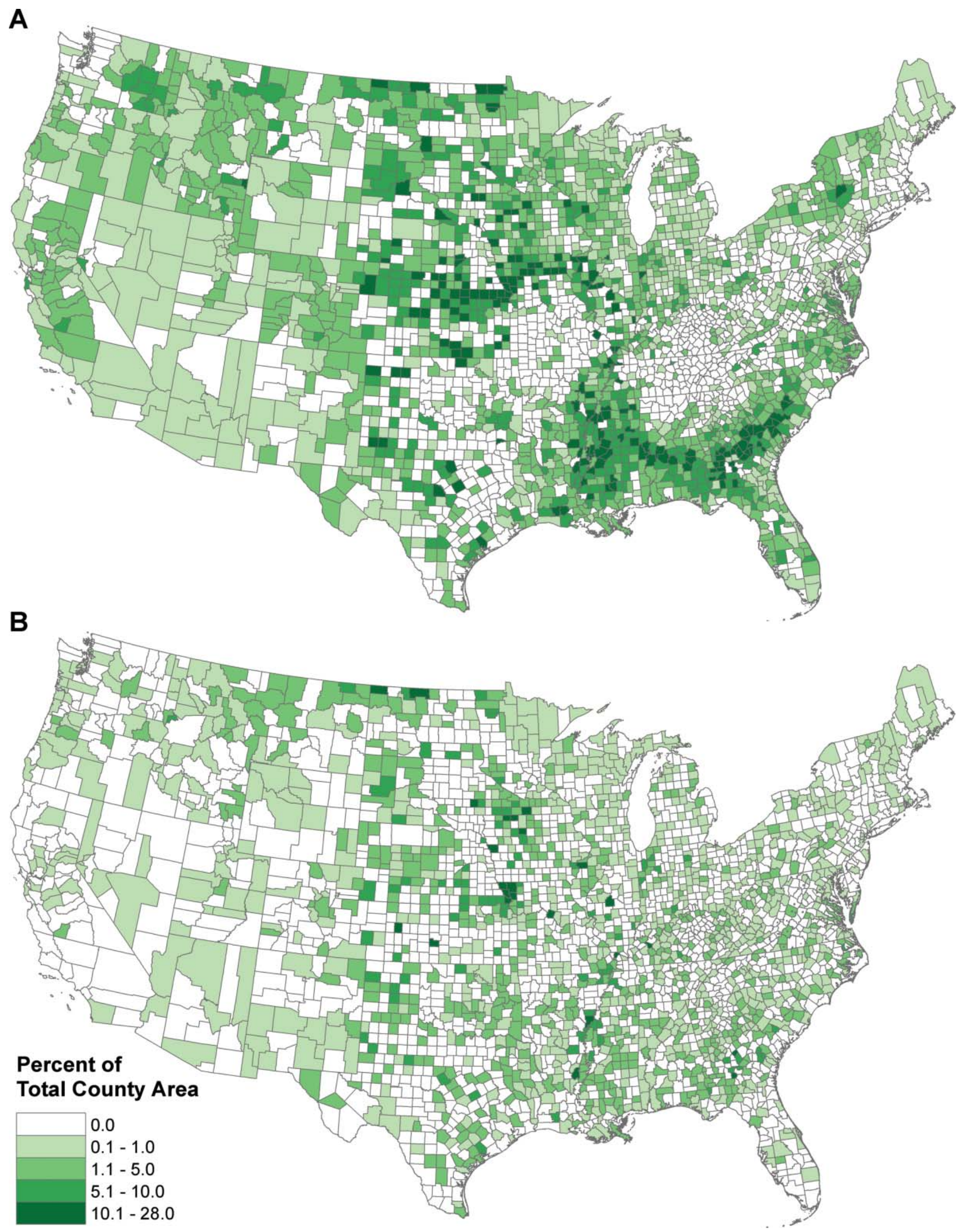

Figure 5. Available abandoned cropland presented as a density of total county area. (A) Scenario 1 (1978–2012). (B) Scenario 2 (2007–2012). (Color figure available online.)

in the distribution of AACL. A concentration is visible in a crescent following the historic Cotton Belt in the southeastern United States, and high concentrations are visible along the lower Mississippi River, near the Missouri River in the Dakotas, and south of the Platte River in Nebraska and Kansas. It is likely that regions with high concentrations of AACL are those where economic conditions are not able to support existing agriculture and also not sufficient to spur new active use of the land, either as urban development or as pasture. Future work will study explanations of cropland abandonment and their persistence in greater detail.

Spatial data can be visualized and communicated to decision makers in many ways, and the choice of visualization method can have impacts on the conclusions drawn from the information. Furthermore, certain visualization options might be better suited for one audience than another. In the case of AACL, four visualizations of the 1978 to 2012 scenario are presented in Figure 6. Figure 6A is a straightforward presentation of the county-level values of AACL in hectares. Although a common approach, presenting total values can be misleading. This is due to the fact that counties with a large spatial area are likely to have more hectares of cropland in them simply because of their size and their aggregation of many small values. Consequently, large counties often appear darker, suggesting high potential for energy crop production, despite the fact that such counties might be largely devoid of cropland. To correct for this phenomenon, values are normalized in Figure 6B, by dividing each county's total value by the county's area to derive density values. For example, Elko County in northeast Nevada displays high amounts of AACL in Figure 6A, but when normalized by area in Figure 6B, the county's lighter shading is more representative of the sparse concentration and relatively low quantity of ACL.

On the other hand, the agricultural community often presents crop commodities and production distributions as a density of total cropland area, rather than a density of total county area (Figure 6C). This data visualization might be more familiar to an agricultural sciences audience but conveys a different message than the other maps. Nevada, Arizona, and New Mexico provide a good example of this, as much of the states appear to have high values. In reality, all values are quite low, but the proportion of ACL to total cropland is high because there is little total cropland to begin with. Finally, data can be presented as total hectares in the form of a dot density map, as shown in Figure 6D. This is also a common visualization method in the agricultural community. This technique allows for the display of total hectares without normalization and would be familiar to individuals who interact with crop production maps often seen in USDA reports. Dot density maps are an effective way to see general distribution patterns but can be a poor tool for deriving values for particular locations.

The audiences for the results of this study are not necessarily agricultural scientists or farmers. Rather,

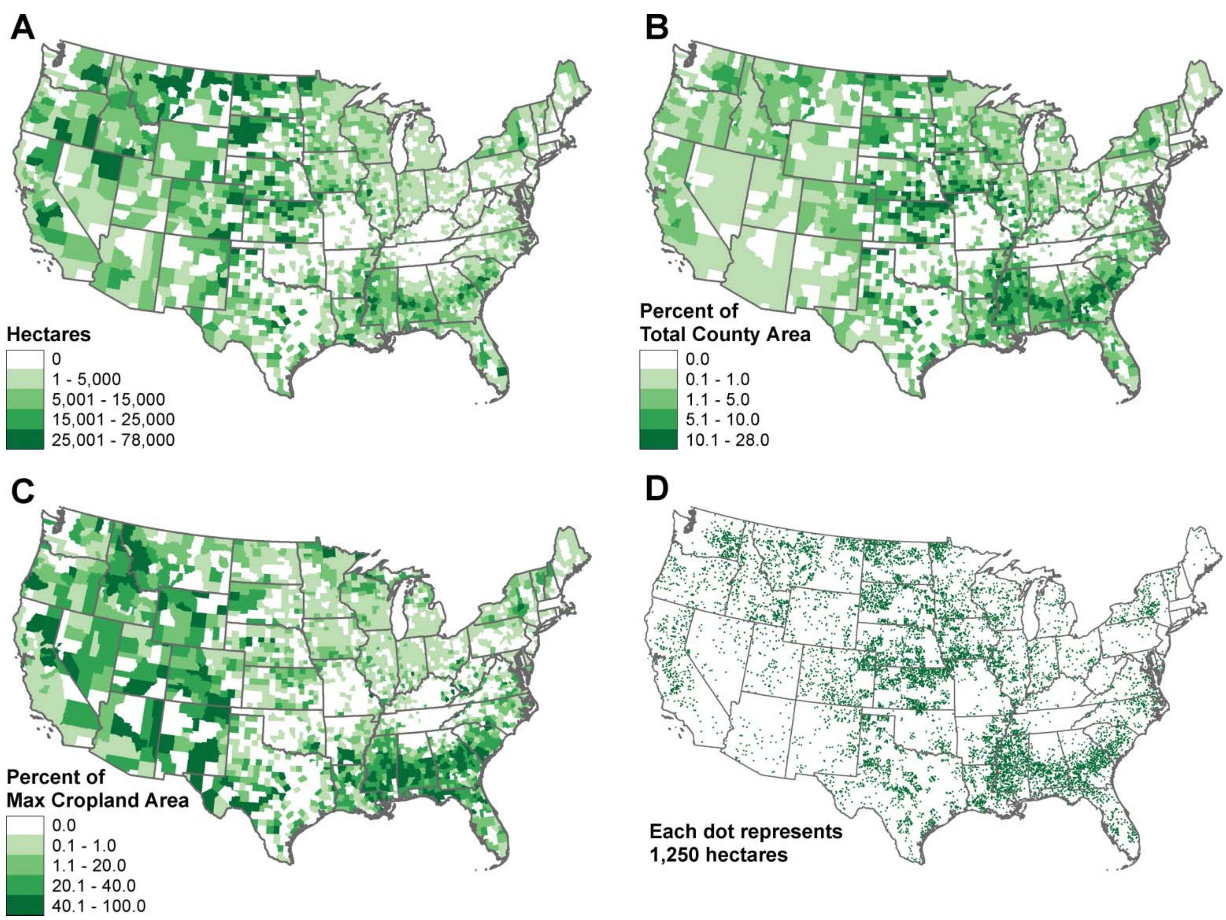

Figure 6. Available abandoned cropland (1978–2012) visualized using four different methods. (A) Total hectares. (B) Density of total county area. (C) Density of maximum cropland area. (D) Dot density. (Color figure available online.)

these results are primarily intended to inform policy decision makers and government officials who operate at a broad scale and make determinations of the value in enacting regulations to pursue the generation of energy crops. Accordingly, it is most relevant to present land resource totals as a density of total county area, so policymakers can see what regions of the country might be most productive and where the greatest concentrations of available land are located. The other visualizations might be valuable for the agricultural community to assess the relative contribution of ACL to other agricultural activities, but they might be less appropriate for broad-scale energy policy decisions.

Conclusion

Estimates of AACL are useful for any number of rural policy domains (e.g., socioeconomic, land use), including energy policy. Differences in estimates of AACL have important policy implications. For example, regional and national energy policies might be recommended or legislated based on production potentials communicated by the scientific community. In this case, policies related to the production of energy crops might be implemented, or not, based on whether there is a meaningful amount of land available and ultimately whether there is the potential to make significant contributions to energy demands. Our literature review and analysis illustrates the sensitivity of ACL estimates to slight changes in data input and methodology. This variability can have serious consequences on the claimed contributions this energy feedstock can make to different energy sectors and, ultimately, the decisions that are made on energy policy. Developing confident and accurate estimates of AACL is therefore critical.

This study develops and applies a methodology to estimate and map AACL across the United States at the county level. In the context of critiques of studies based on the classification of marginal land, our analysis focuses on abandoned agricultural land given that this classification is based on land owner decisions in the context of an agricultural census. Building on previous efforts in this body of work, the methodological framework is flexible in terms of the timescale of analysis, enabling customized scenarios. The framework is also easily replicable; as new data are released by the Census of Agriculture and the NLCD, new urban conversion fractions can be developed, pasture conversion amounts updated, and final results refined. All of these features stand as improvements to previous studies and are useful for decision makers when comparing trends over time or evaluating different policy environments, such as relaxed rules on the use of ACL for energy crop production.

The study in its current form has important policy implications at the nexus of energy, agricultural, and land-use policy. The carbon constraint scenario developed in this study suggests that 15 Mha of AACL is available. When considering limitations on the use of AACL for energy crop production set by the RFS in the regulatory constraint scenario, the area of AACL is reduced to 4.9 Mha. Although potentially significant at regional scales, these numbers are not significant at national scales, as they could potentially supplement only 3 to 8 percent of total light duty gasoline consumption. Discussions about the potential of abandoned or surplus agricultural land to provide meaningful amounts of renewable fuel at a national scale should be tempered by these results. That said, the existing quantity of AACL might be capable of producing enough biomass to support specific sectors, such as aviation or ethylene, and future policy might consider targeting biofuel production at these sectors and in regions with a relatively high concentration of AACL.

A notable limitation of this methodology, as with all of the estimates of ACL to date, is the lack of ground-truthing. Indeed, ground-truthing land-use estimates at a national level is not practical. The results of the study should be interpreted as back-of-envelope estimates for the purpose of making strategic decisions at the national level. To be useful to local land managers or prospective biofuel producers, these results should be used at a screening or prefeasibility level and complemented by more detailed site-level visits within a given county.

To arrive at estimates of AACL, this study relies on the U.S. Census of Agriculture. Although census forms enable the land owner to make some declaration of categorization of land, it is inherently limited in two ways. First, it is an instrument of government that ultimately simplifies an otherwise complex landscape and land-use decision-making process. Indeed, governmental classifications of land can sometimes be at odds with the realities of how land is envisioned or used locally (Baka 2016; Nalepa, Gianotti, and Bauer 2016). The Census of Agriculture's dichotomy of cropland versus noncropland, for instance, has the potential to ignore other land uses that might occur in noncropland areas. This study explicitly address noncropland uses of urban development, pasture, and forest but might miss other activities, such as parkland creation or symbolic importance that land owners might not be able to communicate through the Census of Agriculture. Renewable energy production is just one of many economic and ecological services AACL might provide. Existing AACL also provides opportunities for habitat, carbon sequestration, and recreational areas. As we have learned in other geographic contexts, imposing particular value systems on land resources, in this case a notion of abandoned and therefore suitable for industrial bioenergy and biofuel production, can establish the basis for their reappropriation into an extractive industry with negative consequences for local people (Baka 2014; Hesse, Baka, and Calvert 2016).

Second, there is a political ecology and a micropolitics to land-use classifications that are not reflected in the agricultural census. Decisions to remove land from agricultural production are wrapped up in broader political and economic trends; for example, the shift to intensive agriculture that increased yields on the most productive lands and the globalization of food production systems, which shifts production to the cheapest production zones. Abandoned agricultural land can therefore be considered an outcome (or a symptom) of synthetic fossil fuel–based fertilizer use and global cash-crop production rather than as a solution to these problems. Furthermore, the growing trend toward farming on rented lands in the United States introduces a separation between land owner and land user that is not accounted for when land use is determined on the agricultural census.

Acknowledgment of the political–economic trends shaping land-use decisions in the United States, along with potential landscape value conflicts underpinning abandoned agricultural land, affirms the need to recognize this type of study as a broad-scale assessment of land development opportunities that still requires a local-scale analysis and further integration of qualitative studies. Future research should not only aim to understand and explain the spatial pattern and persistence of agricultural land abandonment but should also seek to understand how land owners, land managers, and the public at large envision these land resources in the context of the myriad other ecosystem services they might provide aside from biofuels. Until then, the estimates of ACL developed in this study need to be understood only as a technical and a potential resource and, perhaps more important, as a focal point for political discussions about the future of land use in the context of sustainability transitions.

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Supplemental Material

Data files used in the preparation of this article are available at the Penn State Data Commons via the data's unique identifier, doi:10.18113/D3NP4Q.

Notes

1. Pasture abandonment is not included because the focus here is on abandoned cropland, the type of land most likely to support dedicated energy crop production (see Bryngelsson and Lindgren [2013] for reasons why considering low-quality pasture land is not practical for energy crop production).
2. Values in the archive were validated by comparing a sample with respective county figures in the original 1978 Census of Agriculture report.
3. The NLCD reports an accuracy of the agriculture classes to be approximately 43 percent in the 1992 data set and 82 percent in the more recent ones (Wickham et al. 2010). The poor level of confidence in the 1992 data set compelled this study to focus instead on changes between 2001 and 2011 despite the fact that the 1992 data would provide a time span that more closely matches the temporal extent of this analysis. Furthermore, Wickham et al. (2013) indicated that accuracies of the observed changes in agriculture classes between 2006 and 2011 are quite low, likely due to the difficulty in distinguishing among grass-dominant land covers. This suggests caution in relying on NLCD for cropland change detection; however, this article focuses on change

specifically from agriculture to developed classes, for which change accuracies are high.

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