A DECISION SUPPORT TOOL FOR IMPROVING LANDSCAPE CONFIGURATION

by

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ABSTRACT

Perennial bioenergy crops provide different ecosystem services (food and fuel production, carbon sequestration, erosion control, nutrient cycling) from those provided by traditional row crops and the delivery of these services varies depending on location (soil type, topography, etc). Strategic placement of perennial bioenergy crops on the landscape can maximize ecosystem services, while minimizing opportunity costs. However, because of social and economic factors, not all land managers are equally willing to convert land to perennial bioenergy crops. We used a computer program to combine modeled ecosystem service data with survey-derived probabilities of conversion to find target areas where perennial bioenergy crops could provide the highest environmental benefit for the lowest economic cost. Our results suggested locations for biomass crops clustered in areas with high soil organic carbon -- traditional row crops in these locations have the potential to lose a large amount of carbon, whereas perennial biomass crops potentially protect and increase soil organic carbon. When farmer willingness to convert was considered, the suggested locations for biomass crops clustered even further. At current prices for perennial biomass, these energy feedstock crops represent a significant opportunity cost when compared to corn. Hence, to reach target quantities of biomass production, policies that incentivize planting of these crops for their provisioning of ecosystem services are likely necessary. Bioenergy policies should be aimed at the "hotspots" where ecosystem services and farmer willingness converge and the decision support tool offered here should facilitate these landscape configurations.

1. INTRODUCTION

1.1. Land use, land cover, and ecosystem services

Human agricultural decisions tend to fall into two different categories: land cover and land use. "Land cover" refers to *what* is being grown, whereas "land use" refers to *how* crops are being grown, e.g. fertilizer applications, tillage system, etc. Both types of decisions can affect ecosystem services provided by land such as food and fuel production, climate stabilization, soil protection, and water quality. Perennial land covers, such as forests and grasslands, tend to have greater environmental benefits than annual cropping systems (Meehan et al. 2013; Werling et al., 2014; Robertson et al., 2011). However, not all land responds equally to these different land covers: in some areas, corn may be highly productive without many environmental tradeoffs, while other areas are very sensitive to any traditional cropping system (Robertson et al., 2011). Differences in terrain and soil type can contribute to large variation in ecosystem responses to land cover changes within a small geographic area (Rao et al., 2014; Yan et al., 2014). Careful land use and land cover (LULC) decision making can take advantage of this variation by growing more environmentally beneficial land covers on more sensitive land.

1.2. Bioenergy landscapes

One way to increase the amount of land growing more environmentally beneficial land covers is to use a combination of the market and policy to encourage farmers to grow perennial bioenergy crops. Both the United States and the State of Wisconsin have set targets for renewable energy production (WI Act 141, 2005; USDoE, 2011). Bioenergy crops are one means of achieving these goals (IPCC, 2013). To avoid potential food-fuel conflicts, cellulosic biofuels have recently gained attention as an alternative to grain-based biofuels. Both annual and perennial crops can be used for cellulosic biofuel, but the crops affect their ecosystems differently. Perennial crops generally provide ecosystem services to a higher degree than annual crops (Meehan et al. 2013; Werling et al., 2014; Robertson et al., 2011); however they are generally less valuable economically than annual crops (Meehan et al. 2013; Kells et al., 2014).

There are several reasons why cellulosic biomass is not a source for large-scale bioenergy production. The current price for biomass feedstock relative to grain ethanol is too low to trigger a major shift toward growing biomass crops. This is partly because transportation and conversion costs are higher for biomass than for grain ethanol (Epplin et al., 2007), yet policies encouraging these crops are similar (Carriquiry et al., 2011). With current market values, the opportunity cost of growing biomass over corn for ethanol is too high for most farmers to be willing to switch (Kells et al. 2014). A combination of strategic placement of biomass crops on the landscape to minimize opportunity cost and policies that differentiate between types of biofuels should encourage a shift to perennial biomass crops (Solomon et al., 2007).

One policy technique to encourage planting of perennial biomass crops over annual biofuel crops is payment for the social value of ecosystem services (PES). The idea behind these programs is that the ecosystem services provided by a specific piece of land extend far beyond the boundaries of that land and therefore benefit more people than just the landowner. For example, water quality services benefit anyone downstream of the land providing the service. A PES program is a way to pay land managers for LULC decisions that benefit other people (Engel et al., 2008). Since perennial crops provide greater ecosystem services than annual crops (Meehan et al. 2013; Werling et al., 2014; Robertson et al., 2011), PES programs would effectively increase the value of perennial biomass crops.

In order for PES programs to be successful, the "social capital" of such a program is important (Bremer et al., 2014). That is, social reasons may cause land managers to decide not to participate in a PES program, even if participation is economically rational. While the shift from corn-as-food to corn ethanol production did not require much farmer buy-in, since they were still growing corn and the infrastructure was already in place (Graham et al., 2000), perennial biomass production would potentially require farmers to buy new equipment and learn new management techniques (Luo et al., 2013). Even when no major financial investment is required, in some cases negative views of perennial biomass crops are simply a reaction to externally-promoted changes (Bremer et al., 2014, Ribeiro, 2013).

1.3. Decision support tools

Strategic placement of perennial biomass crops could improve ecosystem services without reducing current food and fuel production. One method of determining where these crops should be grown is by using a "decision support tool." There are several different ways of interpreting the term "decision support tool," the simplest being any software that organizes information for the purpose of helping a user make a decision in a given field. Any model that allows for a comparison between different possible scenarios could be considered a decision support tool, though if not built with decision-support in mind, the usefulness of the results may vary (Sohl et al., 2013). Since LULC data is spatial, the most useful tools have spatial inputs and outputs that reflect variation over the landscape. Different tools have different purposes – some are designed to model the spatial distribution of goods and services accurately given a landscape, while others focus on combining modeled data into a single assessment for a specific purpose, such as targeting areas for biodiversity conservation (Bottero et al., 2013). Some tools are simple pixel-by-pixel calculations, only requiring a geographic information system (GIS) for display, while others, such as the SWAT model, incorporate spatial relations such as terrain into the analyses (Amatya et al., 2011).

The issue of incomplete information is a challenge for all models. Since no environmental model can include all real-world factors, we must rely on simplifications and representative factors and estimates by experts. Unfortunately, this means that the quality of a decision support tool may vary dramatically, depending on the quality of the simplification and estimates (Sohl et al., 2013). Also, in order to be effective for decision support, a tool must both be easily run for different scenarios and have results that are easy to interpret (D'Erchia et al., 2002). While there are some advantages to a tool that is designed specifically for one region, if a tool proves useful in one location, decision-makers might like to use the same tool elsewhere; this is only possible if the model and data are transferable to the new location. Also, at different times or in different regions policymakers may want to consider different sets of criteria -- for example, water use efficiency may be more important to policymakers in the Southwest than to those in the Midwest. Therefore, a tool that has both spatial and data flexibility would be most widely useable.

Some of the most common decision support tools are assessment and ranking tools -- that is, tools that produce a single “score” for each pixel. These have the advantage of simple results: a user can visually identify what regions are important or not. However, the disadvantage is that such tools need to compare and combine vastly different inputs. Monetization of inputs (to put factors in a common metric) is relatively easy where there is an existing market, such as for crop yields, and even carbon sequestration (though the latter market has had little success) but how does one account for ecosystem service benefits that are not typically monetized, such as enhanced wildlife habitat, or nutrient retention/eutrophication prevention? Moreover, different users may value services differently and not necessarily in ways that can be quantified or compared (Kelly et al., 2013). The solution is to consider multiple objectives simultaneously and provide corresponding results.

1.4. Biomass crops as a potential driver of LULC change

Cellulosic biomass crops represent a huge opportunity for simultaneously increasing both ecosystem services and U.S. production of renewable energy (Robertson et al., 2011).

However, identifying areas where these crops can be grown without significantly decreasing either food production or farmer income is a challenge. Strategic placement of perennial biomass crops on the landscape can promote provisioning of ecosystem services while minimizing the opportunity costs of conversion. Since land use policy generally requires buy-in from landowners, “strategic placement” should also include consideration of whether the farmers are willing to grow biomass crops. A great PES program targeting ideal land for conversion to perennial biomass crops would be ineffective if land managers are unwilling to participate (Bremer et al., 2014). The purpose of this project was to create a tool that finds “hotspots” where perennial biomass crops would have the most benefits with the fewest tradeoffs (Werling et al., 2014; Robertson et al., 2011), and that allows for consideration of farmer likelihood of participation.

Most existing scenario evaluation tools start by painting the landscape with new land uses or land covers and then determine the ecosystem service impacts of such changes (Thomas et al., 2013); however, policy is often aimed at achieving certain ecosystem services goals, such as biomass production targets, soil carbon sequestration, or erosion control. We built a goal-seeking tool that allows one to set multiple desired outcomes and search for land cover change solutions on the landscape that address these goals. This sort of tool allows users to experiment with different goals, such as the renewable energy and biomass targets, without requiring them to understand all of the processes on the landscape that go into achieving those goals.

Finally, many GIS-based tools take a long time to run, and are therefore frustrating to use. We wanted to create a tool that would run quickly enough to allow users to easily experiment with multiple goals.

2. METHODS

2.1. Sauk County as a study area

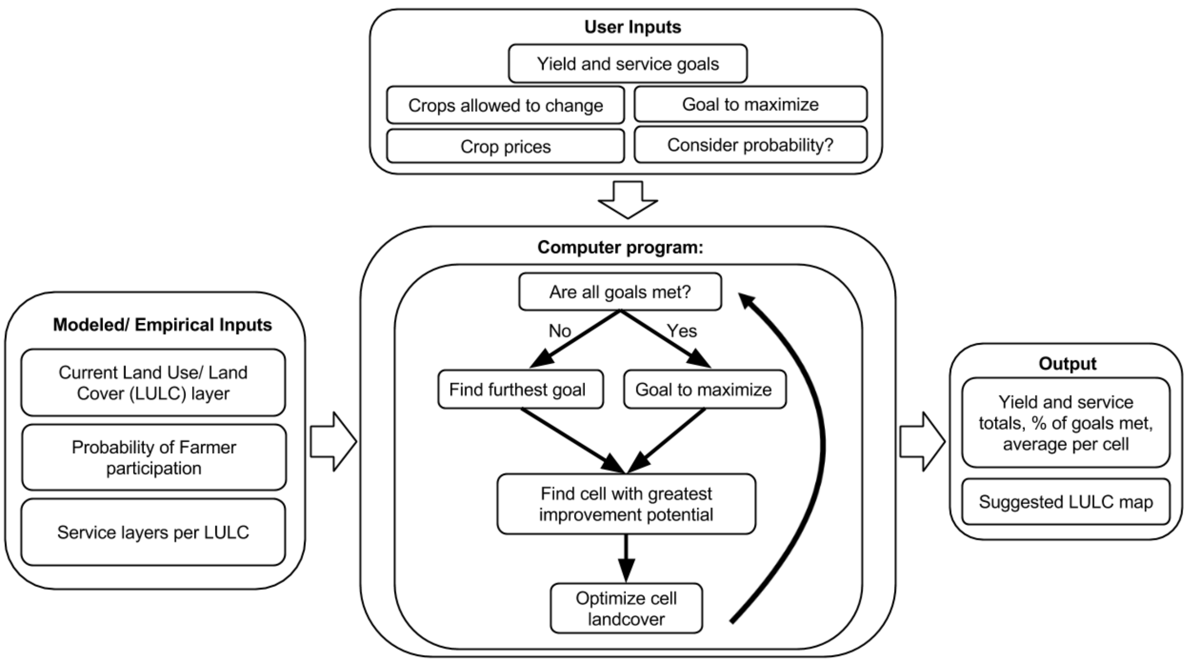
We selected Sauk County, WI as our area of interest. Sauk County is part of the Driftless Area, so it has a wide range of topography. The variety of landscapes and agroecoystems in Sauk County means there may be large differences in the relative productivity and ecosystem services provided by perennial biomass crops versus traditional row crops. While much of the highly sloping land is planted to perennial crops (if cropped at all), some is still supporting traditional row crops, providing a variety of current land uses and corresponding ecosystem responses to consider. Also, we had survey results from land managers in Sauk County about their willingness to grow crops for bioenergy (Mooney et al., 2013). The results of these surveys were useful for determining the likelihood of participation in a biomass cropping system program. Finally, much of the input data we used, such as yield predictions, were provided county-by-county, with noticeable differences between counties. By using just one county, we could reasonably compare different yields under different crops assuming some standardization of data.

2.2. General program process

We wrote a computer program in C++, selected for its run speed and object-oriented capabilities. The program does no modeling itself, but rather uses provided modeled and empirical data to determine ecosystem service responses to different LULC combinations. The program starts by determining if all of the goals have been met. If so, it tries to make improvements on a user-specified “goal to maximize” while continuing to meet other goals (Figure 1). If all goals have not been met, the program finds the service furthest from its goal on a percentage basis. For that service the program finds the cell with the smallest ratio of current service quantity to best service quantity (that is, the cell that is most poorly used for that service), and changes the suggested land cover for that cell from the current to the one providing the best quantity of that service. This continues until the goals are met, or the program finishes the user-set number of iterations.

As currently written, the algorithm does not specify a preference among multiple cells with equal potential for improvement, which means there may be a slight eastern geographic bias for selecting such cells. Highly detailed and variable modeled inputs would lessen the likelihood of multiple cells having the same potential for improvement, and therefore this geographic bias. Future versions of this program could address this bias in a few different ways. One method would be to use a random factor to select which of multiple “equal improvement” cells to change (rather than the furthest east as happens now). Or, perhaps it would be useful to see two opposite geographic biases, such as northwest and southeast. Any “hotspots” that are the same under the two opposite geographic biases must have strong non-geographic pressures to change and could be considered very “hot.” Alternatively, if the two biased maps are very different from each other, the input data may not be sufficiently fine-grained or variable.

Figure 1. Using modeled/empirical data (Modeled/Empirical Inputs) and user-selected goals (User Inputs), this program seeks to find a landscape configuration (Output) that meets multiple ecosystem service and yield goals. The program (Computer program) is designed to run quickly, iterating through all services and cells multiple times while rearranging the landscape to find a combination of cells that meets, exceeds, or approaches the goals (User Inputs).



2.3. Data inputs

The required data included a current LULC map and a layer per crop with the quantity of each service gained in that location under that crop (for example, layers of the predicted corn yield and carbon sequestered by a switchgrass crop).

Only cells currently planted to a crop in the "allowed to change" (Figure 1, User Inputs) list were considered for conversion to a different land use. Also, when data were missing for a cell, the program did not consider that cell for conversion.

When modeling land use change, one often thinks in terms of designing the best landscape to achieve certain goals, and does not consider whether such a change is likely from a socio-economic perspective. For example, the type of farm, the age of the farmer, and the primary income source may all play a role in the likelihood of crop conversion for a particular land parcel. In order to factor in these sorts of real-world considerations, we also included an optional 'probability' data layer. This data layer allows a researcher to provide a probability of conversion on a cell-by-cell basis.

2.3.1. Crops

For this example, we considered crops of corn, pasture, soybeans, alfalfa, and switchgrass. These are the major non-forest crops grown in Sauk County (USDA NASS, 2010). We did not consider forest for conversion due to the non-annual return on investment. Data layers were grids of 581 x 548 cells, each representing one hectare of land. Of these 318,388 cells, a little over 100,000 cells were actually in Sauk County, currently planted to a crop listed in the crops file, and not missing any data.

2.3.2. Services

For services, we considered individual crop yields, net income, soil carbon after 20 years, and soil retention. We used estimated crop yields from the Soil Survey Geographic Database (SSURGO) (USDA NRCS, 2010). We used SSURGO data to estimate current soil carbon, and IPCC 20-year rates of change of +17% for perennial crops and -16.5% for annual crops (IPCC, 2006) to estimate the change in soil carbon. For soil retention, we used the universal soil loss equation (USLE) with erosivity factors from the EPA, and length, slope, and erodibility factors from SSURGO, and focused on soil loss on a cell-by-cell basis.

Net income was calculated based on the price for the crop less the cost of the typical fertilizer application for the crop. We only considered grain income for corn and soy, set at $5 and $11 per bushel respectively, and we used $100 per Mg of biomass for pasture and alfalfa. These prices were approximately market value at the time. We also used $100 per Mg of biomass for switchgrass. This price was set based on feedback from land managers about their willingness to grow switchgrass for bioenergy at different price points (Mooney et al., 2013). When calculating income, we also included the cost of fertilizer for corn and soy crops – we used application rates of 103 kg N per ha for corn, and 17 kg N per ha for soybeans based on the most recent averages for Wisconsin (USDA ERS, 2013), and a price of $500 per Mg N. While we could have included other input costs, such as fuel, or pesticides, we elected to consider only nitrogen input costs for these runs, as they are both significant and applied in relatively predictable quantities.

2.3.3. Determining land manager willingness to convert

Using the aforementioned survey data (Mooney et. al., 2013), we had some specific information about farmer willingness to grow biomass crops at various prices in this county. One of the key factors correlated with likelihood of growing biomass crops was the type of farm. In Sauk County, at $100 per Mg of switchgrass biomass, only 8% of dairy farm managers and 35% of crop farm managers were willing to plant any switchgrass. The low likelihood of dairy and crop farmers to grow switchgrass, in addition to other biophysical and socioeconomic constraints, translated to only 4% of the total farmland in the county potentially being converted. To create the probability layer for Sauk County, we created a grid of "sample farms" of approximately 80 hectares each. We used a data layer of the number of dairies per section (WI DATCP, 2013) to estimate the likelihood of a given "farm" being a dairy. We clearly missed some dairies with this method, as well as mistakenly assigned some non-dairies as dairies, but this produced a rough regional approximation. Using a uniform distribution from 0 to 1, we randomly assigned a value to each farm. Dairies with a value under 0.08 and other farms under 0.35 were selected. When the program ran with probability of conversion considered, only land on these farms could be changed to a new land use. Because of the overall land-change limit of 4%, when running the switchgrass-for-biofuel scenario with probability, we set the maximum percent of land conversion to 0.04, which translated to 4637 of the 115,934 farmland cells.

2.4. Setting goals

In other decision support contexts, users experiment with different “scenarios,” and receive an output with the resulting service response; since this program is goal-seeking, we consider the goals to be the primary input factor, while “scenarios” are LULC maps that would allow us to meet, exceed, or approach those goals. Several inputs were allowed to change for each program run. The most important user inputs are the goals and constraints. By default, we assume that all yields and services should be at least as good as they are in the current landscape, but a user can easily set either yield or service goals for improvement, and/or reduce constraints to make it more likely that the goals can be reached (for example, increasing carbon sequestration in the landscape may require a reduction in row crop yields). The user can also choose a specific service to maximize if the goals are all met. For example, perhaps a user wants to improve income as much as possible while also meeting other service goals. Finally, the user can choose whether to consider manager probability of conversion, how much land to allow to convert, and how many iterations to allow the program to run.

2.4.1. Sauk County selected goals

We experimented with three goals in Sauk County that we expected to represent a range of LULC scenarios. First, we tried to improve income while maintaining yields and services at 100% of their current levels (Goal 1). We consider this to be the “business as usual” scenario – without policy changes, we expect farmer choices to be profit-driven.

Second, we set a goal of producing 36,000 Mg of switchgrass biomass in Sauk County (Goal 2). We selected this biomass goal based on the estimated amount of biomass required for a small biomass processing depot (Eranki et al., 2011). This would be a first step in trying to meet biomass energy goals, potentially allowing us to identify areas to target for policy and infrastructure changes. Finally, in addition to the goal of 36,000 Mg of switchgrass biomass, we added the aforementioned socioeconomic-driven probability of land conversion constraint (Goal 3). This is potentially a better first step for meeting biomass targets than the second goal, in that it considers social constraints when identifying target areas. For both Goals 2 and 3, we set a constraint to keep all other services at or better than 100% of their current levels and other yields at or better than 90% of their current levels.

3. RESULTS

The outputs from this program are relatively simple. The program provides 1) before and after aggregated totals for each crop and service across the landscape, 2) the number of cells in each crop, and 3) an average yield per cell. It also lists the total count of cells changed, both as a raw number and as a percent of the landscape. If a probability layer is used, these numbers are displayed both for the whole county, and for the cells with a probability greater than 0. The program also creates a white-space delimited ASCII raster file of the suggested land use, which can easily be imported to a program such as ArcGIS to be displayed as a map.

3.1. How did different goals drive suggested LULC scenarios?

3.1.1. Goal 1: Improve income while holding yields & services at or better than current levels

In this “improve income” run, 9% of the cells changed to a new land cover, but the changes were diffuse and difficult to discern on the maps (Figure 2). In the suggested landscape (Figure 2B) much of the solid corn areas in the south and southeast have transitioned to pasture. Despite the large number of cells changed, the corresponding changes in yield and service quantities were tiny (Table 1). The fact that soil retention decreased is an indication that some of the more productive land is also more vulnerable to erosion. With current prices, we were unable to converge on a landscape layout that resulted in a positive increase in all services.

Figure 2. Current land use and land cover (A) and the suggested LULC (B) resulting from an “improve income” goal (Goal 1) for Sauk County. The suggested changes mostly consist of replacing corn with pasture in previously large blocks of corn crops.

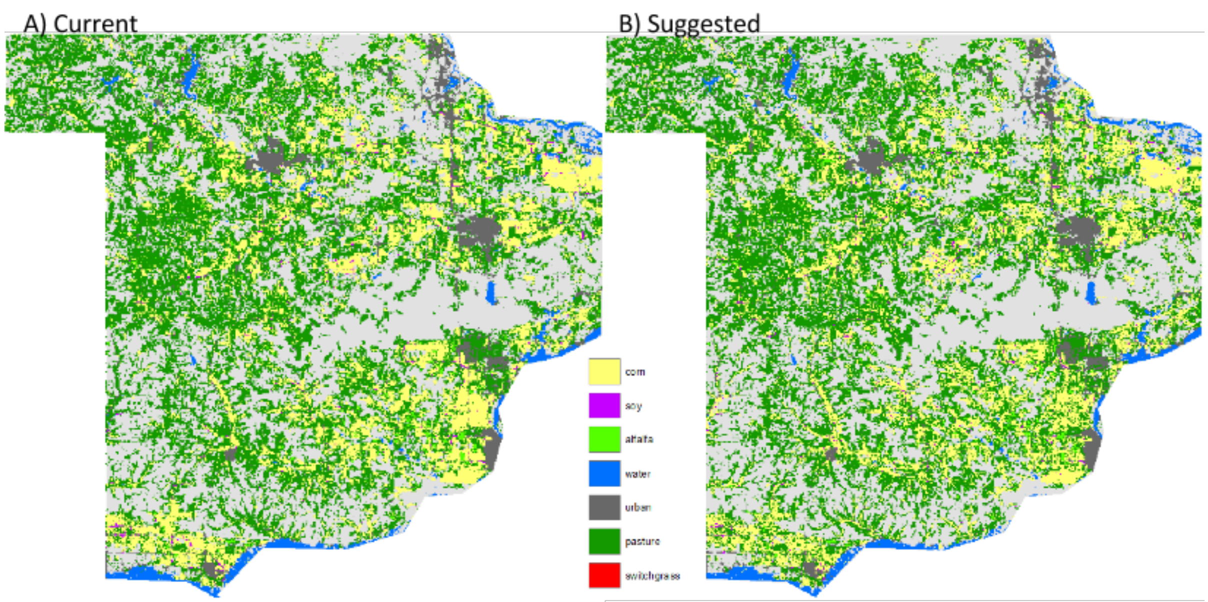


Table 1. Modeled service changes as a result of setting an "improve income" goal for Sauk County. The program was unable to find a layout that increased all yields and services. Income and soil loss appear to be inversely related in this area. 116,316 total cells (hectares) were considered in these calculations.

	Current			Suggested			%
Modeled Service Response	Value	Area (ha)	Per ha	Value	Area (ha)	Per ha	Change in value
Corn biomass (Mg)	410,081	35,471	11.561	410,091	35,158	11.664	<0.001
Pasture biomass (Mg)	636,088	77,969	8.158	637,129	78,297	8.137	0.002
Soy biomass (Mg)	4,610	858	5.373	4,615	839	5.501	0.001
Alfalfa biomass (Mg)	18,656	2,018	9.245	18,660	2,022	9.228	<0.001
Estimated annual income	$111,288,001	116,316	$957	$111,414,272	116,316	$958	0.001
Soil Carbon after 20 years (Mg)	8,702,923	116,316	74.821	8,706,612	116,316	74.853	<0.001
Soil Loss (Mg)	-235,290	116,316	-2.023	-235,613	116,316	-2.026	0.001

3.1.2. Goal 2: 36,000 Mg of switchgrass biomass, while holding services at or better than current levels, and non-switchgrass yields at or better than 90% of current levels

When trying to place switchgrass crops to achieve 36,000 Mg of biomass, the resulting map shows large areas where switchgrass has been clustered (Figure 3B). The program does not specifically force such clustering; rather it is a result of better yields and services for switchgrass than for the current crops in those areas. The program could not converge on a layout that would meet the 36,000 Mg switchgrass goal, unless we allowed other crop yield totals to drop (Table 2). The program took most advantage of the land currently in soy, dropping it to just over the 90% limit. The corn and soy yield tradeoffs required to meet the switchgrass goal were significant enough that overall income for the county dropped even at a switchgrass price of $100 per Mg. This is an indication that in order to encourage planting of enough switchgrass for a biomass depot, either through market forces or PES programs the relative price of switchgrass biomass to corn and soy must be higher.

Figure 3. Current land use and land cover (A) and the suggested LULC (B) resulting from a "biomass" goal (Goal 2) for Sauk County. Clustering of switchgrass placement is driven by relative gains in yields and services

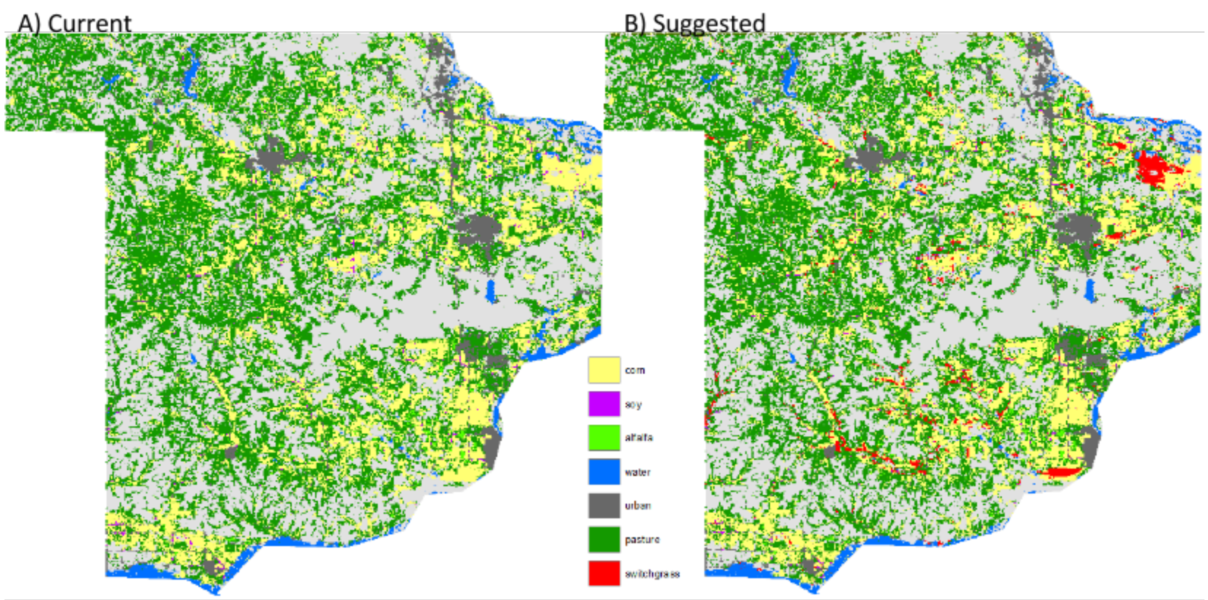


Table 2. Modeled service changes as a result of setting a "biomass" goal for Sauk County. Most ecosystem services increased, but even at $100/Mg, income dropped under the switchgrass biomass goal. 116,316 total cells (hectares) were considered in these calculations.

Modeled Service Response	Current			Suggested			%
	Value	Area (ha)	Per ha	Value	Area (ha)	Per ha	Change in value
Corn biomass (Mg)	410,081	35,471	11.561	392,403	34,136	11.495	-4.3
Pasture biomass (Mg)	636,088	77,969	8.158	614,745	75,834	8.106	-3.4
Soy biomass (Mg)	4,610	858	5.373	4,150	777	5.341	-10.0
Alfalfa biomass (Mg)	18,656	2,018	9.245	18,423	2,003	9.198	-1.2
Switchgrass biomass (Mg)	0	0	0.000	36,005	3,566	10.097	
Estimated annual income	$111,288,001	116,316	$957	$110,695,659	116,316	$952	-0.5
Soil Carbon after 20 years (Mg)	8,702,923	116,316	74.821	8,749,060	116,316	75.218	0.5

Soil Loss (Mg)	-235,290	116,316	-2.023	-235,261	116,316	-2.023	>-0.1

3.1.3. Goal 3: 36,000 Mg of switchgrass biomass using probability of conversion, while holding services at or better than current levels, and non-switchgrass yields at or better than 90% of current levels

When LULC conversion was restricted to specific "farms" based on probability of change clustering still occurred, but in slightly different areas than in Goal 2, where no probability restrictions were included (Figure 4B). Many of the preferred cells for switchgrass that we saw change under Goal 2 were not allowed to convert for this goal, so the program found the next-best options. As in the second goal, all yields were at or greater than 90% of the original yield (Table 3), but we lost considerably more soy yield than other crops. This is an indication that some soy is currently planted in areas that are better suited to other crops. Also, when averaged over the whole county (Table 3), the income losses were small ($-6 on average), but for the cells that were allowed to change (Table 4) the income loss was significantly higher ($-19), and the losses were even higher for the individual cells that actually did change (i.e., $-660,601/4,637 cells = $-142 per cell). This is an indication that the income losses associated with growing switchgrass biomass at $100 per Mg are masked by land in the county planted to other crops. While the ecosystem service benefits may be felt across the county, without a PES program the income losses are internalized by the switchgrass growers.

Figure 4. Current land use and land cover (A) and the suggested LULC (B) resulting from a "biomass with probability" goal (Goal 3) for Sauk County. Switchgrass placement is clustered, although limited by participating farms

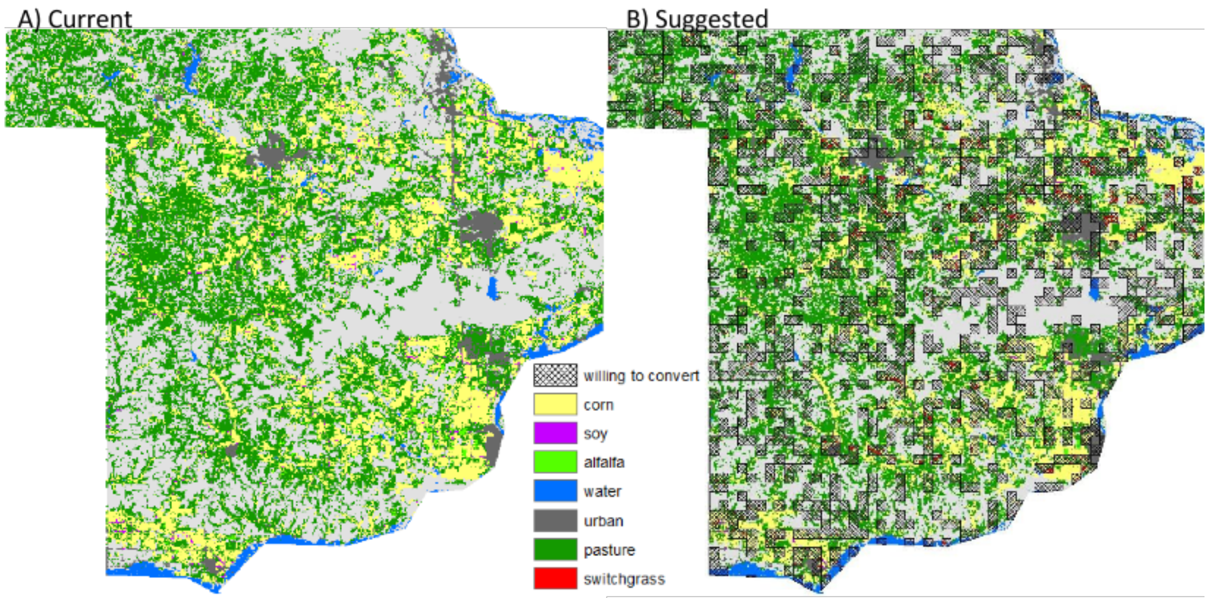


Table 3. Modeled service changes as a result of setting a "biomass with probability" goal for Sauk County. Outputs calculated over the whole of Sauk County (including farms with probability 0. When limited by farmer willingness, placement of switchgrass is less optimal, and total income loss is greater. 115,934 total cells (hectares) were considered in these calculations.

Modeled Service Response	Current			Suggested			% Change in value
	Value	Area (ha)	Per ha	Value	Area (ha)	Per ha	
Corn biomass (Mg)	407,684	35,286	11.554	383,779	33,413	11.486	-5.9
Pasture biomass (Mg)	634,328	77,779	8.156	619,520	75,953	8.157	-2.3
Soy biomass (Mg)	4,600	856	5.374	4,140	766	5.405	-10.0
Alfalfa biomass (Mg)	18,610	2,013	9.245	17,661	1,922	9.189	-5.1
Switchgrass biomass (Mg)	0	0	0.000	36,003	3,880	9.279	
Estimated annual income	$110,841,417	115,934	$956	$110,147,816	115,934	$950	-0.6
Soil Carbon after 20 years (Mg)	8,671,983	115,934	74.801	8,738,737	115,934	75.377	0.8
Soil Loss (Mg)	-234,357	115,934	-2.021	-225,542	115,934	-1.945	-3.8

Table 4. Modeled service changes as a result of setting a "biomass with probability" goal for Sauk County. When calculated for just participating farms, all of the service changes are larger. 37,413 total cells (hectares) were considered in these calculations.

	Current			Suggested			%
Modeled Service Response	Value	Area (ha)	Per ha	Value	Area (ha)	Per ha	Change in value
Corn biomass (Mg)	132,121	11,627	11.363	108,216	9,754	11.095	-18.1
Pasture biomass (Mg)	200,574	24,837	8.076	185,766	23,011	8.073	-7.4
Soy biomass (Mg)	1,362	264	5.159	903	174	5.190	-33.7
Alfalfa biomass (Mg)	6,163	685	8.997	5,214	594	8.778	-15.4
Switchgrass biomass (Mg)	0	0	0.000	36,003	3,880	0.000	
Estimated annual income	$35,399,047	37,413	$946	$34,705,446	37,413	$928	-2.0
Soil Carbon after 20 years (Mg)	2,660,249	37,413	71.105	2,727,004	37,413	72.889	2.5
Soil Loss (Mg)	-81,814	37,413	-2.187	-73,000	37,413	-1.951	-10.8

3.2. Soil carbon drives switchgrass placement

The placement of switchgrass for both of the switchgrass goals (Goal 2 and Goal 3) tended to result in LULC change clusters (figures 3 & 4). Computationally, this means that the ratios of estimated switchgrass yields and services compared to the current crops in those locations were relatively high. But, what is the "real-world" explanation for these higher ratios? Comparing these "hotspots" with a map of current soil carbon (USDA NRCS, 2010), shows a clear correlation between areas with high soil carbon and the suggested placement of switchgrass. Corn is currently planted on much of this land (Figure 4), and according to the IPCC model used, if the land were to stay in corn, a large quantity of soil carbon would be lost over the next 20 years. If these lands were growing perennial biomass crops, they would maintain current carbon levels and potentially even gain carbon.

When we limited the algorithm by socioeconomic probabilities of conversion, the placement of switchgrass was still driven by soil carbon, but since the “participating” farms did not include some of the largest areas with high soil carbon, areas with lower soil carbon were selected for transition to switchgrass in order to meet the 36,000 Mg of biomass goal (figure 7).

Figure 6. Current soil carbon (A) and the suggested LULC (B) resulting from a “biomass” goal (Goal 2). The algorithm tends to suggest placement in areas that have high soil carbon. This is an indication that the soil carbon criterion is a driver for conversion to switchgrass.

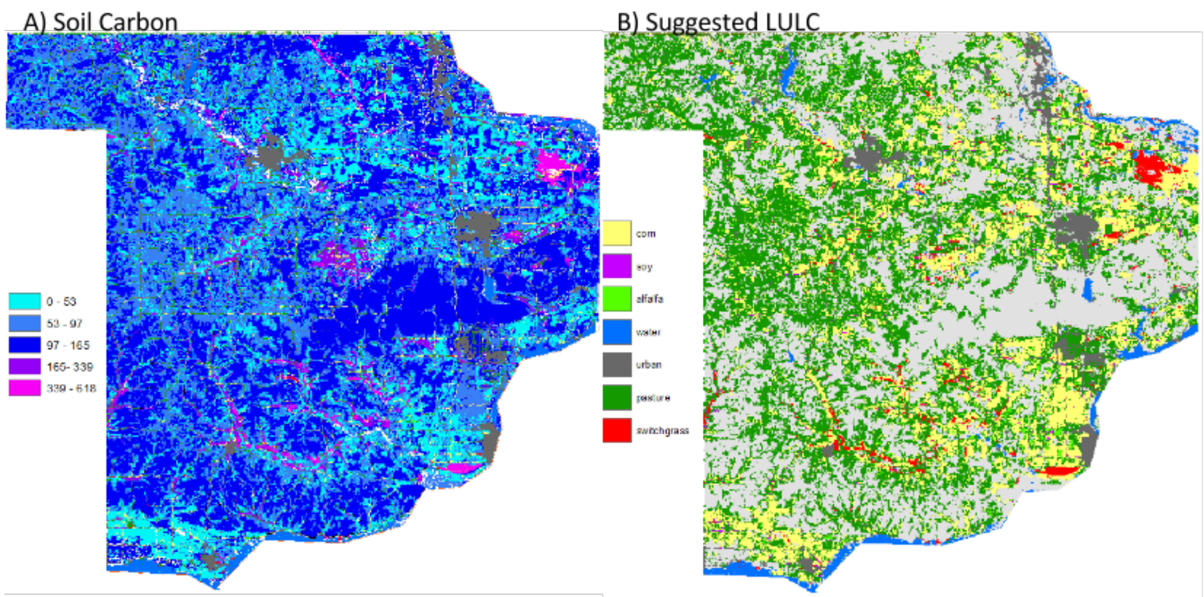
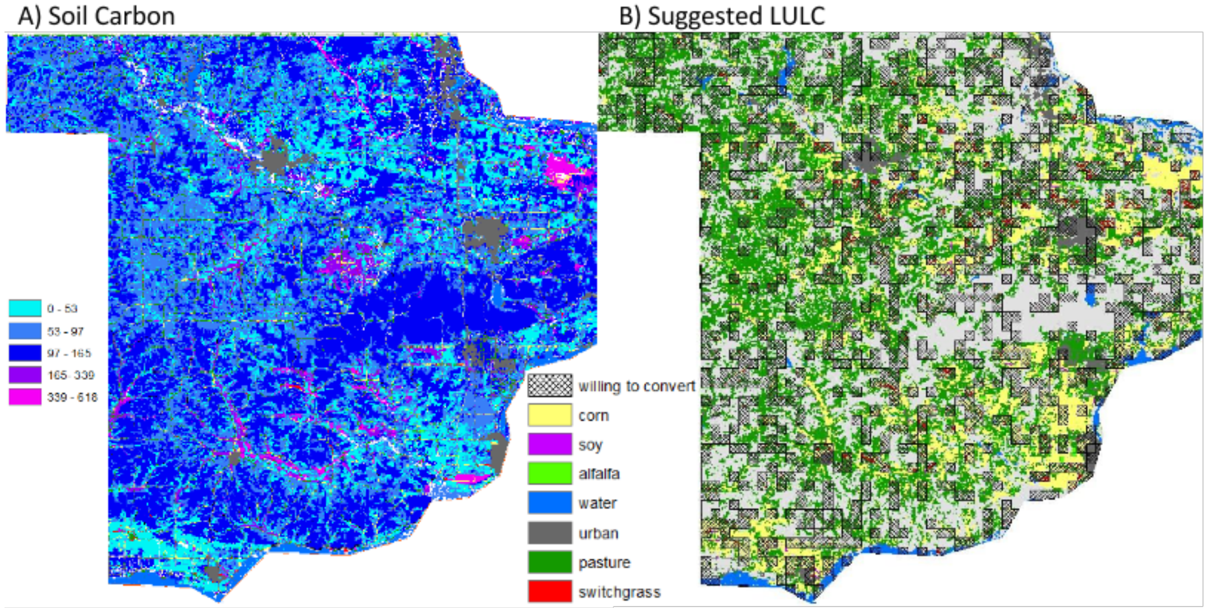


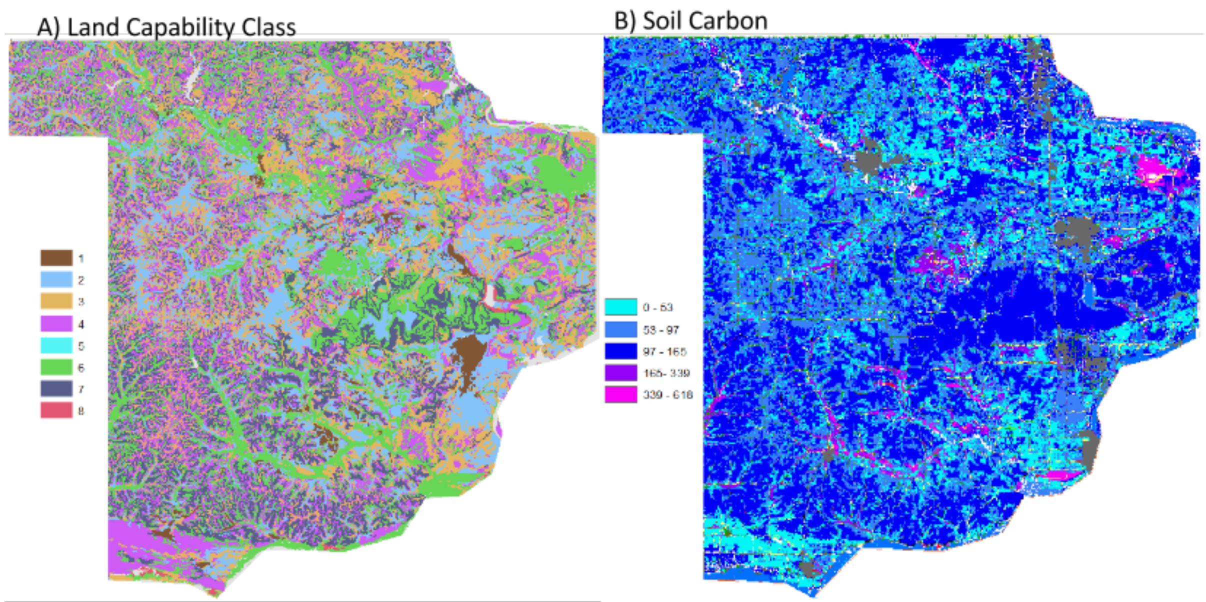
Figure 7. Current soil carbon (A) and the suggested LULC (B) resulting from a "biomass with probability" goal (Goal 3). The algorithm is limited by participating farms, but still tends to suggest growing switchgrass in areas of high soil carbon. Because some of the large areas of high soil carbon were unavailable under this goal, the areas suggested for switchgrass tended to be lower in soil carbon than those suggested for Goal 2.



These areas of high carbon tended to have a land capability class rating of 6 (Figure 8): "soils have severe limitations that make them generally unsuitable for cultivation and that restrict their use mainly to pasture, rangeland, forestland, or wildlife habitat" (USDA NRCS, 2010). Based on this classification, if these areas are cropped at all they should be growing perennial crops; however much of this land is currently planted in corn (Figure 2). This may be an indication that the current corn prices are so high that even corn grown on unsuitable land is profitable. The high soil carbon is an indication that these lands may not have been growing corn for long and they have the potential to lose a large amount of soil carbon to the atmosphere if they remain planted to corn, if they have not already.

Conversion to switchgrass would be considerably more in line with the recommended use for these lands and should help preserve the remaining soil carbon.

Figure 8. NRCS land capability classes (A) and current soil carbon (B) are correlated. The areas of high carbon where the program suggests placing switchgrass generally have a capability class of 6.



3.3. Land cover shifts to meet goals

In the run to improve income (Goal 1), there was no apparent pattern for which cells changed to a different land use. Since the average corn and soy yields increased (Table 1), this indicated that some of the land currently growing pasture and corn is particularly productive for soy. Similar numbers of cells changed from pasture to corn and from corn to pasture (Table 6), but some soy also shifted to corn, so it is hard to interpret which change drove the increased average corn yield.

Almost all of the land use change for the switchgrass goal was just a shift to switchgrass. The sole exception was the 133 cells that moved from pasture to soy (Table 6). This indicated a comparative advantage in shifting some pasture to soy so that the 90% restriction was met and land currently in soy could be shifted to switchgrass.

When the algorithm considered farmer willingness, most of the switchgrass was placed on land currently growing corn (Table 6). Given that we were trying to maintain income at 100% of current levels, in order for this much corn to shift to switchgrass, other crops had to shift to corn. In this case, some pasture land seemed to have a comparative advantage for growing corn, allowing more land in corn to convert to switchgrass, rather than simply converting that pasture to switchgrass directly.

Table 6. This change matrix shows the number of cells (hectares) in each crop recommended for a different crop in the suggested LULC. For the "improve income" goal (Goal 1), much of the pasture in the suggested LULC is currently planted to corn and vice-versa. For both of the biomass goals (Goals 2 & 3), most of the suggested change is to switchgrass.

	Suggested LULC				
Current LULC	Corn	Soy	Alfalfa	Pasture	Switchgrass
Goal 1					
Corn	0	79	2	4560	0
Soy	189	0	2	22	0
Alfalfa	16	0	0	0	0
Pasture	4123	115	16	0	0
Goal 2					
Corn	0	0	0	0	1335
Soy	0	0	0	0	214
Alfalfa	0	0	0	0	15
Pasture	0	133	0	0	2002
Goal 3					
Corn	0	1	3	185	2224
Soy	2	0	0	0	114
Alfalfa	21	0	0	3	70
Pasture	517	25	0	0	1472

3.4. No hotspots with probabilities in Sauk County

Since we had such limited specific location data when creating the probabilities, there were no obvious hotspots. In fact, dairies tended to cluster in west-central Sauk County, and even the run without probabilities did not tend to recommend that switchgrass be grown there. Since the Sauk County dairies are not generally on land that is desirable for switchgrass, the placement of switchgrass was more affected by the random farm selection than the locations of dairies. Limiting participating farms provided a sense of how concentrated the impact of growing switchgrass is likely to be; instead of many people each growing a little switchgrass and taking a small income loss, the suggestion was for a few people to grow a lot of switchgrass and have a corresponding loss of income.

4. DISCUSSION

4.1. Tradeoffs and implications for land use changes in Sauk County

Using the decision support tool we built, we were able to find ways to rearrange the landscape in Sauk County to meet certain yield and ecosystem service goals. Since the modeled input data was coarse, the results of these runs should not be used to identify target areas for policy. However, the results for all three goals did show that tradeoffs are unavoidable, which points to some policy considerations.

When we attempted to find ways to improve income without sacrificing any ecosystem services (Goal 1), we found that income in Sauk County could not be increased without some negative effects on ecosystem services, such as decreased soil retention. This is not to say that income is currently maximized in Sauk County; in fact, at current prices, income would almost definitely rise if more land were converted to corn. Conversely, if we allowed income to fall, we would undoubtedly see positive ecosystem service effects. The results from our runs for Goals 2 and 3 support this relationship. When we set switchgrass biomass goals, carbon sequestration and soil retention both increased, but even at $100 per Mg of switchgrass biomass, there were significant economic tradeoffs.

While these economic tradeoffs are small if the cost of growing switchgrass is spread over the entire county, this is not the case in Sauk County, which has a limited pool of potential biomass crop growers. The hotspots where the program suggested growing perennial biomass crops for Goals 2 and 3 were an indication that, even if it were possible, not all farmers should grow biomass crops. Additionally, not all farmers are equally willing to grow biomass crops (Mooney et al., 2013). In order to produce the 36,000 Mg required by a biomass processing depot (Eranki et al., 2011), the small pool of willing farmers on "hotspot" land would need to devote more land to biomass crops to make up for the unwilling farmers, thereby increasing their opportunity costs even further. To make growing perennial biomass crops a rational decision, the associated economic tradeoffs would need to be reduced. To do this, the relative value of biomass to corn would need to increase, either through the market, PES programs, or both.

4.2. How might this type of tool impact policy making?

Our decision support tool has two key factors that distinguish it from most existing LULC decision support tools. First, by separating the modeled/empirical inputs from the user inputs and making the tool goal-seeking, policymakers can identify ways to meet various targets without needing a detailed understanding of the mechanics of ecosystem processes. Once ecosystem service goals such as renewable energy targets (WI Act 141, 2005; USDoE, 2011) are set, policymakers know the desired outcomes but are left to determine how to achieve those targets. By allowing for multiple simultaneous goals, we also avoid forcing policymakers to decide how to value and compare different ecosystem services. Most decision support tools allow the user to experiment with different LULC changes and then estimate the impacts of proposed landscape changes and/or provide a map of hotspots based on valuations of various goals. The primary problem with this is that these tools are modeling complex systems and useful experimentation relies on the user having some understanding of the probable ecosystem service responses, which is not necessarily the case with policymakers (Carriquiry et al. 2011). Our tool considers the complexity of these ecosystems with the modeled/empirical data inputs, which could be set up by experts in advance. Once set up, the simple goal-oriented inputs and quick run-time make this tool easy for a policymaker to use (Sohl et al., 2013).

The second key characteristic of this tool is that it can consider social factors (i.e. the probability layer). In the past, when PES programs have not had social buy-in from stakeholders, some potential participants have not enrolled (Bremer et al., 2014), with some programs even causing a backlash, resulting in worse environmental impacts (Cranford et al., 2011). Many solutions to this problem suggest a two-step approach to PES policies: an education/social policy that builds support for the financial incentives that are implemented later (Cranford et al., 2011). Despite the recognition of stakeholder buy-in as an important factor in the success of a PES program, decision support tools do not often take it into account. A tool that considers stakeholder willingness to participate before determining target areas would allow for immediate implementation of financial incentives (and necessary infrastructure changes) in areas that already have stakeholder buy-in. This tool could also identify areas where ecosystem service gains would be large except for the lack of social capital -- these areas could then be targeted for the education and social policies mentioned above.

Even though we did not study the utility of this tool across multiple scales, the “separate-inputs” design allows it to run at any scale and granularity for which the spatial input data is available. That said, the modeled/empirical data does need to be sufficiently variable for the program to find improvements. All of the spatial data we used is available for the entire U.S., however, as noted in Section 1.5, some of our data sources were inconsistent between counties. As a result, we would not recommend running this tool with these inputs at a higher level than the “county” level. Policymakers would probably prefer to run this tool at a regional scale consistent with the political boundaries of their areas of influence.

4.3. Implications for cellulosic biomass production

Despite renewable energy goals and large studies on the potential of biomass crops as an energy source (WI Act 141, 2005; USDoE, 2011), there is currently no real market for cellulosic biomass. This lack of demand partly stems from the fact that energy policy only minimally distinguishes between perennial biomass crops and annual bioenergy crops (Carriquiry et al., 2011). Grain ethanol is currently cheaper and easier to produce, transport and process (Solomon et al., 2007; Epplin et al. 2007), so without strong policies, cellulosic processing plants will remain few and far-between, and farmers have no incentive to convert any of their land to growing perennial bioenergy crops. Additionally, market or policy incentives have not yet increased the rate of technological advances required to lower the processing costs of cellulosic biofuels.

Since one purpose of the renewable energy goals is sustainability (USDoE, 2011), policymakers should consider whether annual crops can actually be considered "sustainable" given their potential for detrimental ecosystem service impacts. Perennial biomass crops, on the other hand, are a source of bioenergy that is sustainable, in addition to the potential greenhouse gas and downstream water quality benefits (Gelfand et al., 2013). The varied productivity and ecosystem service impacts on the landscape provide an opportunity for well-designed policies to target regions where annual crops are least sustainable, and promote a transition to perennial crops.

Finally, there are some farmers who may never be willing to grow perennial bioenergy crops, no matter how unsuitable their land may be for traditional row crops. In some cases, the attitudes and behaviors represent a backlash against the government promoting the policy (Bremer et al., 2014). In other cases, such as for the dairies in Sauk County, the annual crops are used to support livestock, and converting to a perennial biomass crop would represent a food-fuel conflict (Mooney et al., 2013). By taking this sort of social and cultural data into account, bioenergy policies that encourage perennial cellulosic crops can be implemented more efficiently and effectively.

5. CONCLUSIONS

Using this decision support tool, or similar goal-seeking techniques with fine-tuned and validated input data, would help policymakers determine where to focus efforts to encourage the growing of biomass crops. In order to achieve specific ecosystem service goals, such as those set by state and federal governments, it is important to determine where high willingness to convert overlaps with high benefit-cost physical environments for growing perennial biomass crops. Once policymakers are able to identify these hotspots, policies targeting these areas will be more effective, resulting in a shift to perennial crops across the landscape and corresponding ecosystem services benefits.

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