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Land-Use Analysis of Croplands for Sustainable Food and Energy Production in the
United States

A Thesis submitted in partial satisfaction of the requirements for the degree of Master of
Science

in

Environmental Systems

by

Andrew Lee Zumkehr

Committee in Charge:
        Professor J. Elliott Campbell, Chair
        Professor Qinghua Guo
        Professor Lara Kueppers

2013

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University of California, Merced

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Abstract of the Thesis

Land-Use Analysis of Croplands for Sustainable Food and Energy Production in the
United States

Master of Science in Environmental Systems

University of California, Merced

by

Andrew Lee Zumkehr

Professor J. Elliott Campbell, Chair

Energy security and environmental sustainability are major concerns to many in the U.S. Energy from biomass has been proposed as a strategy to help meet future energy needs; however, widespread cultivation for biofuels could have significant impacts on food security and the environment. One solution to minimizing the impacts of biofuel cultivation is to limit production to abandoned croplands where competition from food crops and environmental degradation will be minimized. Here I estimate the spatial distribution of historical U.S. cropland areas from 1850 to 2000 and subsequently calculate abandoned cropland areas for the year 2000. From this data I estimate the potential biomass energy that could be obtained from abandoned croplands. I also estimate the potential for biomass energy to contribute to a renewable energy system consisting of wind and solar power by meeting seasonal energy storage needs that are a result of the intermittent nature of renewable energy sources. Lastly, I use the historical cropland areas result to estimate the ability of U.S. croplands to supply food to local populations at the county level.

Introduction: Executive Summary of Chapters

This Thesis is a three part analysis of energy and sustainability related topics concerning the use of U.S. croplands. U.S. croplands can be used as a major resource for bioenergy production that can be applied to energy needs directly or as a component of a renewable energy system by mitigating the effects of intermittent power production. However, the sustainability and environmental impacts of U.S. agriculture are a concern and the localization of food production and consumption has been proposed as a strategy for reaching sustainability goals. Some studies have explored the topics mentioned above but either use relatively coarse input data or operate within relatively restricted spatial scales. The goal of this work is to improve the understanding of all of the issues mentioned above by creating an estimate of the spatial distribution of historical U.S. croplands, estimating the biomass energy potential on U.S. abandoned croplands, estimating the potential of U.S. abandoned croplands to provide an energy resource for mitigating the intermittent quality of renewable energy production and then assessing the capacity for U.S. croplands to feed U.S. populations at the county level.

In Chapter 1, historical gridded U.S. cropland maps are estimated from 1850 to 2000. This dataset can be useful for variety applications including atmospheric modeling, ecology, and economics. I apply this dataset to estimate the area and distribution of U.S. abandoned croplands (as they are considered to be a preferred land resource for bioenergy production) in the year 2000 and subsequently estimate the bioenergy potential of U.S. abandoned croplands. I find that there are about 45 Mha of abandoned croplands in the conterminous U.S. that could be suitable for bioenergy cultivation. Using a range of assumptions about biofuel feedstock yields on abandoned croplands, I estimate an upper-limit potential bioenergy resource that could meet 5% to 30% of the current U.S. primary energy demand or 4% to 30% of the current U.S. liquid fuel demand.

Chapter 2 is an analysis of the seasonal energy storage requirement that would be needed to allow all of the U.S. electricity demand to be met by wind and solar power. The motivation for this section is the increasing interest in the adoption of renewable energy as the longevity of fossil fuel reserves are uncertain and the environmental impacts of fossil fuel consumption are becoming more apparent. However, a need to store energy is created by the general intermittent quality of renewable energy sources that can cause production potentials to differ temporally from demands. I estimate that the US will need energy storage capabilities that are on the order of 7%-26% of the annual energy demand to offset the effects of intermittency and allow renewable energy sources to be a viable option. Furthermore, I estimate that biomass energy on abandoned lands would be able to provide a significant portion of the seasonal energy storage requirement but would likely be insufficient in being an independent solution.

In Chapter 3 I estimate the ability of U.S. croplands to feed U.S. populations locally at the county level using cropland area estimates from Chapter 1 and a variety of yield assumptions for food crops from 1850 to 2000. The motivation for this section is that the sustainability of agriculture is often scrutinized and recently it has been proposed that the localization of food production and consumption could mitigate environmental and other negative impacts of agriculture; however, the extent that localization can occur is largely unknown. Here I do not attempt to argue for or against the merits of food

localization but only intend to comment on the capacity of U.S. croplands for food localization. Here I find that the U.S. ability to feed populations within county borders is diminishing. Less than 46% of the U.S. population could be fed within the county of residence under the most optimistic assumptions in the year 2000.

Chapter 1: Historical U.S. Cropland Areas and the Potential for Bioenergy Production on Abandoned Croplands

1.1 Abstract

Agriculture is historically a dominant form of global environmental degradation and the potential for increased future degradation may be driven by growing demand for food and biofuels. While these impacts have been explored using global gridded maps of croplands, such maps are based on relatively coarse spatial data. Here I apply high-resolution cropland inventories for the conterminous U.S. with a land-use model to develop historical gridded cropland areas for the years 1850 to 2000 and year 2000 abandoned cropland maps. While the historical cropland maps are consistent with generally accepted land-use trends, the U.S. abandoned cropland estimates of 68 Mha presented here are as much as 70% larger than previous gridded estimates due to a reduction in aggregation effects. Renewed cultivation on the subset of abandoned croplands that have not become forests or urban lands represents one approach to mitigating the future expansion of agriculture. Potential bioenergy production from these abandoned lands using a wide range of biomass yields and conversion efficiencies has an upper-limit of 5% to 30% of current U.S. primary energy demand or 4% to 30% of current U.S. liquid fuel demand.

1.2 Introduction

Gridded global maps of historical cropland and modern abandoned agriculture lands have been developed using agriculture census data and land-use models (1-3). These maps of historical agriculture lands and current abandoned agriculture lands are useful for a wide range of applications such as climate science, food security, and bioenergy sustainability (4, 5). Land abandonment is the process where land that was once under human control is released and left to nature (6). Drivers of agricultural abandonment include complex interactions between natural constraints, land degradation, change in demographic structure, socio-economic factors and institutional frameworks (6-8).

The development of these global gridded maps was based on input data from agriculture censuses that are spatially coarse, with a state- or country-level resolution. A critical source of uncertainty in these gridded maps stems from the different spatial resolutions of the relatively course-scaled census data used as input and the relatively-fine scaled gridded maps that are the output. Thus, using input data with a higher resolution than state or country level may reduce the uncertainty in gridded maps of historical agriculture and current abandoned agriculture. However, existing gridded maps have not yet made use of higher-resolution data sets.

Here I use county-level input data to develop new gridded maps of historical croplands (years 1850 to 2000) and year 2000 abandoned croplands for the conterminous U.S. I examine the reduction in aggregation effects associated with the differences between my high-resolution gridded maps based on county-level input data and

previously published global maps from the SAGE and HYDE databases that are based on state-level data (8, 9). Aggregation is the loss of information pertaining to croplands when considering the sum of areas from multiple spatial units. The gridded maps of historical croplands and abandoned croplands resulting from this study will be made available online (https://eng.ucmerced.edu/campbell).

In addition to developing new gridded maps for the U.S., I explore one potential application of these maps for providing an upper-limit estimate of the order of magnitude of bioenergy that may be produced on U.S. abandoned croplands. Abandoned cropland is considered to be one important potential resource for sustainable bioenergy production (2, 10-13), though other marginal land resources have also been proposed (14). Field experiments at the plot (15) and farm (16) scale demonstrate the potential for substantial biomass yields on abandoned and degraded lands that may not be suitable for food production. The use of abandoned croplands for bioenergy may minimize the competition for land between biofuels and food production, thus reducing the potential for adverse impacts on global food markets. Furthermore, the restriction of bioenergy crop cultivation to abandoned croplands may minimize the deforestation impacts associated with growing biomass crops on either current agriculture lands or current forestlands (17, 18). Additionally, depending on the extent of land degradation and the biomass cultivation approach, bioenergy agriculture may enhance soil carbon sequestration and prevent further land degradation (15, 19).

1.3 Methods

1.3.1 Historical Cropland

I develop gridded historical cropland maps using a simple land-use model (1) driven by historical county-level census data and a gridded map of year 2000 croplands. The input data include county-level historical areas of cropland from 1850 to 1997 (20), the U.S. Department of Agriculture Census of Agriculture inventory data for 1997 and 2002 (21), and a satellite-derived gridded map of cropland areas for the year 2000 (22). The resulting gridded maps of cropland density have a spatial extent of the conterminous U.S., a time span of 1850 to 2000, a spatial resolution of 5 minutes, and a temporal resolution of one year.

Past studies have used a wide range of land-use change models to reconstruct historical cropland areas. Many of these models require historical cropland inventory data which provide historical areas in which the spatial unit is a political unit (e.g., country, state, province etc.). The models redistribute these political unit areas to higher resolution maps using a variety of assumptions. Some models determine the spatial allocation using land suitability that is based on parameters such as topography, soil quality or proximity to population centers (9, 23-26). Such models make assumptions regarding the relationship between long-term historical land-use change and land quality which are poorly validated at large scales. In the absence of validation I have chosen to apply the simplest possible land-use change model of Ramankutty and Foley (1). This land-use change model requires a gridded map of cropland areas at the most recent time step and

then steps backwards in time using inventory data as a historical constraint (see supporting online material).

As in previous global cropland studies, I use a definition of croplands that includes multiple categories of arable lands. I follow the approach of Waisanen and Bliss (20) who define croplands as the sum of six census land-use categories in which harvested cropland is the dominant category while other categories include crop failure, cropland idle, cropland in cover crops, cropland in cultivated summer fallow, plowable pasture (1940 and before) or cropland-used for pasture (1945 and after). This cropland definition includes land that is only temporarily abandoned and Conservation Reserve Program lands which are not included in my abandoned cropland estimate.

Temporal changes in land-use definitions over the study period have been a source of error for many analyses and this analysis is no exception (1, 8, 20, 27). In 1945, the U.S. census changed a land cover definition that was used to quantify areas of temporary pasture. The definition was changed from "plowable pasture" to "cropland used for pasture". This land-use definition change introduced a break in the consistent time series of data for cropland. Previous studies have proposed approaches for estimating the error introduced by this definition change (8, 20) but it is unclear whether such approaches can make a meaningful correction for this error at the county-level. The magnitude of the error introduced into studies that do not account for the definition change is on the order of 16% of the national cropland area for 1940 (20).

In an attempt to reconcile cropland area estimates on either side of the definition change, I find the difference between the cropland areas from the years 1940 and 1945 for each county and subtract this difference from cropland areas before 1945. After I apply this correction, I linearly interpolate four time steps from either side of the definition change in order to estimate the cropland change from 1940 to 1945. Because there is a minimal change in cropland area in the 15 years prior to the definition change (an average of <1% of total U.S. cropland from one year to the next), the difference correction may provide a reasonable estimate of the magnitude of the error associated with the definition change.

I compare my historical gridded cropland estimates with previously published historical gridded maps from the SAGE and HYDE databases that were developed using related land-use models but used state- and/or country-level inventory data instead of county-level inventory data (8, 9). Although the SAGE data were originally presented at a 5 minute spatial resolution, I used the maps from the SAGE website that have a 0.5 degree resolution.

1.3.2 Abandoned Cropland

From the historical cropland dataset it is possible to create an estimate of abandoned cropland for each grid cell by finding the difference between the maximum historical cropland area and the cropland area of the most recent time step. I also used this method to estimate abandoned croplands using the historical cropland maps from the SAGE and HYDE databases.

An abandoned cropland map created from the corrected historical cropland maps mentioned in the previous section as well as an abandoned cropland estimate using the uncorrected historical cropland maps are presented here. The MODIS land cover dataset is used here to remove abandoned croplands that may have transitioned to forest or urban areas in order to estimate the area of abandoned cropland that may be available for bioenergy production.

1.3.3 Bioenergy Potential on Abandoned Croplands

To quantify the biomass energy that is potentially available by cultivating second generation (cellulosic) bioenergy crops on abandoned croplands, a range of biomass yield estimates for natural vegetation and cellulosic biomass crops and a range of conversion efficiencies are used. Managed systems that are based on natural vegetation have been proposed as an approach to using degraded lands that achieves biomass production and soil carbon sequestration goals (15). The natural vegetation yields are based on the CASA ecosystem estimates of net primary production (NPP) that were driven by NDVI derived from the NOAA/NASA Pathfinder data set, surface solar insulation (28), mean temperature and precipitation data (29), soil texture (30), and land cover classifications (31, 32). The abandoned cropland areas are up-scaled to conform to the 1 degree spatial resolution of the CASA data. To convert CASA NPP to dry biomass a mass ratio of 2.2 for dry biomass to carbon is applied and it is assumed that 50% of the NPP is above-ground.

Additionally I estimate the potential yields for the dedicated biomass crops Miscanthus and switchgrass on abandoned croplands. Multi-year field trials suggest the potential for yields in Illinois of 29.6 t dry biomass ha^{-1} y^{-1} and 10.4 t dry biomass ha^{-1} y^{-1} for Miscanthus and switchgrass, respectively (33). I extrapolate these field trials to a gridded map using CASA NPP and the ratio of biomass crop yields to CASA yields in Illinois (CASA Illinois yield is 9.9 t dry biomass ha^{-1} y^{-1}). I compare my spatially-explicit yield estimates with yields reported from farm-scale switchgrass experiments on marginal lands (16).

For bioenergy potential I consider both the energy content of the biomass in comparison to U.S. primary energy demand and the potential ethanol production in comparison to U.S. liquid fuel demand. For conversion efficiencies from biomass to ethanol I consider a range of potential yields from 0.28 to 0.38 L ethanol kg $biomass^{-1}$ (34, 35) with a biomass heating value of 20 kJ g dry $biomass^{-1}$ (3).

The bioenergy estimates presented here are most likely an upper-limit for the potential production on U.S. abandoned croplands. The high biomass yields from Miscanthus are based on plot-scale data and farm-scale experiments in diverse regions of the U.S. are needed. While I assume here that all above-ground biomass is harvested, the ratio of harvestable biomass relative to the total above-ground biomass is dependent on long-term soil sustainability which is relatively uncertain for emerging biomass cultivation and abandoned lands. Economic constraints will also require that only a subset of the abandoned lands may be suitable for cultivation. The potential ethanol production from biomass is also highly uncertain as the technology for converting cellulosic biomass to ethanol is at the pilot stage.

1.4 Results

Figure 1.1 presents my historical gridded cropland maps for select years. These maps show the general trend of westward agricultural expansion that largely stabilized in the Midwest. Figure 1.2 shows the total U.S. cropland history for my analysis as well as from the original county-level data without correcting for the land-use definition change from 1940 to 1945. The uncorrected history results in an erroneous decrease in cropland area from 1940 to 1945 that would lead to an overestimate of abandoned cropland. Cropland abandonment is not evident from the total U.S. cropland areas shown in Figure 1.2 because regions of increasing cropland area offset regions of decreasing cropland area. The year of maximum cropland area (Figure 1.3) indicates the onset of cropland abandonment showing the Northeast preceded most other areas of the U.S.
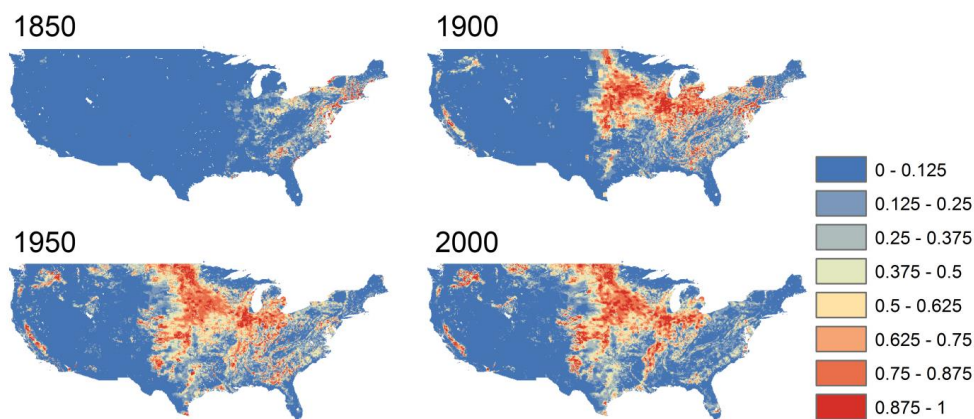
Figure 1.1. Gridded cropland area estimated in this study for select years 1850, 1900, 1950, and 2000. Pixels represent fractional cropland area relative to total grid cell area with a resolution of 5 minutes latitude/longitude and values adjusted for the census definition change in 1940.
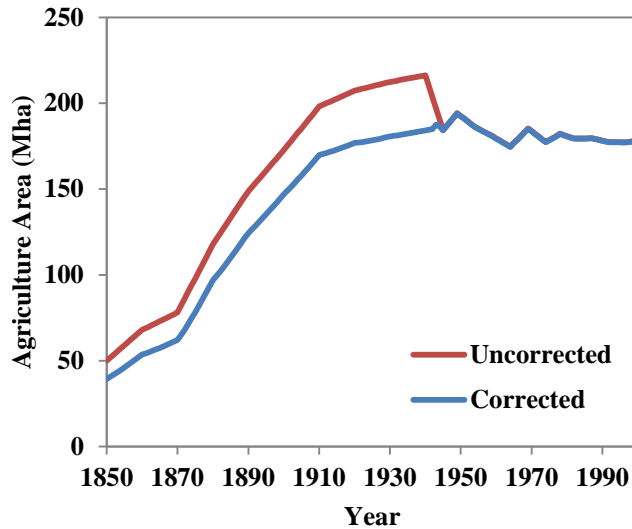
Figure 1.2. Historical cropland areas for the conterminous U.S. Uncorrected areas do not account for the 1940-1945 land-use definition change for cropland in historical county-level census data.
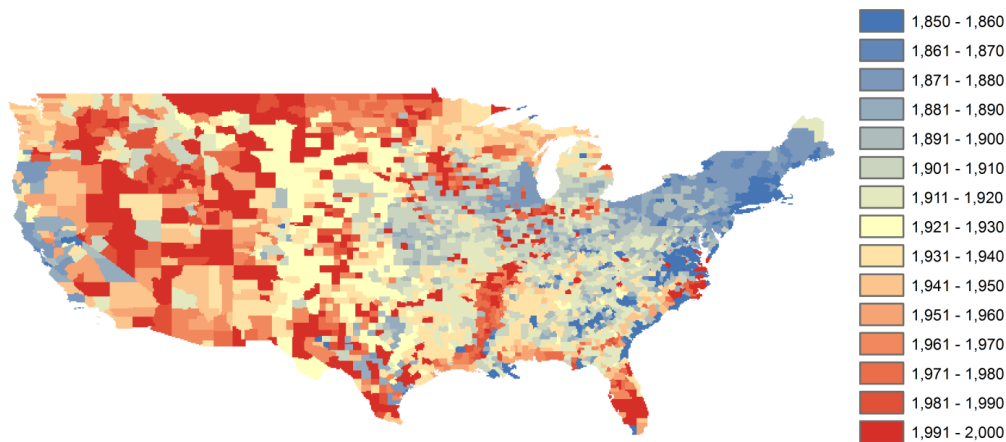
Figure 1.3. Year of maximum cropland area from maps developed in this study.

I perform a regional comparison of my gridded estimates of historical and abandoned areas with the widely used SAGE and HYDE global gridded data that were based on similar land-use change models but state-level inventory data (8, 9). The historical cropland areas exhibit similar temporal trends for all data sets at the regional scale (Figure 1.4). To further compare my data with SAGE and HYDE I calculate the root mean squared error (RMSE) and mean absolute error (MAE) for all pixels and all years where the error is the difference between my historical croplands and those from the SAGE and HYDE data. The RMSE and MAE with respect to the SAGE data are 0.16 and 0.10, respectively (possible pixel values range from 0 to 1). The RMSE and MAE with respect to the HYDE data are 0.21 and 0.11, respectively. The relatively low values

of these comparative statistics suggest that there is general agreement between my maps and these global databases.

Figure 1.4. Historical cropland areas by region using the gridded data developed in this study (blue) and previously published gridded cropland areas from the SAGE (red) and HYDE (black) databases that are based on similar land-use models and state-level inventories.

I find that the abandoned cropland area for the U.S. is 68 million hectares (Mha) based on my gridded maps. Using SAGE and HYDE data, I estimate abandoned cropland areas that are 40% and 2% smaller, respectively (Figure 1.5). The spatial distributions of these differences are mapped in Figure 1.6. Abandoned cropland estimates from my gridded results and the SAGE and HYDE datasets all show the highest regional areas in the Southeast. My abandoned cropland estimates include high abandonment regions in the Midwest and in Texas which are not detected in the SAGE data and are detected to a lesser extent by the HYDE data. The highest concentrations in the estimates presented here are higher than in the state-level estimates. This is of importance because high concentrations of cropland area are more efficient for production and simplify infrastructure demand. The exception is that the HYDE dataset predicts higher concentrations of abandoned cropland in the western region of the U.S. Because the HYDE dataset distributes agriculture areas based on population densities, this high prediction of abandoned cropland may be due to the unique spatial characteristics of the migration of populations to large cities.
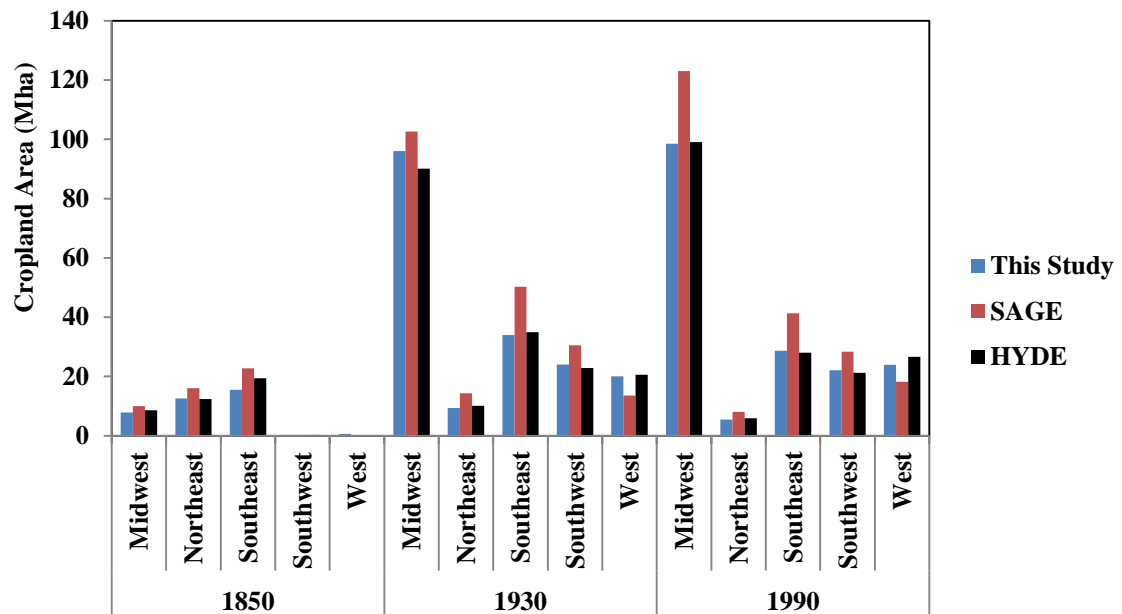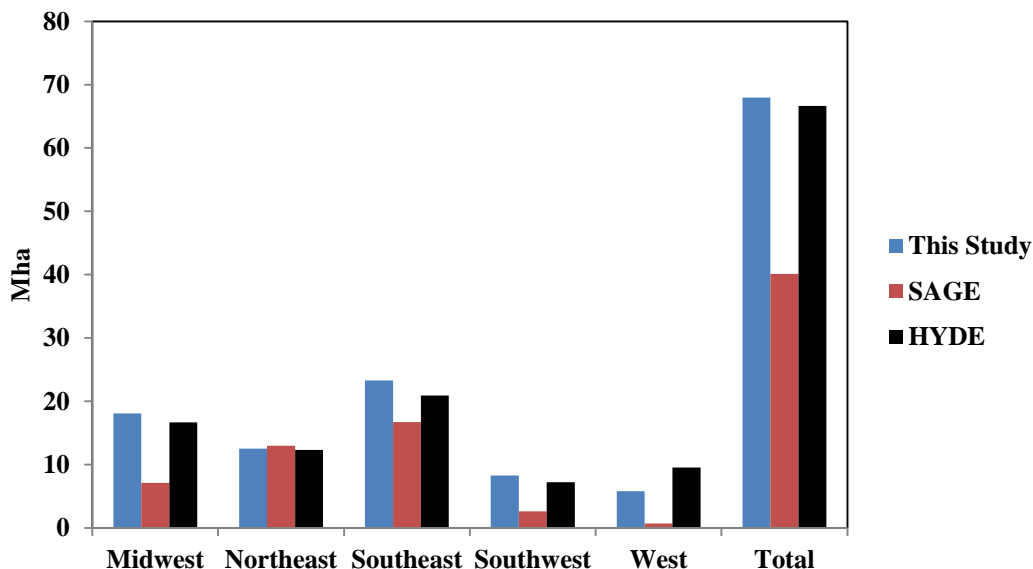
Figure 1.5. Abandoned cropland areas by region using the gridded data developed in this study (blue) and previously published gridded cropland areas based on state-level data SAGE (red) and HYDE (black).

Table 1.1 shows the areas of abandoned cropland calculated for a range of time periods using the gridded maps presented here. The 68 Mha of cropland abandonment from the years 1850 to 2000 is based on corrected historical cropland estimates. Without a correction for the cropland definition change in 1940, abandoned cropland would be estimated at 90 Mha. An area of 2 Mha of the 68 Mha of abandoned cropland has been converted to urban areas and 21 Mha has been reclaimed by forests. A large portion of the abandoned cropland reclaimed by forests is in the eastern U.S. (Figure 1.7) which is consistent with the early timing of abandonment in this region (Figure 1.3). The remaining 45 Mha of abandoned croplands that are not forest or urban areas provides my upper-limit estimate for abandoned croplands that may be suitable for renewed cultivation.
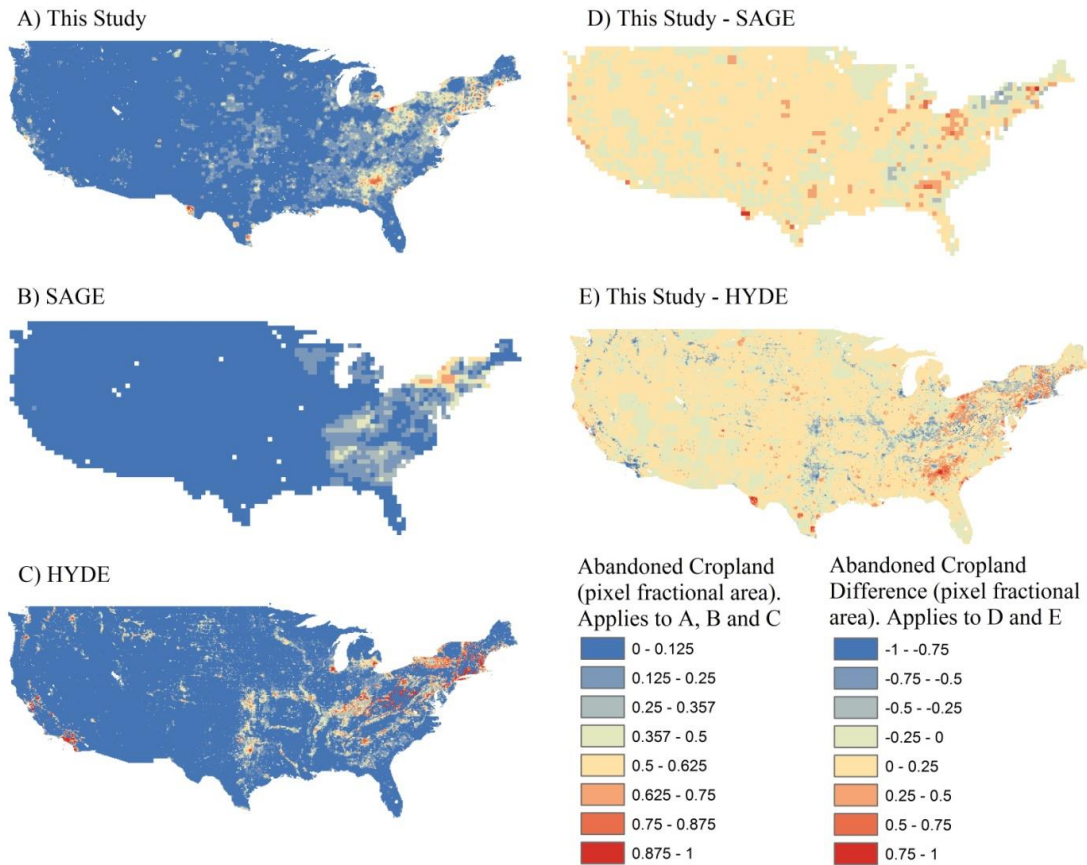
Figure 1.6. Fraction of pixel area under abandoned cropland from this study at a 5 minute spatial resolution (A), fraction of pixel area under abandoned cropland from the 0.5 degree SAGE dataset (B), fraction of pixel area under abandoned cropland from the HYDE dataset at a 5 minute spatial resolution (C), the difference between abandoned cropland areas for this study and the SAGE (D) and HYDE (E) databases (the red values in (D) and (E) represent areas where my estimates are larger than the SAGE or HYDE estimates).

Table 1.1. Abandoned cropland area estimates (Mha). The column headings represent the years that were used to produce the abandoned cropland map. The column that is marked as "corrected" denotes estimates using my method that reconciles the census definition changes in 1940. The row headings indicate the type of abandoned cropland estimate.

	1850-2000 Corrected	1850-2000 Not Corrected	1850-1940	1945-2000
Total abandoned cropland	68.1	90.2	37.7	43.0
Abandoned cropland that is now forests	20.8	25.5	11.6	10.3
Abandoned cropland that is now urban areas	2.4	2.8	1.4	1.2
Abandoned cropland excluding urban/forest	45.0	61.9	24.7	31.5
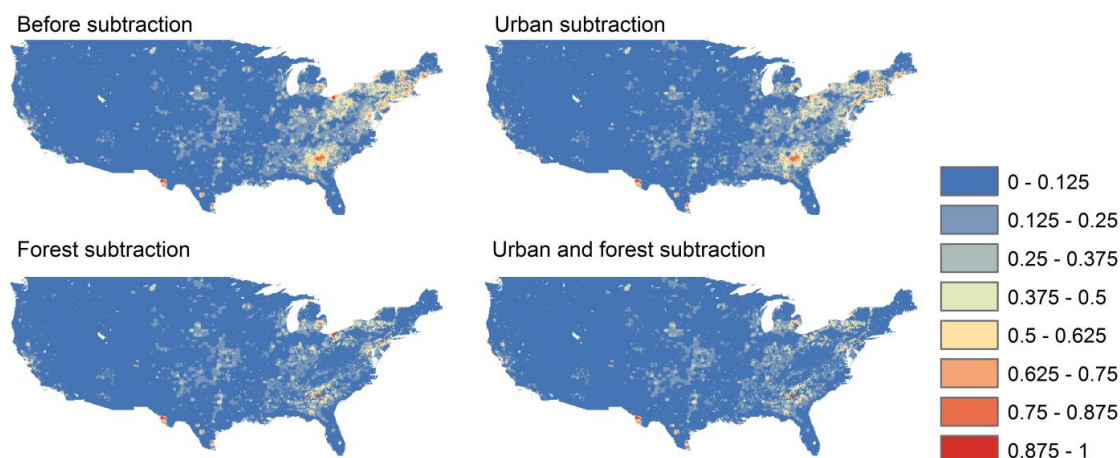
Figure 1.7. Fraction of pixel area covered by abandoned cropland area and the result of subtracting urban and forest areas from estimates of abandoned cropland that were corrected for the census definition change.

Upper-limit estimates of bioenergy potentials on abandoned croplands using the wide range of crop yields and energy conversion efficiencies used in this study are shown in Table 1.2. The annual biomass production from abandoned croplands (excluding forest and urban areas) for natural ecosystems, switchgrass, and Miscanthus feedstocks are 0.26, 0.56, and 1.58 billion metric tonnes, respectively. The energy content of this biomass is equivalent to 5% to 30% of the 106 EJ y^{-1} U.S. primary energy demand. The potential ethanol production from the biomass ranges from 4% to 30% of the 43 EJ y^{-1} liquid fuel demand in the U.S.

Table 1.2. Potential biomass, energy content, and liquid fuel yields from cultivation of cellulosic crops on 45 Mha of abandoned croplands. Potential primary energy content and liquid fuel yields are presented next to the energy content as a percentage relative to U.S. primary energy demand of 106 EJ or liquid fuel demand of 43 EJ, respectively.

Biomass Source	Biomass Yield (Billion Tonnes y^{-1})	Energy Yield (EJ y^{-1})	Liquid Fuel High Yield (L y^{-1})	Liquid Fuel Low Yield (L y^{-1})
CASA NPP	0.26	5.2 (4.9%)	9.9E+10 (4.9%)	7.3E+10 (3.6%)
Miscanthus	1.58	31.6 (29.8%)	6.0E+11 (29.5%)	4.4E+11 (21.7%)
Switchgrass	0.56	11.2 (10.6%)	2.1E+11 (10.4%)	1.6E+11 (7.7%)

1.5 Discussion

This analysis presents new gridded historical cropland maps using higher resolution input data than applied in previous work. Agriculture trends or characteristics of individual counties that may have otherwise been masked or hidden by overlying state trends can now be better understood and explored by performing analyses that incorporate other spatially explicit data. In particular this new gridded data set suggests larger abandoned cropland areas than revealed by analysis of previous global gridded data sets.

The method described in the paper to down-scale county level inventory data using a land-use change model in conjunction with satellite derived representations of cropland distributions introduces uncertainty. The uncertainty is largely a result of the assumption that recent crop cover roughly represents the spatial extent of historical crop cover. As discussed in Ramankutty and Foley (1) there are few historical cropland distribution maps to compare products of this kind to, so there is no direct means of validation. However, I have likely reduced the associated uncertainties relative to the previously available data by using high resolution inventory data that is a closer match to the resolution of the resulting down-scaled data.

The method for correcting for the inconsistency of definitions used by the U.S. Census of Agriculture assumes that the change in cropland areas between the years 1940 and 1945 was similar to the adjacent time periods. I proceed on the assumption that there was relatively little change in cropland area before and after the 1940 to 1945 period and that any change that did occur would introduce much less error than making no correction at all.

Using the MODIS land cover dataset to perform the subtraction of forest and urban areas from the abandoned cropland estimate introduces uncertainty due to pixilation errors. This may be compounded by how the MODIS land cover dataset classifies whole pixels as being of one type of land cover and not a fraction of land cover. If a pixel is comprised of partial abandoned croplands and partial forest/urban lands, then abandoned cropland area may be gained or lost depending on the nature of the pixel classification.

In addition to these sources of uncertainty for cropland areas, the application of these areas to bioenergy assessment is associated with significant uncertainties. The approach outlined here for using a large range of biomass productivity estimates may provide a range of biomass yields that encompass this uncertainty. The NPP estimates from the CASA model used in this analysis to calculate potential biofuel production are a representation of natural ecosystems and may not be directly applicable for calculating high accuracy estimates of managed crops (due to fertilizer, irrigation and natural differences in productivity between plant types). While I was able to compare my results for switchgrass to actual yields from several studies, Miscanthus yield data is much more limited. From Table 1.2, it can be see that, while switchgrass reports slightly higher yields than obtained from the CASA NPP model, Miscanthus yields are much higher. Because yield measurements for Miscanthus are only available for Illinois, the results may be biased if Miscanthus does especially well on these lands relative to croplands. However, the switchgrass yield estimates presented here are generally consistent with

farm-scale experimental data (16) of biomass production on marginal lands (Figure 1.8). While a more detailed understanding of spatial and temporal variability of yields could be achieved with process models, my approach of using a broad range of biomass productivities is likely sufficient for the order of magnitude analysis presented here.
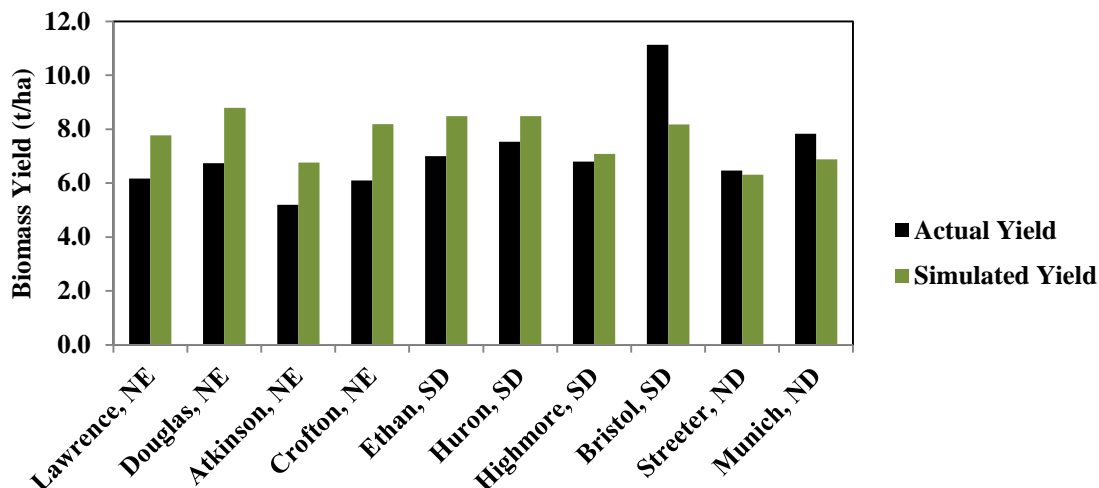
Figure 1.8. A comparison of switchgrass dry biomass yields from field trials on marginal lands (black) (16) and spatial extrapolation of Illinois plots (green).

Because of low energy densities of lignocellulosic feedstocks, it may not be viable to cultivate small outlying abandoned croplands for bioenergy (36). The density of land required for viable biomass production will depend on a range of factors including but not limited to the biomass crop yield, size of the biomass conversion facility, and the cost of transportation. Additionally, this analysis only discounts abandoned cropland areas for use of biofuel production that have been abandoned to urban or forest areas while there are also large abandoned areas that have significant environmental value. Because of these economic and environmental constrains, the results presented here of bioenergy production on abandoned croplands are best suited as an upper-limit estimate. Future work examining additional constraints will be needed to further define the potential of the abandoned croplands resource. Additionally, ethanol production potentials are subject to complicated technology process chains and the estimations made here should only be interpreted as a rough estimate used to understand the order of magnitude of production potentials.

The historical croplands and abandoned cropland areas created in this analysis could be valuable datasets in investigating a wide range of land-use impacts including biophysical climate forcing, carbon sequestration, and bioenergy production. Further research is required to create a more comprehensive study of potential bioenergy yields using a greater variety of yield data, economic constraints, and ecological constraints than presented here.

1.6 Supporting Information

1.6.1 Yearly Agriculture Inventory Data (1850 to 1997)

The temporal resolution of the census data varies from 4 to 10 years. I estimated yearly cropland areas from this inventory data by linear interpolation. These values are removed from the inventory that reports agriculture proportions over 100% of the county area and are linearly interpolated over these values to fill the gap created by the deletion. This issue affects less than 0.01% of the data.

Some farms extend over county boundaries and were sometimes accounted in the census data by both counties that the farm spanned. These errors are more significant for analysis of a single county than for applications of my data at regional and domain-wide spatial scales.

1.6.2 Year 2000 Cropland Estimates

The land-use model requires that the agriculture inventory data be available for the same year as the boundary condition from the satellite-based cropland map. However, the Waisanen and Bliss (2000) (20) data only extend to 1997 and the gridded cropland map is for the year 2000. A year 2000 inventory estimate was created by linearly interpolating between these 1997 data and the USDA Census of Agriculture data for the year 2002 (21).

1.6.3 Duplicate County Data

Within the Waisanen and Bliss (2000) dataset (20), duplicate values for many counties exist for the same year. These duplicates are due to the fact that some counties were partitioned into separate areas, particularly for counties that include islands (personal correspondence, Norman Bliss). I summed these duplicates together. This summing resulted in agriculture areas that exceeded the total county area in rare cases. For these cases I constrained the agriculture area to the total county area.

1.6.4 Land-Use Model

The land-use model of Ramankutty and Foley (1) was applied to produce gridded maps of historical cropland areas with a spatial resolution of 5 minutes by 5 minutes, a spatial extent of the conterminous U.S., a temporal resolution of one year, and a temporal extent of the years 1850 through 2000. The model is initialized at the year 2000 using gridded cropland areas based on MODIS data (4) and then run backwards in time to the year 1850. The model formulation is as follows,

$$A_s^{t_2}(k) = \propto (k) \left[A_s^{t_1}(k) \frac{A_I^{t_2}(k)}{A_I^{t_1}(k)} \right] + \left(1 - \propto (k) \right) \left[A_s^{t_1}(k) + \left(A_I^{t_2}(k) - A_I^{t_1}(k) \right) \right]$$

Where:

t_1 = the starting time of simulation

t_2 = the ending time of the simulation

$A_I^{t_1}(k)$ = Crop area from inventory data for time t_1 for political unit k

$A_I^{t_2}(k)$ = Crop area from inventory data for time t_2 for political unit k

$A_S^{t_1}(k)$ = Gridded crop area for time t_1 and political unit k.

$A_S^{t_2}(k)$ = Gridded crop area for the time t_2, for political unit k

$$\propto (k) = min \left[1, exp \left\{ -0.5 \left(\frac{A_I^{t_2}}{A_I^{t_1}} - 1.1 \right) \right\} \right]$$

This land-use model estimates the gridded cropland area for the i-1 year as a function of the gridded map for the ith year and the county-level inventory data for the i-1 and i[th] years. This land use model applies the assumption that gridded spatial crop cover patterns throughout time will remain roughly similar to year 2000 gridded distributions.

As in Ramankutty and Foley (1), I apply a smoothing to my abandoned cropland maps. I only apply smoothing to county boundaries to simulate farms that may extend across boundary lines. The impact of smoothing on the resulting abandoned cropland estimate is a minimal reduction in abandoned cropland area of less than 1%.

1.6.5 Cropland Overflow Redistribution

The land-use model resulted in cases of pixels having a fraction of greater than one for the gridded cropland area within the pixel relative to the total pixel area. For these pixels, I constrained the cropland area to the total pixel area and redistributed the excess cropland area to the surrounding pixels within the same county. When this redistribution causes another pixel to have a value of greater than one, then the process was repeated recursively. This approach maintains a consistent county-level cropland area between the gridded maps and the county-level inventory data.

1.6.6 Energy Demand

The U.S. liquid fuel demand is approximately 19.2 million barrels of oil per day (37). At 5.8 million Btu per barrel of oil, there is a need of 42.8 EJ of liquid fuels per year. The relative demand of ethanol is determined based on an ethanol lower heating value of 21 MJ l[-1]. Conversion of cellulosic biomass to ethanol is highly uncertain as this technology is at the pilot stage. I assume a wide range of conversion efficiencies from 0.28 to 0.38 L ethanol per kg biomass (34, 35).

1.6.7 Summary of Input Data

The regional boundaries used in the study described above are depicted in Figure 1.9. and a summary of the input data can for this study can be found in Table 1.3
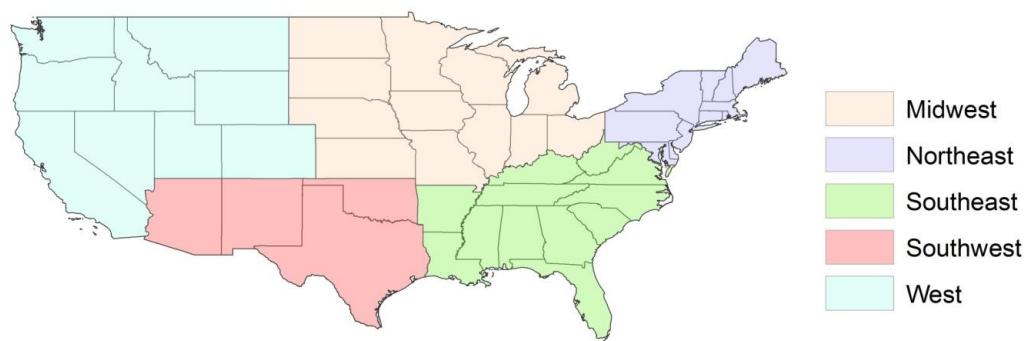
Figure 1.9. Region boundaries used in regional analyses in this study.

Table 1.3. Summary of Input Data

Name	Type	Time Period and Resolution	Spatial Extent and Resolution
M3-Cropland Agriculture Lands 2000 dataset (22)	Satellite derived gridded crop cover map	Year 2000	Global, 5 minutes lat/long
History of agricultural development (20)	Cropland inventory data compilation	Years 1850-1997 (time step 4-10 years)	U.S. counties
United States Census of Agriculture (21)	United states cropland inventory data	Year 2002	U.S. counties
MODIS land cover map (4)	Gridded land use map	Year 2000	Global, 3 minutes lat/long
CASA NPP (32)	Gridded map of net primary productivity	Climatological, Monthly	Global, 1 degree lat/long

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Chapter 2: Biomass as a Possible Solution to the Intermittency of Renewable Electric Power

2.1 Abstract

As the longevity of fossil fuel reserves is uncertain and the associated impacts on the climate are becoming clearer, wind and solar energy options need to be further explored. However, the intermittent nature of wind and solar energy sources is one of the main obstacles that needs to be overcome before such energy production can completely replace fossil fuels. One solution to the intermittency problem is to find a way to store excess energy produced by renewable sources and then use that stored energy at a later time when the energy demand exceeds the wind and solar energy production. There have been many proposed energy storage systems (some of which are in use). While these options are sufficient for energy storage at small time scales (seconds to hours), they are not well suited for addressing the seasonal variations in solar and wind production that would become a challenge if fossil fuels were completely eliminated. Here the use of biomass as a backup energy source is considered as an option when energy demand exceeds wind and solar energy production at the seasonal time scale. I calculate the seasonal backup energy needs in the U.S. if the annual wind and solar production is equivalent to 100% of the annual energy demand and investigate the potential for biomass energy to satisfy this backup energy requirement. I consider energy from biomass because it is easily stored, dispatched and has the potential to provide a carbon negative solution. I estimate that the U.S. will need backup energy that is on the order of 7%-26% of its annual energy demand. Bioenergy produced on abandoned croplands can meet more than half of the backup energy requirements for most cases considered.

2.2 Introduction

Wind and solar energy production generally possess an intermittent quality in their ability to provide energy. The temporal variability of wind and solar energy production will not always match the temporal variability of energy demand. This problem can be overcome by storing energy produced by renewable sources when production is higher than demand and then using the stored energy at some later time when demand is higher than production. Notable storage systems include pumped hydro storage, thermal energy storage, compressed air energy storage, natural gas storage, flow battery energy storage, fuel cell hydrogen energy storage, flywheel energy storage, and superconducting magnetic energy storage (1).

These storage systems have been designed to address intermittency at short time-scales (seconds to hours). However, wind and solar energy also have considerable variability at seasonal time scales which would require much larger volumes of energy storage for which existing storage methods would be cost prohibitive. If fossil fuels were completely replaced by wind and solar energy, some form of backup energy would be required to meet this seasonal intermittency.

Here I investigate the potential for biomass energy to provide seasonal backup power in the U.S. if the annual wind and solar production had a capacity equivalent to the annual U.S. energy demand. To do this I estimate the seasonal backup energy needs and potential energy yields from biomass on U.S. abandoned croplands and then compare the two estimates. I choose to investigate biomass because it is easily stored in piles or warehouses, easily dispatched (can be processed on demand), can be processed in some existing types of power plants and can even be a carbon negative solution to energy storage needs under certain land-use practices for biomass cultivation and energy production (2).

2.3 Methods

2.3.1 Seasonal Energy Storage

Recent work by Converse considers a range of energy storage options for compensating for the seasonal-scale intermittency of wind and solar power (3). This analysis considers the seasonal energy storage requirements for a renewable energy system that uses no fossil fuels. The seasonal energy storage requirement was based on current national wind and solar production data for the U.S. while the storage potential was based on U.S. bioenergy potential from previous work using coarse global land-use databases. This approach is designed to assess the seasonal storage required for a futuristic U.S. energy system in which all of the electricity is provided by renewable energy. Three renewable energy scenarios are examined including all energy provided by wind, all energy provided by solar, and the energy production divided evenly between wind and solar. This approach assumes that current seasonal variations of electricity demand, solar production, and wind production will be similar in the future. Furthermore, this analysis assumes that the magnitude of the renewable energy production (wind and/or solar) is equal to the total annual energy demand. This approach only estimates energy storage requirements at the seasonal scale and does not consider storage requirements at different time scales (e.g., diurnal storage requirements). Alternatively, if a larger generation capacity is assumed then the seasonal storage requirements would be reduced.

Here I follow the general approach presented in Converse (3) but applying high-resolution U.S. bioenergy data developed in my present work. I use the abandoned cropland areas (excluding conversion to forest and urban areas) for this analysis rather than abandoned pasture due to the higher yields and greater economic viability expected for abandoned croplands. Furthermore, I quantify the seasonal-energy storage requirement using state-level, monthly data for current electricity demand, wind production, and solar production rather than the national-scale data used in Converse (4). The monthly storage is,

$$S_{m+1} = S_m - (D_m - P_m) \ [eqn.\ 1]$$

where S is the normalized monthly storage, D is the normalized electricity demand, P is the normalized electricity production, and m represents the month. The monthly storage

was simulated for three scenarios of production (P) in which the production was all solar, all wind, or 50% solar and 50% wind. The initial storage value is an arbitrary value that does not influence the estimate of the total seasonal storage required for the year but does influence the monthly distribution of storage. The total seasonal storage requirement (*SD*) is,

$$SD = \max_{1 \leq m \leq 12}(S_m) - \min_{1 \leq m \leq 12}(S_m) \ [eqn.\,2]$$

By using equations 1 and 2 to calculate the difference between the maximum and minimum monthly storage requirement it is possible to calculate the storage capacity that would be required to offset energy deficits due to seasonal intermittency of production without knowing the current energy storage capacity. The energy storage requirement that is calculated in eqn. 2 represents a storage requirement assuming that all excess production energy can be stored. Annual energy deficits (production is less than demand) that are compared to annual bioenergy potentials are calculated by simply summing monthly energy deficits.

2.3.2 Biomass as Energy Storage

Biomass yields and the energy conversion efficiencies are based on approaches applied in previous global assessments (5, 6). Crop yields are based on the CASA primary production model and are in the range of observed yields for the candidate biomass crop switchgrass (7) but lower than the relatively sparse observations available for the candidate crop Miscanthus (8). The CASA model was used to spatially extrapolate the reported biomass yields for switchgrass and Miscanthus (8). The ratios of the observed Miscanthus and switchgrass yields in Illinois with respect to the CASA yield simulations in Illinois were applied to the CASA yield map to provide a map of Miscanthus and switchgrass yields. Biomass yields are calculated separately for available abandoned cropland within each of the three US electric power grids (see Figure 2.4). More complex approaches to spatial extrapolation will be possible once more field observations data become available.

2.4 Results

The normalized seasonal energy production and energy demand are aggregated from the state-level to three production regions and plotted in Figure 2.1 (see Figure 2.4 for information on the spatial extent of the production regions). The seasonality of solar is considerably larger than that of wind and the demand. While the seasonality of wind is lower it is not in phase with the demand seasonality.
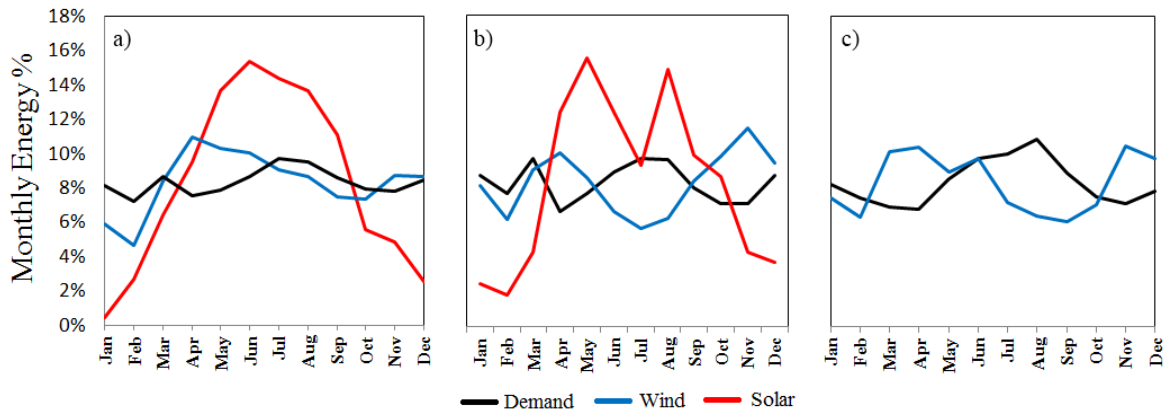
Figure 2.1. Monthly wind electricity production, solar electricity production and electricity demand as a percentage of the annual totals for each. Seasonal energy profiles for states within the (a) Western electric grid, (b) Eastern electric grid and (c) ERCOT (Texas) electric grid.

The seasonal storage requirement is plotted as a fraction of the total electricity demand in Figure 2.2. The required storage varies from 7% to 26% of total electricity demand suggesting that seasonal storage would be an important component of a renewable energy system based on wind and solar (the residual demand of 74% to 93% is met by wind or solar). Because of the relatively low seasonal variability of wind energy, it follows that required seasonal storage by the wind energy scenario is low relative to the solar scenario while the wind and solar mixed scenario falls in between. My analysis yields similar overall storage requirement estimates to the previous analysis based on national-scale data (though slightly higher) (3), but differ in terms of the storage required for each specific pathway and add a regional component to the analysis. I find that wind energy production is a better pathway for producing renewable energy if the goal is to reduce the need for seasonal energy storage. However, adding solar power to a renewable energy portfolio to increase production capacity beyond demand would reduce the seasonal storage requirement.

The capacity of biomass to meet the seasonal storage requirement is plotted for a range of biomass feedstocks, energy production scenarios, and regions in Figure 2.3. In the estimates shown in Figure 2.3, the biomass energy values represent biomass energy that can be potentially obtained from available abandoned cropland within the respective region. Bioenergy can meet more than half of the storage requirements for most cases considered. Bioenergy only meets the seasonal storage requirements of a 100% solar production scenario for the most optimistic assumptions regarding biomass crop yields. However, biomass can be a very substantial contribution to the solution to seasonal storage needs when combined with other storage technologies (especially if production capacity exceeds demands and power plants can be brought on and offline as needed to further diminish storage needs).
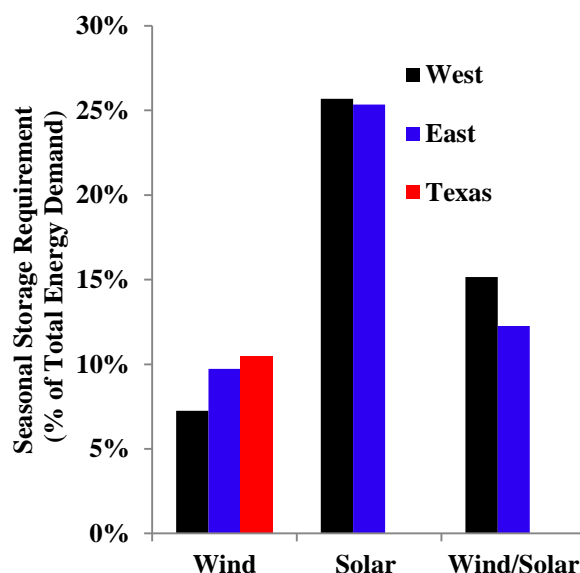
Figure 2.2. Seasonal electricity storage requirement for the Western electric grid, Eastern electric grid and ERCOT (Texas) electric grid based on an energy production system that is entirely wind, entirely solar, or a 50% mix of wind and solar.
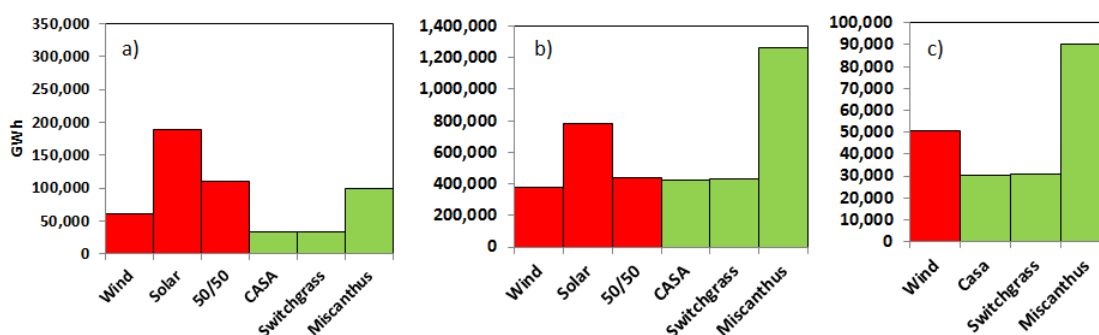

Figure 2.3. Annual electricity energy storage deficit and bioenergy availability for a range of biomass feedstock crops. Storage needs by resource are in red (if 100% of the annual demand was met only by the specified resource) and estimates of available energy from CASA NPP estimates, Switchgrass and Miscanthus at a 30% conversion efficiency from biomass to electricity in green. Energy storage is plotted for a) Western electric grid, b) Eastern electric grid and c) ERCOT (Texas) electric grid.

2.5 Discussion

Seasonal energy storage is required to address the intermittency of a future energy production system that may be based on renewable energy without the use of fossil fuel energy. Examining seasonal storage requirements for a hypothetical future energy system may be useful in the development of technologies and infrastructure investments that are needed to bridge the near-term energy system to the endpoint sustainable energy system.

My approach suggests the need for a large seasonal storage capacity from 7% to 26% of the national annual energy demand (based on production from wind only and solar only, respectively). This is a slightly larger range compared to estimates of 10% to 20% from a previous study using national energy data as input (3). I found that bioenergy could provide 46% to over 100% of the seasonal storage requirements; however, the higher estimate depends on very optimistic yields assumptions based on Miscanthus. This means that while the lower-end estimate is currently more realistic, the development of future production technologies may make seasonal energy storage from biomass adequate.

These results focused on the application of abandoned croplands for meeting seasonal energy storage needs. Additional seasonal storage may be provided by bioenergy resources from abandoned pasture lands or waste biomass. I did not consider the use of forest biomass or the use of prime agriculture lands for bioenergy production due to potential ecological, social and economic impacts.

As higher resolution, more recent abandoned agriculture distribution data and bioenergy crop yield data are developed, better estimates of the ability of bioenergy to meet the seasonal energy storage requirement of intermittent renewable energy sources will be possible. Additionally, this analysis could be updated to include other types of renewable energy sources such as hydro-electric and tidal energy, for example. After including all renewable energy sources into the energy portfolio, the next step would be to incorporate other types of storage technologies into this analysis. Utilizing all renewable energy sources and storage technologies may make it feasible to remove fossil fuels from the U.S. primary energy demand portfolio. While calculating the ability of bioenergy to meet renewable energy storage requirements, I do not consider the physical space required to store harvested biomass when it is not in demand nor do I account for the effect of intermittency on smaller time scales (e.g., daily, weekly); however, these are outside the intended scope of this study.

In this analysis the annual solar and wind production was assumed to be equal to the annual demand. Installing a greater solar and wind production capacity to exceed the yearly demand would reduce the amount of energy storage required. However, this would reduce the capacity factor of the installed power plants and may not be economically viable. Economic analysis of this renewable energy system is necessary.

2.6 Supporting Information

2.6.1 Methods for Land-Use Availability

A GIS-based modeling approach is employed to develop maps for the U.S. of land availability, biomass yields, and bioenergy production with a county-level resolution. The GIS model was developed using the ArcGIS spatial analyst extension to conduct the raster and vector calculations described below. The land-use model quantifies the spatial distribution of abandoned agriculture. Abandoned agriculture is divided into abandoned cropland and abandoned pasture. Here available abandoned agriculture lands are defined as an area of land that was once classified as cropland or pasture and is currently not classified as cropland, pasture, forestland, urban areas. The input data for the land-use analysis is USDA county-level cropland database which includes cropland

areas for each county from years 1850 to 1997 (9). Between 1850 and 1940, the data is in 10 year increments. Between 1940 and 1997 the data is in 4 or 5 year increments. The abandoned cropland area for each county is the difference between maximum area over the time series (years 1850 to 1997) and the area in the final time step (year 1997),

$$A_i = \max_{1850 \leq t \leq 1997} \left(C_{i,t}\right) - C_{i,1997} \ [eqn. A1]$$

where A_i is the abandoned cropland areas, C is the cropland area, and i and t are the indices for county and year, respectively. More recent cropland area changes were explored using the USDA/NASS database and found to be small relative to area changes from 1850 to 1997. The county-level cropland data had erroneous spikes (9) for less than 5% of the data which were removed prior to the analysis. Spatially-explicit estimates of abandoned pasture land as well as exclusions required for conversion of agriculture land to urban and forestlands are obtained from a previous analysis (5, 6).

The county-level data suffered from a change in land-use definition between 1940 and 1945 which introduces an artificial decline in cropland area (9, 10). The period of 1945 to 1997 has a more restrictive definition of cropland used for pasture than for the period of 1850 to 1940. An adjustment was made for the definition change by subtracting the 1940 to 1945 area change from the county areas for years 1850 through 1940.There are several sources of uncertainty in these land availability estimates. The spatial resolution of the croplands (county-level) is not consistent with the pasture, forest, and urban land (5 minute by 5 minute) data. Furthermore while the crop and pasture data have a different format than the forest and urban area data. The crop and pasture data are density data, providing the percent of each pixel that is occupied by crops or pastures. Alternatively, the forest and urban data classify each pixel as entirely forest or urban or other land cover without providing the fraction of the pixel that is covered by such land cover. Validation data is not currently available for determining the magnitude of this uncertainty associated with the range of spatial resolutions and classification schemes. However, abandoned cropland areas that are not combined with pasture areas and are not filtered using forest and urban areas are also reported in order to provide an upper estimate for land availability that is not associated with these uncertainties.

These new abandoned cropland area estimates are compared to previous estimates that were based on the relatively coarse data from the SAGE and HYDE global gridded databases (11, 12). HYDE crop and pasture estimates range from 1700 to 2000 in 10-year increments. HYDE-based areas were developed using only data from 1850 to 2000 (as opposed to the original 1700 to 2000). Estimating abandoned cropland from HYDE using data from 1850 to 2000 yielded the same results as using data from 1700 to 2000. SAGE crop areas range from years 1700 to 1992 in 10-year increments. Abandoned crop estimates were calculated using data from 1850 to 1992.

2.6.1 US Power Grid Spatial Approximation

Figure 2.4 shows the spatial approximation of the three major US electric power grids used in this analysis. Approximations of the spatial extents were made to the nearest state boundary because the input data for the analysis was available at the state level. Because of this, some quantity of electricity production and consumption near the edges of the three grids would actually belong to adjacent grids.
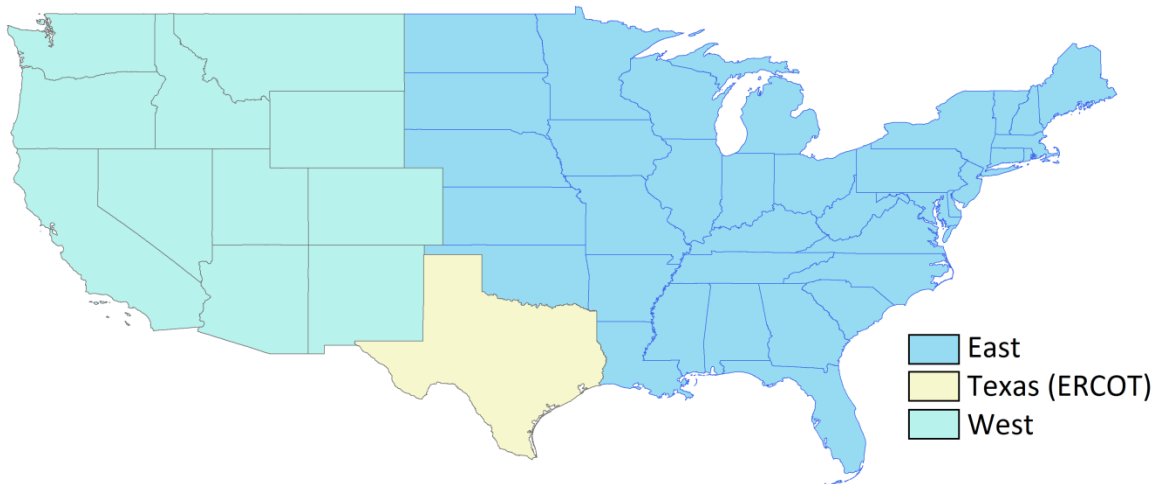

Figure 2.4: Delineations used to approximate the spatial extent of the three major US electric power grids.

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Chapter 3: An Assessment of the County-Level Carrying Capacity of Croplands within the Conterminous United States in a Localized Food Production Scenario

3.1 Abstract

There is a rapidly increasing interest in localizing food production and consumption to reduce environmental, economic and social stressors. However, currently it is unknown whether agriculture lands can support local populations. Here I provide an estimate of the county-level carrying capacity of croplands within the conterminous U.S. This is accomplished by utilizing historical county-level cropland area maps, gridded historical population density maps, U.S. Census inventory data of county-level crop yields and estimates of per capita food consumption from previous studies. I find that most counties could meet their internal food needs if they are not required to help support other counties with deficits. However, less than 46% of the year 2000 U.S. population could be fed within their respective counties; a 35% reduction from the year 1850.

3.2 Introduction

An increased interest in "local" food has resulted in efforts to investigate the merits of pursuing the localization of food production and consumption and the distance food travels from production to consumption (1-4)."Local" food production has been defined as being within a political unit (sub-province/county, etc.), within foodsheds associated with population centers (5-8), or simply within a certain distance (9).

Food localization is motivated by several factors. One motivation is that as the population increases globally and the demand for food increases, it is questioned whether the current industrialized agriculture scheme can meet food needs in a responsible, environmentally friendly and sustainable way (5). Specifically, shorter distances traveled from the producer to the consumer are associated with reduced transportation energy requirements and lower associated greenhouse gas emissions (4, 10, 11). Energy consumption and greenhouse gas emissions from the production phase may also be reduced if animal feed and other similar resources are produced in close proximity to where they will be consumed (12). Aside from environmental benefits, there are also several proposed social and economic benefits of growing food locally. Some of these benefits may include allowing local economies to retain greater shares of the value of food produced and an increased local involvement in food production issues such as land use practices, pesticide use, and groundwater contamination (4, 11, 13).

The rising global population has also stimulated interest in investigating the sustainability of current agricultural practices. Increased population and affluence will result in higher demand for food and an increase of emissions and environmental impacts associated with both agricultural and non-agricultural activities. Because agriculture is a dominant form of land-use change and degradation globally, agriculture is often a target for environmental reforms. Figure 3.1 shows an estimate of the rise in U.S. regional populations for the years 1850 to 2000 (for information on region definitions, see Figure

1.9.) using HYDE population density data (14). The U.S. population is projected to continue to grow and exceed 400 million around 2050 (15) .
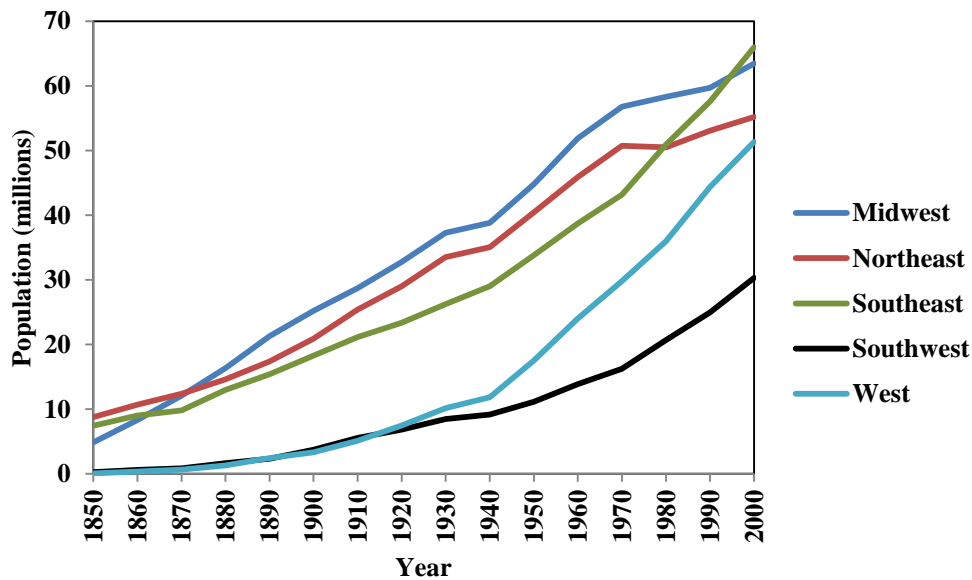

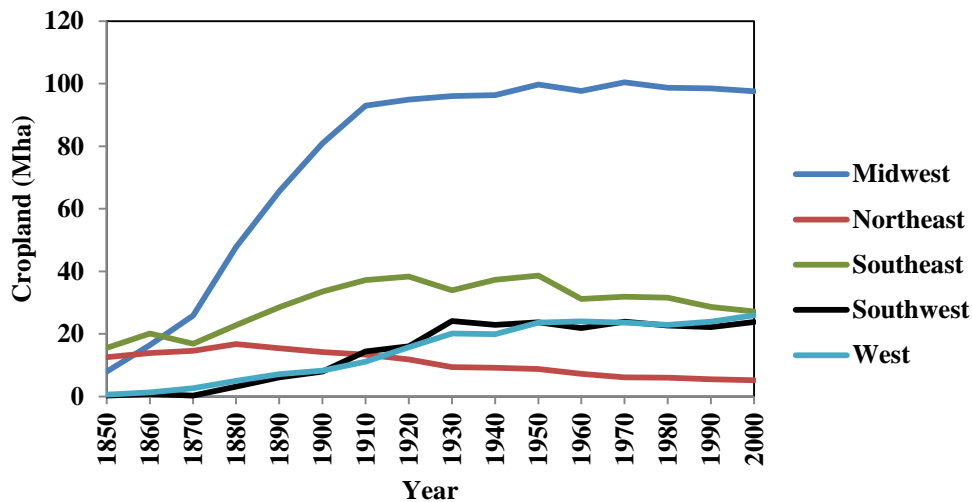Figure 3.1. United States population trends by region.

Figure 3.2. Cropland area in the U.S. by region.

Despite a growing U.S. population, regional cropland areas have remained relatively stable in recent years (Figure 3.2) (16). Figure 3.3 compares U.S. national cropland and population estimates and shows that the U.S. has used roughly the same area of cropland over the last century. This demand for agriculture products is exacerbated by increasing biofuel production and international demand for food (17, 18). The U.S. has so far been able to respond to this growth in demand by increasing crop

yields (Figure 3.4) but there is likely a limit to the extent that yields can continue to increase. Additionally, in many cases, increased crop yields are largely due to the intensification of fertilizer application and intensified land-use practices that can lead to additional environmental concerns. In an attempt to mitigate the impacts of agriculture in light of a growing demand for agricultural production, localization has been proposed.

There has also been considerable criticism of the merits of local food. In some cases the terms sustainable, organic, and local food have been confused or conflated by the general public and the media and often local food is assumed to be inherently good (2, 10). Born (2006) makes a thorough case for the argument that several aspects of the supposed merits of local food production are misconceptions and that local food production does not mean that an improved ecological, environmental, social or economic state will result.
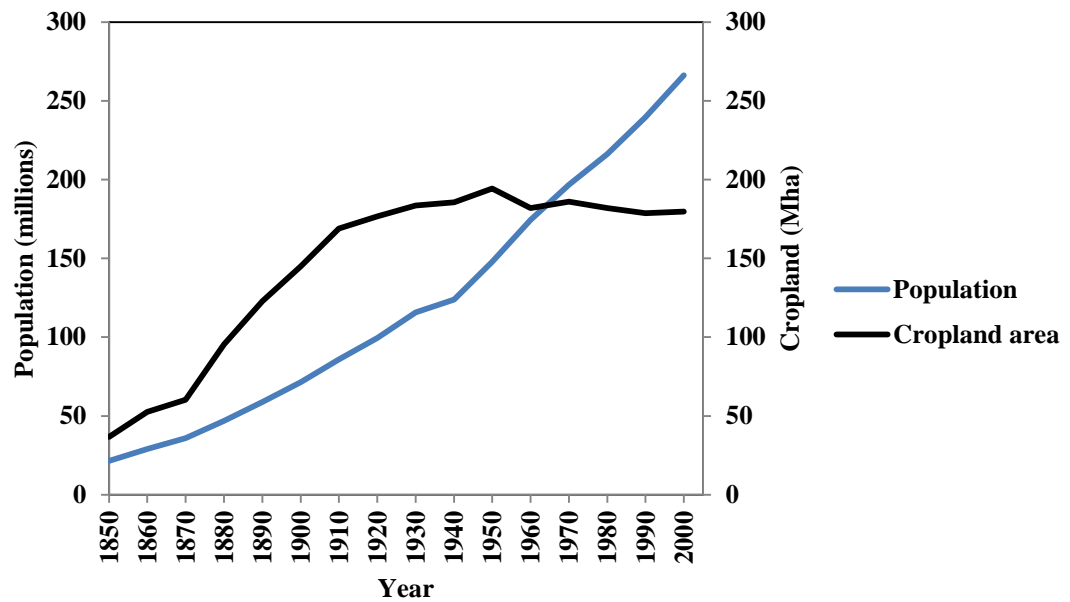

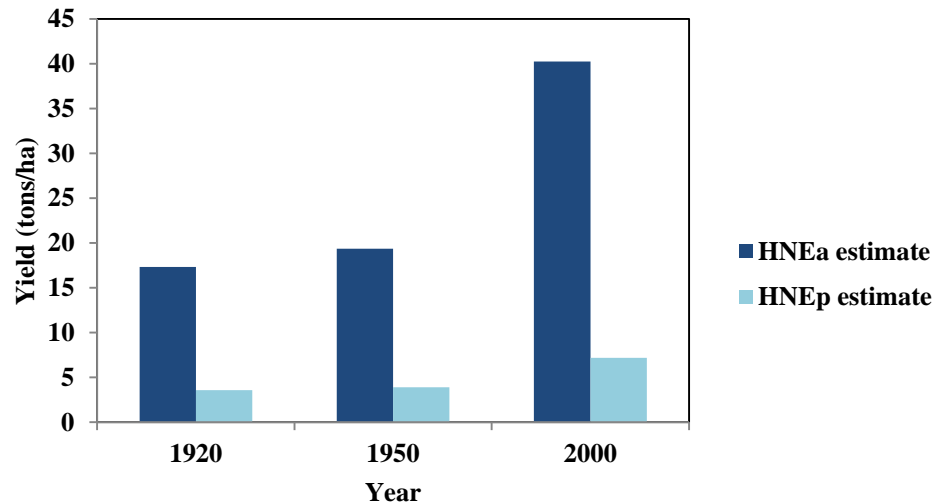Figure 3.3. A comparison of U.S. population and cropland area trends.

Figure 3.4. National cropland area weighted average yields by commodity type. HNE_a represents commodities that contribute to the portion of the diet derived from annual and high-value crops while HNE_p contributes to the portion of the diet derived from perennial forages.

Others have even contended that the distance that food travels does not necessarily correlate with associated energy and emissions costs but instead they depend on a much more complicated resource production/supply chain and storage needs (19, 20). There are many situations where available land use practices and agricultural inputs may outweigh any benefit that may result from growing food locally (e.g., consider the water input required for growing local food in a desert) (2, 20).

Assuming that localizing food production would be beneficial, policy makers still need to know where localization is possible. Several studies have made estimates of the potential extent of food localization (5-7); however, none of these studies have made a national estimate for the U.S. Here I provide an upper-estimate of the carrying capacity of croplands as the number of people that can be supported by the available cropland within each county in the conterminous U.S. While local food is defined as food production within a county, alternative definitions could be explored in future work (e.g., foodsheds, distances from farm to consumption)

3.3 Methods

The procedure for estimating the historical (1850-2000) ability of the U.S. to provide food for its population locally (within a county) is outlined in Figure 3.5.
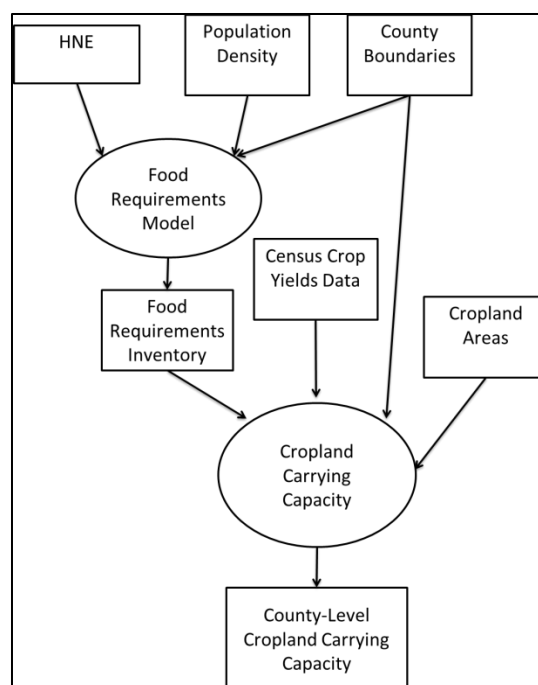
Figure 3.5. Combined, simplified data flow diagram of the food requirements and cropland carrying capacity models.

3.3.1 Food requirements model

First I will describe in detail the process of estimating the food requirements for the total population of each county by means of the food requirements model.

To quantify the amount of agricultural resources that should be allocated to a person per year, it is important to first have an understanding of how much a person consumes. To estimate this quantity of food, I use a metric called the Human Nutritional Equivalent (HNE) that is described as a basket of food that contains representatives from all food groups combined in the proper proportions to constitute a complete diet for one person for 1 year and consists of 1.25 Mg of food yr^{-1} (6). This metric is an extension of previous work done by the USDA to assess the components of a healthy diet. The HNE is divided into two sub categories: HNE_a and HNE_p. HNE_a is the portion of the diet derived from annual and high-value crops while HNE_p is derived from perennial forages with respective proportions of 81% and 19% of the total HNE. The amount of the required food weight, as defined by the HNE, is described in terms of farm weight of food (6). This makes the HNE particularly convenient for converting yields data into food production estimates. It is also important to note that the estimated land and crop requirements to produce the HNE_p estimate is based only on the quantity of feed required to produce food in this category (21).

HYDE gridded population density maps with a resolution of 5 minutes were used to estimate the population within each county (14). First the population density maps were multiplied throughout by respective areas of each grid cell to obtain population totals. County population totals were estimated by using a Geographic Information

System (GIS) to sum populations within county boundaries defined by the U.S. Census Geography Division (22). The food requirements were then obtained by combining the definition of the HNE with population totals.

3.3.2 Cropland Carrying Capacity Model

The output form the food requirements model is then used as input for the cropland carrying capacity model (also Figure 3.5). The purpose of the cropland carrying capacity model is to estimate how many people can be fed within a given county given a certain amount of cropland and estimates of expected crop yields. Here I follow Peters (2009) (6) by using corn silage and hay as indicator crops for estimating HNE_a and HNE_p yields respectively. A current picture of crop yields are derived from county-level production and area harvested estimates from the most recent U.S. Census of Agriculture publications from 1997, 2002 and 2007 (23-25). These three years are averaged in an attempt eliminate the annual fluctuation of yields (influenced by climate, water availability, policies, etc.) and is assumed to be a reasonable representation of agricultural yields circa 2000. Previous years estimates of yields are calculated by applying the ratio of national averages of crop yields (from the National Agricultural Statistics Service (26)) for corn silage and hay for the year in question to the national averages from the year 2000. Survey data is used here because it has a higher temporal resolution than the census data.

However, the Census of Agriculture did not have data for corn silage and hay for certain counties. The yields in these counties were estimated by using corn grain and haylage as substitute indicators of relative crop yields of corn silage and hay. This was done by first calculating the state mean yields of the substitute crops and then examining the yield's deviation from the mean experienced by the a county with missing corn silage or hay data and then assuming a similar deviation for corn silage or hay. For example, a county with missing corn silage data that reports corn grain yields 2% lower than the state mean value for corn grain yields would be assumed to have a corn silage yield that is 2% lower than the state mean value for corn silage yields.

Even after using the indicator crop substitutions mentioned above, some counties still had insufficient data for calculating yields. One solution to this problem could be to assume that counties without data would have no yield (yields equal to zero) because missing data implies that the cropland within this county is likely unsuitable for supporting the indicator crop. The other solution is to assume that a state average is a reasonable estimate of potential yields. Here I continue with the latter solution as my goal is to provide an upper-estimate of the county-level cropland carrying capacity but also provide supplemental information pertaining to the former solution for counties with missing data (Figures 3.8-3.11).

Yields estimates adjusted for losses that occur from the farm to consumption were calculated by applying loss estimates of different food groups obtained from worksheets made by the Economic Research Service (27). Loss percentages were calculated by averaging ratios from each food group weighted by food group proportions of a complete diet based on USDA recommendations for servings (28). Yield information prior to 1910 are not available for the indicator crops used; however, yields data for similar crops from

the USDA agriculture surveys suggests that yields prior to 1920 were relatively stable with only small annual variations in most cases (26). For this reason, I assume 1920 yields estimates for all years prior to 1920.

The next step in the cropland carrying capacity model is to calculate the available cropland within each county. Using a GIS, total cropland areas were calculated for each county using county boundaries defined by the U.S. Census Geography Division along with historical gridded cropland data with a resolution of 5 minutes as input (16). Once cropland area totals are calculated, the distribution of HNE$_a$ and HNE$_p$ crops upon the available cropland must be determined. Crop allocation is decided in a way where an equal proportion of HNE$_a$ and HNE$_p$ can be created based on relative needs. In other words, the percentage of HNE$_a$ and HNE$_p$ that is met should be the same to maximize the number of people fed and provide an upper-limit estimate. The proportions should be as close to equal as possible because having uneven proportions will result in more people not having their complete dietary requirements met (this does not mean that equal areas of cropland should be devoted to each type of crop but that the same proportion of the demand met for each should be equivalent). The amount of cropland planted to each type of crop (crops that contribute to HNE$_a$ or HNE$_p$) is calculated from the following equations:

$$A_t^i = A_a^i + A_p^i \ [eqn. 1]$$

$$\frac{A_a^i * Y_a^i}{N_a} = \frac{A_p^i * Y_p^i}{N_p} \ [eqn. 2]$$

Where A_t^i, A_a^i, A_p^i represent the total agriculture area available within the county, the cropland dedicated to HNE$_a$ and the cropland dedicated to HNE$_p$ respectively for year i. Y_a^i and Y_p^i are the relative estimated county yields of HNE$_a$ and HNE$_p$ croplands respectively for year i. N_a and N_p represent the respective proportions of HNE requirements that need to be met by HNE$_a$ and HNE$_p$ and are constant values of 0.81 for HNE$_a$ and 0.19 for HNE$_p$ (6). The two unknown cropland areas A_a and A_p can be calculated by solving the two equations above for A_a and A_p.

The cropland carrying capacity (the number of people that can be fed) for each county is then calculated by multiplying the yields of the indicator crops by the respective allocated cropland areas and then comparing these quantities with HNE requirements.

3.4 Results

Figure 3.6 shows that crop production would historically exceed the U.S. need for food. In Figures 3.6 and 3.7 the production estimate is based on the amount of food that can be produced while meeting the highest number of HNE requirements and using optimal cropland distributions between crop types. Food needs are estimated based on HNE requirements per capita. The potential food production capability estimated here under my assumptions is high enough that the U.S. would likely still be able to meet food needs for both commodity types given actual crop allocations.
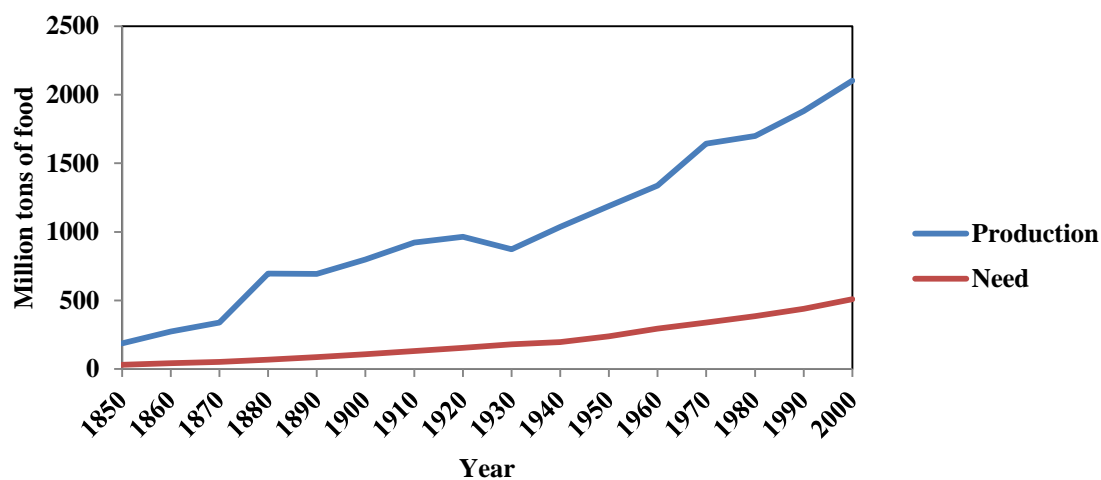
Figure 3.6. National food production and need from 1850 to 2000. Production and need estimates are measured in units of loss adjusted farm weights of combined HNE$_a$ and HNE$_p$ indicator crops.
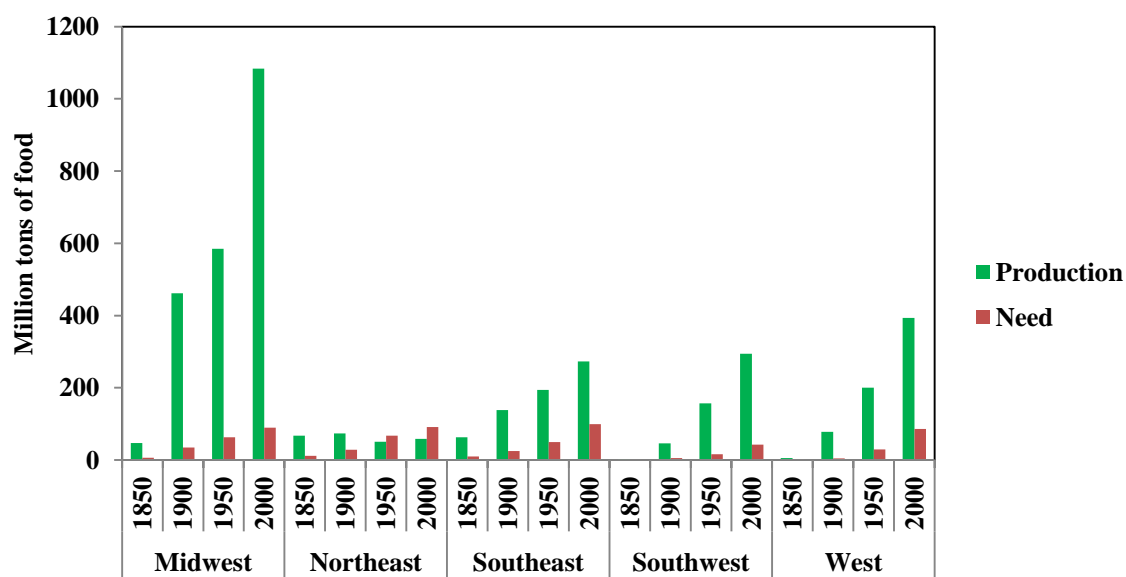

Figure 3.7. Food production and need by region by year. Production and need estimates are measured in units of loss adjusted farm weights of combined HNE$_a$ and HNE$_p$ indicator crops.

Similarly, analyzing my results on a regional scale, Figure 3.7 shows that most regions would be able to meet their own food needs under my assumptions. However, the Northeast was already unable to meet food needs as of 1950. Real crop distributions, competition from biofuel crops and other factors would reduce the amount of the U.S. food requirements that could actually be met. While the Northeast is not able to meet local food needs, the Midwest produces so much that it necessarily needs to export large portions of its yield so as not to waste. Figure 3.7 also helps to support the story told by figures 3.3 and 3.4 of increasing production due to increased yields despite relatively stable cropland areas.

Figure 3.8a provides estimates for select year of the percentage of the people that can be fed within each county (without replacing missing data with state averages) and Figure 3.8b (replacing missing data with state averages). Both Figures show that most counties for all years can produce significantly more food than is required locally and that county level self-sustainability may be a viable option for many counties that are seeking the benefits of localized agriculture.

Figure 3.8b shows that if using state averages is a reasonable assumption for counties missing data then many more counties would be able to support local populations. However, demand for food from counties with large metropolitan areas will likely significantly diminish the percentage of the population that can be fed in surrounding counties as they imports food to meet demands.

Figures 3.9a and 3.9b (missing values not approximated and missing values substituted with state averages, respectively) provide a simpler look at which counties can meet their food needs locally by showing counties that can meet needs in green and counties that cannot in red. Notice that counties that are not able to meet internal food requirements are often associated with large population centers. Again, counties that are displayed in figure 3.9 as being able to meet internal food needs may in reality not be able to as they assist surrounding counties that are struggling to meet their own food needs. From figure 3.9, historical trends suggest an increasing inability for the U.S. to meet internal food requirements at the county level.
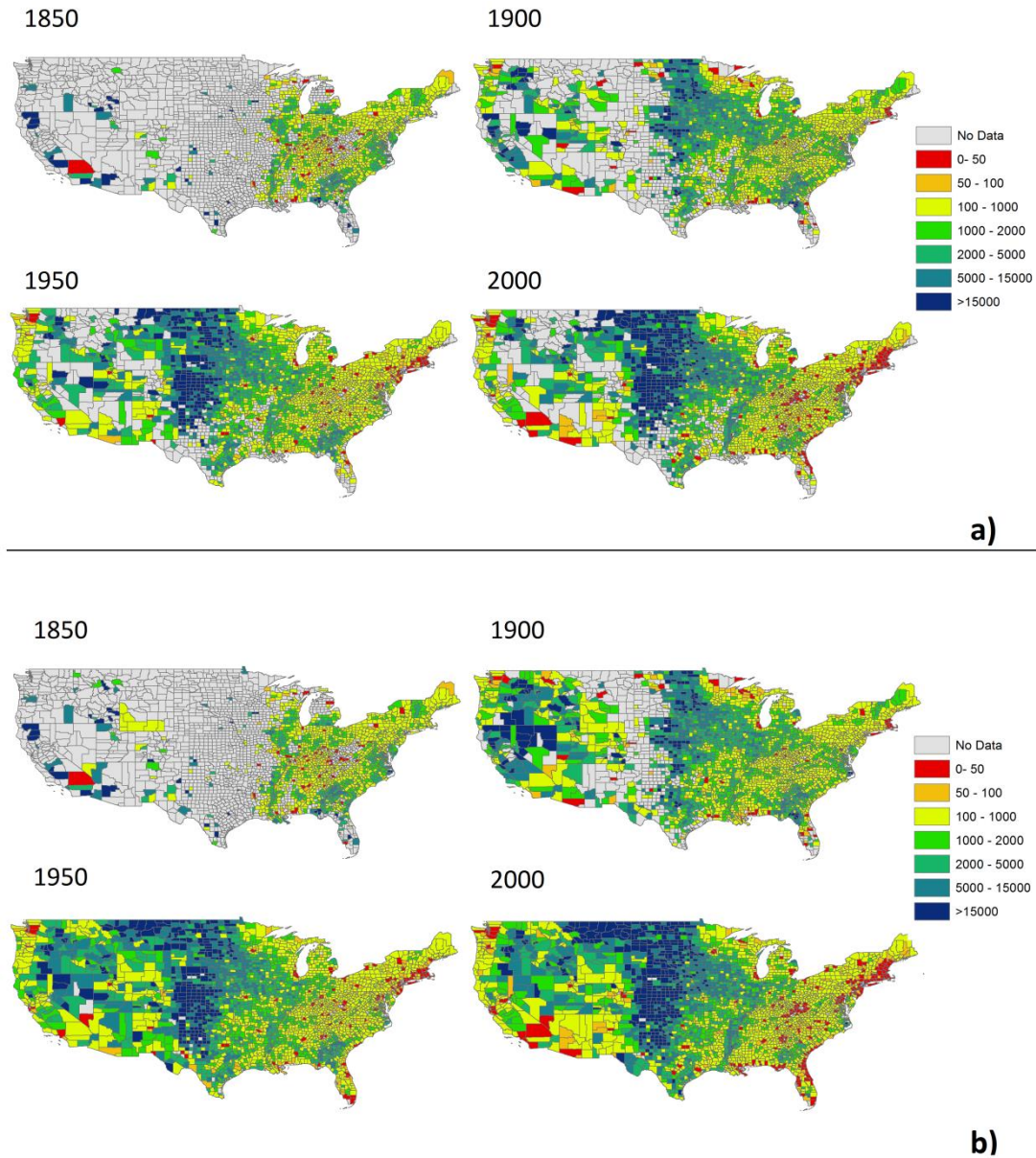
Figure 3.8. Estimated percentage of the population that can be fed locally. a) Missing data has not been approximated by state averages and b) missing data approximated by state averages. Counties with missing yields data are estimated by using state averages of yields data. Persisting "no data" counties exist due to insufficient population information.
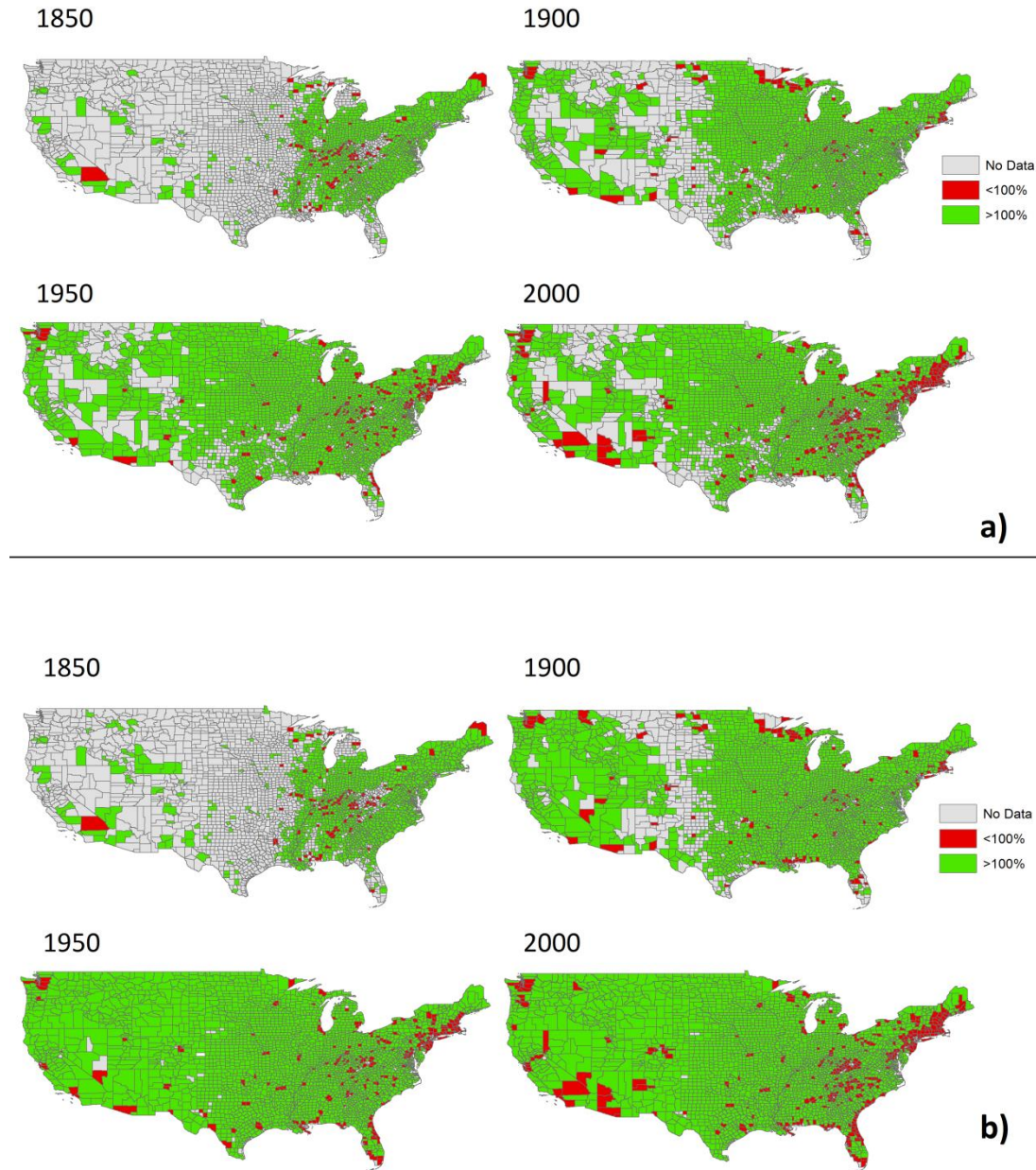
Figure 3.9. Counties that can feed local populations (green) and counties that cannot (red). Gray counties have insufficient data. a) Missing data has not been approximated by state averages and b) missing data approximated by state averages.

Figures 3.10 and 3.11 show the county-level cropland carrying capacity (national and regional, respectively) when a) missing data is not approximated and b) missing data is approximated by state averages. Despite increasing crop yields, there is a steady downward trend from 1850 to 2000 of the percentage of the population that can be fed within their respective counties as the population increases and people migrate to large population centers. It is also important to note that the percentages provided in Figure 3.10 and 3.11 are representative of idealized upper-estimate conditions and are likely

lower. In Figure 3.11, from 1950 to 2000 some regions show an increased county-level cropland carrying capacity while others show a decrease. However, if only the last few decades are considered in Figure 3.11, all regions are showing a decreasing ability to meet food needs locally. This suggests that the U.S. will probably not be able to rely on the localization of agriculture alone for a long-term solution to any adverse effects of the current agricultural scheme. However, it may be used in conjunction with other efforts to reach a sufficient cooperative solution.
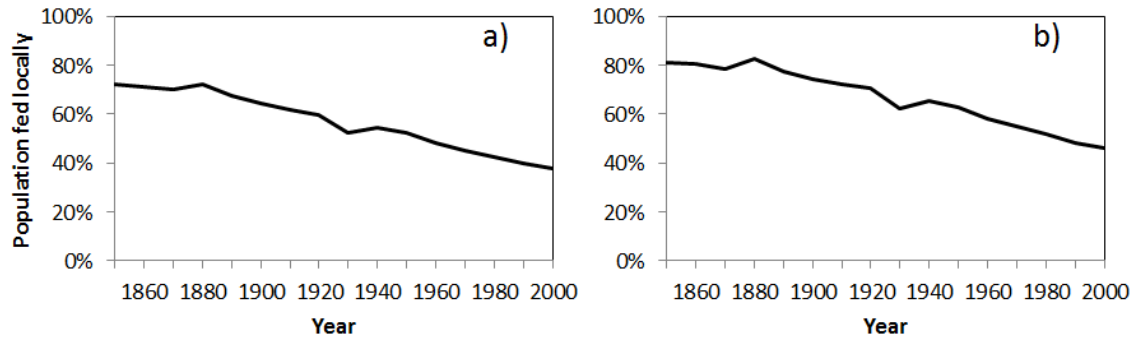

Figure 3.10. The percentage of the U.S. populations that can be fed within their respective counties. a) Missing data has not been approximated by state averages and b) missing data approximated by state averages.
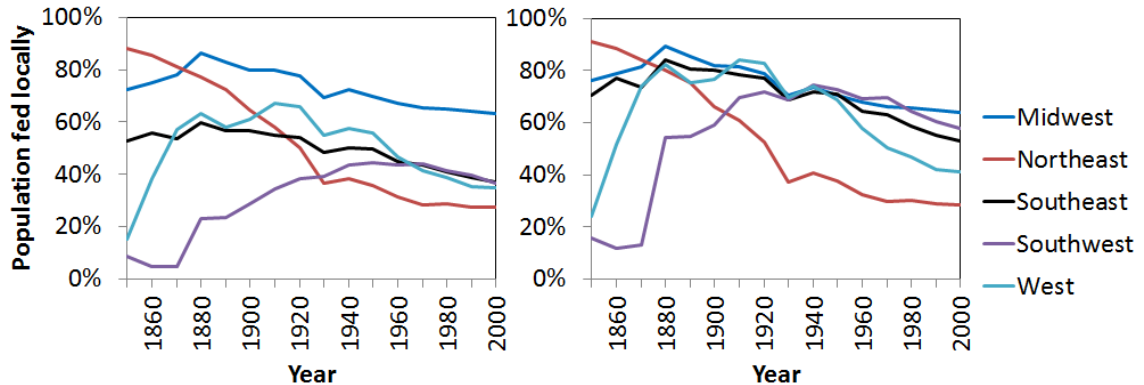

Figure 3.11. The percentage of U.S. populations that can be fed locally within their respective counties by region. a) Missing data has not been approximated by state averages and b) missing data approximated by state averages.

The required land needed to feed one person can be calculated as a function of total food needed per person, crop yields and food losses in eqn. 3:

$$A^i = \frac{N^i + L^i}{Y^i} \ [eqn.\,3]$$

Where A is the cropland area needed to support one person for a year, N is the food requirement per person, L is the estimated food losses, Y is the estimated local cropland yield and i indicates the year. L is added to N to represent extra cropland allocation to

offset food losses. Figure 3.12 shows the lower-limit land requirement to feed one person for one year in the U.S. from 1920 to 2000. While cropland area requirements per person have historically decreased, Figure 3.12 also shows that this trend is slowing and that perhaps U.S. croplands are approaching their upper-limit for carrying capacity/yields.
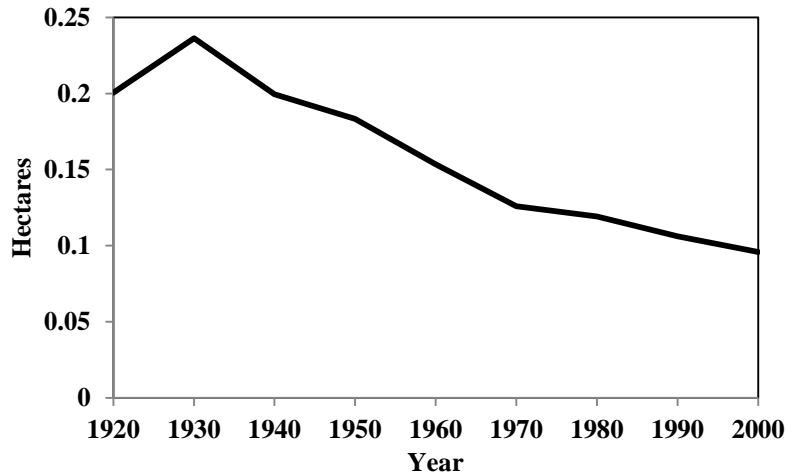

Figure 3.12. Average U.S. cropland area in hectares required to feed one person for one year.

3.5 Discussion

Peters (2009) calculated the ability of New York State to be able to feed its populations. Peters defined localization as the division of cropland into foodsheds that serve population centers while I use a county-level analysis. Peters estimates that about 34% of New York State food needs can be met in state and my analysis predicts that about 47% of food needs can be met in New York State but only 24% could be met if food is only produced and consumed within the same county. The smaller capacity from my analysis than the Peters study may be due to differences in the definition of local cropland or the differences in estimates of the area of land required to feed a single person. Estimates of the land area requirement to feed a single person are 0.18 to 0.86 ha per capita for the New York State foodsheds in the Peters study and about 0.12 ha per capita for the counties of New York State in my analysis. The land area requirements are a function of the estimated crop productivities, food waste, and human food demand. The lower estimate of per capita land area requirements in my work would tend to make my estimate of supported population in New York State larger than Peters. However, when considering localized agriculture, the relatively restricted definition of county level localization presented here as opposed to foodsheds that are presented by Peters results in lower estimates of local cropland carrying capacity.

Previous work by Hu et al. (2011) estimated that about 0.2 ha of cropland per capita would be needed in a subset of the Midwest to meet local food needs (7, 21). My analysis results in a 0.11 ha per capita requirement in the same region. The per capita cropland requirements in Hu et al. are based on crop productivities using a wide range of crops rather than just the two indicator crops used here.

Differences in my estimates from Peters (2009) and Hu (2011) are a result of several factors. I believe the most influential factors include different input data type and resolution, different definitions of "local" and methods for analyzing crop losses and allocations. Specifically, my upper-limit estimate of local cropland carrying capacity does not use spatially explicit soil data as Peters (2009) but instead assumes that crop yields (acquired from the Census of Agriculture, see methods) throughout a county for a given crop will be relatively uniform. I also do not consider the need for crop rotation when allocating cropland to commodity types because I want to provide an upper-limit estimate and any deviation from the idealized distribution of cropland between indicator crops will result in a reduction of the amount of people that can be fed (also, sometimes sustainable agricultural practices such as crop rotations are not utilized anyway). By not accounting for crop rotations more people could be fed within a given year; however, over time, yields will likely be reduced due to poor land-use practices and soil degradation. The combination of factors listed above results in lower land requirements per person and allows my estimate to represent an upper-limit estimate of the potential for counties to meet their internal food requirements. However, further research building on my methods that use a wider range of indicator crops while also accounting for sustainable crop distributions will provide a more accurate estimate of the local cropland carrying capacity.

As mentioned above, I use corn grain and haylage to estimate corn silage and hay yields in counties were data is sparse. Considering the similarity of these crops, using relative differences in yields from the mean state-level yield of corn grain and haylage is a reasonable approach for estimating the yields of my indicator crops. For this reason I argue that it is reasonable to assume that if the indicator crops were not planted in a county, but the substitution indicator crops were, that it was only by chance and that the available cropland within the county should be capable of supporting either type of crop. By using this method to estimate known values for of corn silage and hay yields, I found that using indicator crops to predict missing yields data is a 7% and 1% accuracy improvement over using state averages for predicting corn silage and hay yields respectively.

Additionally, in the case that a county does not have yield data for the indicator or substitute indicator crops, I use state averages to estimate yields. Actual county-level yields for both corn silage and hay fluctuate about 30% from the mean state yield on a national average. However, because it is possible that the available cropland may not be supportive of the indicator crops if both indicator and substitute indicator crop data are absent, I also provide results that do not assume state averages for counties with missing data to clearly show where assumptions were made in Figures 3.8 and 3.9.

Lastly, because this analysis uses data with a yearly temporal resolution, I do not account for seasonal fluctuations in food availability or food storage requirements, which are outside the scope of this study. However, one should keep in mind that some types of agricultural products cannot be grown in certain regions at certain times of the year and therefore, a localized food system may require significant food storage.

The data provided in this study show the U.S. maximum potential of localizing food production and consumption at the county level. This data may be a valuable starting point in investigating a wide range of local food applications and may also be valuable to nationwide policy decisions concerning food localization. However, before implementing any county-level policy, more detailed, county-specific analysis is recommended.

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