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Analyzing crop change scenario with the SmartScape™ spatial decision support system

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ABSTRACT

Agricultural land use is increasingly changing due to different anthropogenic activities. A combination of economic, socio-political, and cultural factors exerts a direct impact on agricultural changes. This study aims to illustrate how stakeholders and policymakers can take advantage of a web-based spatial decision support system (SDSS), namely SmartScape™ to either test existing crop change policies or produce effective crop change decisions using tradeoff analysis. We addressed the consequences of two common crop change scenarios for Dane county in Wisconsin, United States, (a) replacing perennial energy crops with annual energy crops and (b) replacing annual energy crops with perennial energy crops. The results suggested that converting areas under grass and alfalfa production that were located on high quality soil and flat slope to corn promoted a net-income and availability of gross biofuel. Additionally, the model outcome proposed that converting areas under corn and soy production that were located on high slope to grass promoted net-energy, phosphorus loading, soil loss, soil carbon sequestration, nitrous oxide emission, grassland bird habitat, pollinator abundance, and biocontrol. Therefore, SmartScape™ can assist strategic crop change policy by comparing the tradeoff among ecosystem services to ensure that crop change policies have outcomes that are agreeable to a diversity of policymakers.

1. Introduction

1.1. Sustainability in agricultural landscape

Agricultural landscapes provide our society with a variety of valuable goods and services such as food, fiber, and animal feed (Filipe-Lucia et al., 2014; Song and Pijanowski, 2014). They also regulate the quality of water (Tayyebi et al., 2015), sequester greenhouse gases (Searchinger et al., 2008), host beneficial insects (Pekin 2013), and guaranteeing the sustainability of our heritage landscapes (Vaz, 2016). In the Midwestern of United States, agricultural areas (Pijanowski et al., 2014; Tayyebi et al., 2014a,b) have experienced considerable changes in the past decades due to new United States ethanol production regulations (Meehan et al., 2013). In 2007, the Energy Independence and Security Act mandated that production of corn grain ethanol be increased to 15 billion gallons per year (Tyner 2008). The sudden increase in corn grain demand for ethanol production contributed to a rise in grain prices. This increase in grain price was a strong incentive for agricultural intensification (Wallander et al., 2011).

Two forms of agricultural intensification have been documented in the United States. The first one involves changes in land cover, where land previously planted in perennial grasses was converted to annual row crops. For example, Wright and Wimberly (2013) showed that more than 500 million hectares of grassland were converted to corn and soy production between 2006 and 2011 in the western corn-belt of the central United States. Land cover change of this magnitude (1.0–5.4% annually) is comparable to deforestation rates of tropical forests in Brazil, Malaysia, and Indonesia. The

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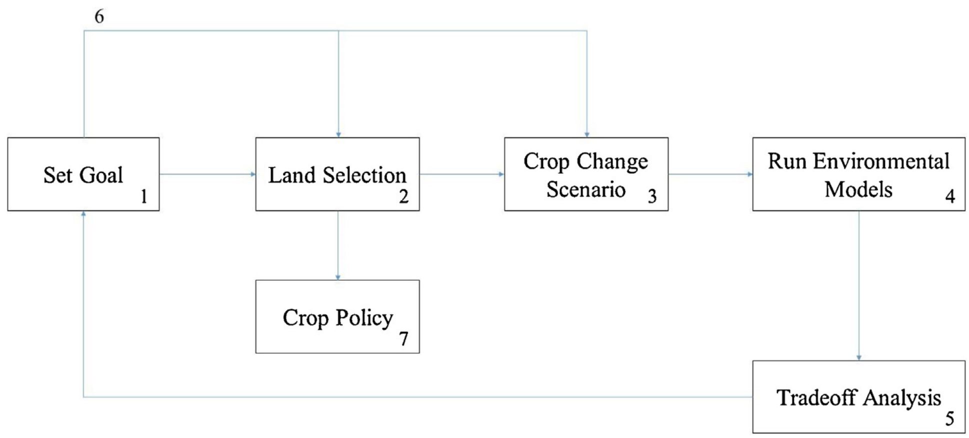


Fig. 1. Application of AmsrtScape™ to help policymakers: (1) Set goal enables users to aim what they expect from SmartScape™ (Item 1); (2) land selection enables users to select parts of the landscape using set of spatial criteria (Items 2); (3) build scenario enables users to make hypothetical crop change (Item 3); (4) users then run multiple environmental models (Item 4); (5) tradeoff analysis enables users to compare crop change scenarios with each other using a variety of visual outputs (Items 5); (6) double check goal enables user to check their goal/goals satisfied or not; and (7) users can then extract series of spatial criteria as a crop change policy.

second form of intensification involves changes in land use or land management. For example, Plourde et al. (2013) showed that the amount of row crop land in the Midwestern of the United States planted to a continuous corn rotation has doubled over the last decade. Wallander et al. (2011) showed that increases in corn production have been further facilitated by increased double cropping, where two crops of the same or different types are produced in series on the same land in the same year.

Despite the importance of balancing multiple ecosystem services for sustainable development, agricultural landscapes tend to be configured to maximize only provisioning services, such as crop production, as these generate goods that can be sold in existing markets, yielding income for producers. This resulted in dominance by annual crops and a marked decline in other services that are often poorly quantified and undervalued (Carpenter et al., 2009). As such, crop policy promoting bioenergy crop production must be also compatible with other valuable ecosystem services (Meehan et al., 2013). Thus, public policy currently involves tradeoffs, and policymakers face the challenge of understanding the relative value of these tradeoffs to achieve multidimensional goals. To judge the effect of policy options on sustainability, we need a new, integrated approach that simultaneously considers environmental, social, and economic outcomes and their complexity (Foley et al., 2005; Tayyebi et al., 2014a,b,c).Establishing a sustainable system requires a consensus definition of sustainability. Generally, sustainability describes the ability to meet current needs not jeopardizing the capacity of future generations to meet their needs (Rowe et al., 2009). The Ecological Society of America (2008) concluded that, to be environmentally sustainable, production of biofuels must not negatively affect energy flow, nutrient cycles, and ecosystem services. The Global Bioenergy Partnership (2011) has developed a list of 24 indicators to evaluate the sustainability of bioenergy systems.

1.2. Spatial decision support systems

While several scientific models are available to determine effects of crop on any single ecosystem service, these models are seldom used by policymakers (McIntosh et al., 2007; Tayyebi et al., 2011; Tayyebi and Pijanowski, 2014). Following reasons might be critical for this lack of adoption: (a) policymakers and model builders tend to speak in different languages and view problems through different conceptual lenses, (b) cultural barriers are immanent. For example, policymaking has a long history, within which computer models are a recent arrival. Thus, there is an institutional momentum that slows adoption of model-based approaches to policymaking (Geertman 2006), (c) technical barriers impede the adoption. For instance, the user interface is very important to uptake of decision support systems (Van Delden et al., 2011). Modeling tools are not likely to be used unless they look and feel like other familiar software packages (McIntosh et al., 2007), (d) another factor that slows adoption is missing functionality for synthesis and presentation of results (Uran and Janssen 2003). In sum, effective spatial decision support systems (SDSSs) are most likely to be created and adopted through an iterative effort, which brings together scientists and decision makers. This type of group effort seems more likely to promote user-friendly tools that are intentionally built to answer fundamental practical questions. Finally, these tools should be transparent and well documented (Van Delden et al., 2011), which is crucial for practical usage and acceptance.

SDSSs facilitate crop policy development where multiple criteria have to be taken into account (Figueira et al., 2005). SDSSs have been employed as a powerful tool for regional management problems related to forest (Fürst et al., 2013), water quality (Arnold and Fohrer, 2005) and air quality (Tayyebi et al., 2010). In this respect, SDSSs are promising to achieve a balance between multiple ecosystem services if they can incorporate spatial and temporal data and use environmental models to simulate the consequence of crop change (Pijanowski et al., 2009; Jokar Arsanjani et al., 2013). We have recently developed SmartScape™, a novel SDSS on the web,[1] allows planners to evaluate the effects of bioenergy crop production using numerous sustainability criteria (e.g., soil carbon, phosphorus loading, biodiversity support, net-income) in a geographically-explicit fashion. This study aims to illustrate how policymakers can use SmartScape™ to produce effective crop change decisions. We specifically quantify the consequences of two crop change scenarios in Dane county, Wisconsin (United States). While the first scenario replaces perennial energy crops with annual energy crops, the second one replaces annual energy crops with perennial energy crops.

2. SmartScape™

SmartScape™ has an interactive, user-friendly interface for strategic crop change planning and scenario building quantitatively and visually using "what if" types of questions. We worked closely

[1] http://gratton.entomology.wisc.edu/smartscape.

with regional stakeholders (biofuel producers, non-governmental conservation groups, and government planners and policymakers) as well as an interdisciplinary group of scientists. The resolution of raster data (inputs, outputs and land cover) in SmartScape^{TM} is 30 m × 30 m. SmartScape^{TM} is designed to evaluate ecosystem service changes associated with four cropping system changes (i.e., corn, soybean, alfalfa, perennial grasses). Except gross biofuel, net-energy and net-income models require using the outcome of yield model, other models run independently.

Users are encouraged to follow the steps below to develop an effective crop policy at regional scale (Fig. 1):

1) Set goal: Users must aim what they expect from SmartScape^{TM} either by setting a goal or series of goals (Fig. 1, Items 1). For example, landowners are interested to maximize their benefit from their land. Thus, their goal is to maximize net-income ecosystem service,
2) Land selection: After setting a goal, users must select parts of the landscape utilizing spatial criteria (Fig. 1, Items 2). The land selection should be performed strategically to satisfy the goal. For example, landowners should select lands that maximize their chance to produce more yield (e.g., lands located in flat areas with a better soil condition),
3) Crop change scenario: After selecting lands, users are required to change the current crop to the hypothetical crop in future (Fig. 1, Items 3). The crop change scenario should be performed strategically to satisfy the goal. For example, it has been shown that the selling price of a perennial energy crop (e.g., grass and alfalfa) is usually lower than annual energy crop (e.g., corn, soy; Meehan et al., 2013). Thus, it is more likely for landowners to maximize the net-income if they rotate the current grass or alfalfa to either corn or soy in future,
4) Run environmental models: After selecting lands and defining crop change scenario, users run multiple environmental models (Fig. 1, Item 4),
5) Tradeoff analysis: Users can then assess the tradeoff among multiple ecosystem services (Fig. 1, Items 5) as a result of crop change scenario visually (e.g., spider graph and maps) and quantitatively (e.g., tables). The tradeoff assessment enables users to figure out how much they succeed to satisfy their goal. For example, landowners can check how much they could maximize their net-income with selected lands and crop change in future,
6) Double check goal: After tradeoff assessment, if users are not satisfied with their goal (Fig. 1, Items 6), they can either modify land selection (Fig. 1, Items 2) or change crop change scenario (Fig. 1, Items 3). Users then repeat these steps (Fig. 1, Items 3–5) to satisfy their goal,
7) Crop change policy: After users' satisfaction, they use land selection panel (Fig. 1, Item 2) and crop change scenario (Fig. 1, Item 3) to extract series of spatial criteria they utilized to select landscape as well as crop change scenario they used to transfer landscape. Those spatial criteria and crop change scenario as a crop policy can help users to satisfy their goal. For example, for landowners, the crop policy can be replacement of lands under grass and alfalfa production that are located on high quality soil and flat slope (land selection) and convert them to corn (crop change scenario).

The Millennium Ecosystem Assessment (2003) introduced a conceptual framework for better understanding the effects of environmental changes on ecosystem services whereas ecosystem services are classified into provisioning services (e.g., provision of food), regulation services (e.g., regulation of climate), supporting services (e.g., nutrient cycling) and cultural services (e.g., recreational values). SmartScape^{TM} estimates 11 ecosystem services including provisioning services (i.e., crop yield, gross biofuel, net-income and net-energy), regulation services (i.e., soil carbon sequestration and nitrous oxide emission), supporting services (i.e., phosphorous loading and soil loss) and cultural services (i.e., pollinator abundance, biocontrol and grassland bird). The following section summarizes environmental models implemented in SmartScape^{TM}.

2.1. Provisioning services

2.1.1. Crop yield

The crop yield models are statistical models that predict typical crop yields (bushels or short tons at standard reporting moisture levels per year) based on local soil and topographic characteristics. The model inputs (Meehan et al., 2013) are slope, soil depth, percent silt, and cation-exchange capacity. Slope estimates are based on a digital elevation model. Soil depth, percent silt, and cation exchange capacity estimates come from the Soil Survey Geographic database soil Geo-database (SSURGO) of the United States Department of Agriculture (USDA). Depending on the crop, these statistical models describe 72–77% of the variation in typical yields reported in SSURGO.

2.1.2. Gross biofuel

The biofuel production models predict the amount of liquid biofuel generated from the crop yield. For corn, grass, and alfalfa, the biofuel predicted is ethanol (gallons per year). For soybean, the biofuel predicted is biodiesel (gallons per year). The model inputs comprise yield from the crop yield model, and conversion ratios from Farrell et al. (2006) (ethanol) or Hill et al. (2006) (biodiesel) describing the volume of liquid fuel (gallons) that can be obtained from a mass (ton) of feedstock. The estimation accuracy of the biofuel production models depend on the accuracies of both the crop yield and the conversion ratios, which are industry averages or modeled estimates.

2.1.3. Net-income

The net-income model predicts annual net-income (US dollars) generated from the crop yield. Inputs to the net-income model include yield estimates from the crop yield model, current crop prices from,[2] and crop production costs pulled from crop enterprise budgets[3] (Meehan et al., 2013). Net-income is calculated simply as gross returns minus production costs. The accuracy of this estimate depends first on the accuracy of the crop yield and the accuracy of the crop prices and production costs, which can be updated or modified by the user.

2.1.4. Net-energy

The net-energy model is a life-cycle analysis model that predicts the net-energy embodied in the ethanol and co-products produced annually with biomass from each pixel of land. Net-energy is calculated as the gross energy of ethanol and co-products minus the gross life-cycle energy requirements for production (Meehan et al., 2013). Gross energy of ethanol and co-products depends on feedstock yield at a given location (i.e., pixel), based on the yield model described above, and conversion ratios that convert feedstock to liquid fuel and liquid fuel to units of energy. Gross life-cycle energy requirements of production incorporate energy input during agricultural production, transportation of feedstock, and processing of feedstock into fuel and co-products. Uncertainty in estimates comes from uncertainties in crop yield estimates, energy inputs, and conversion ratios, which derived from the life-cycle analysis model.

[2] http://www.cmegroup.com.
[3] http://www.uwex.edu/ces/farmteam/budgets/fieldcrop.cfm.

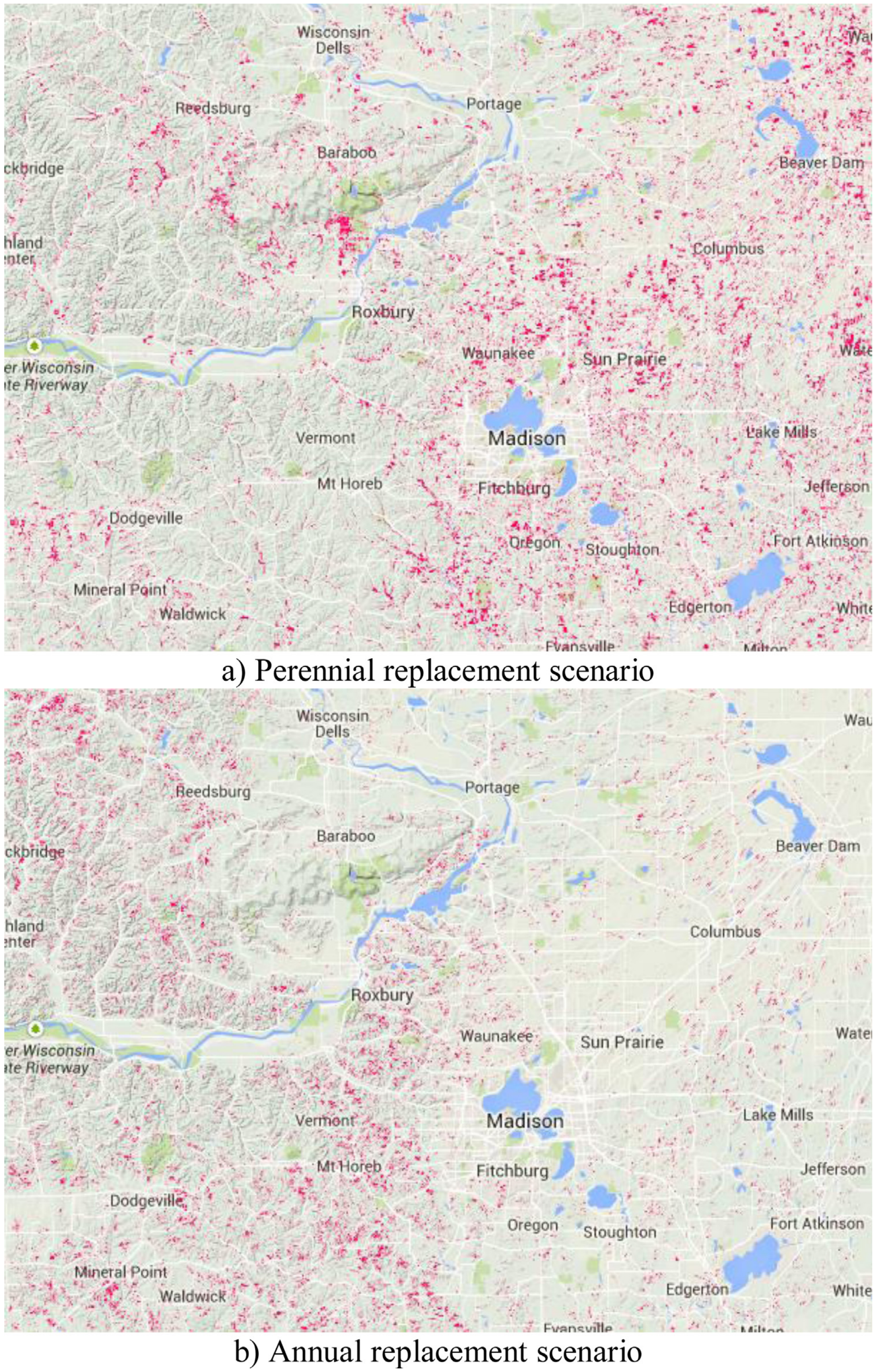
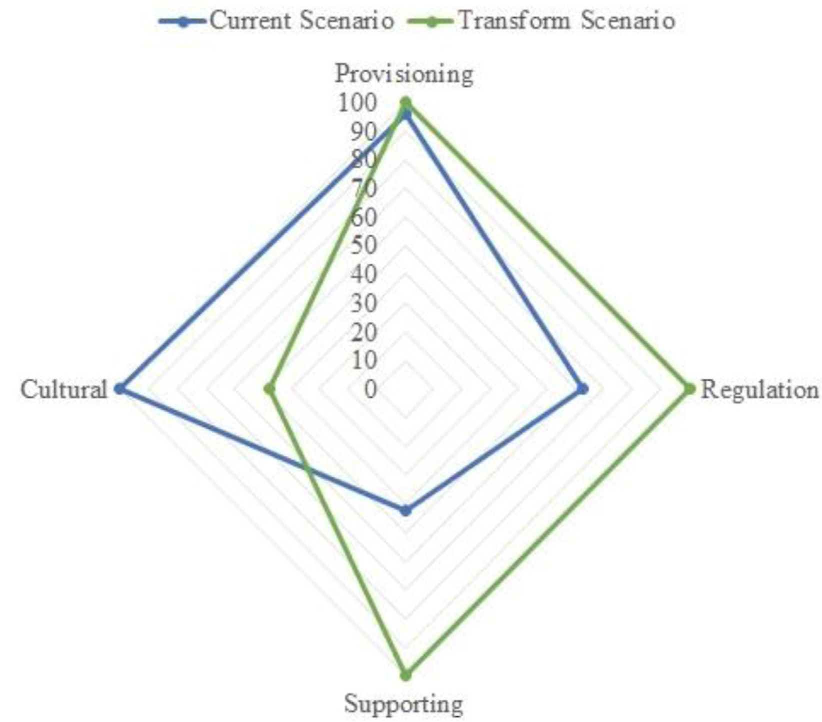


Fig. 2. Selected cells (red areas) in landscape for two land change scenarios including (a) perennial replacement scenario: Areas under grass and alfalfa production that were located on high quality soil (cropland 1 and 2) and flat slope (less than 5°) were selected and converted to corn (5.47% of the landscape) and (b) annual replacement scenario: Areas under corn and soy production that were located on high slope (over 10°) were selected and converted to grass (2.98% of the landscape). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

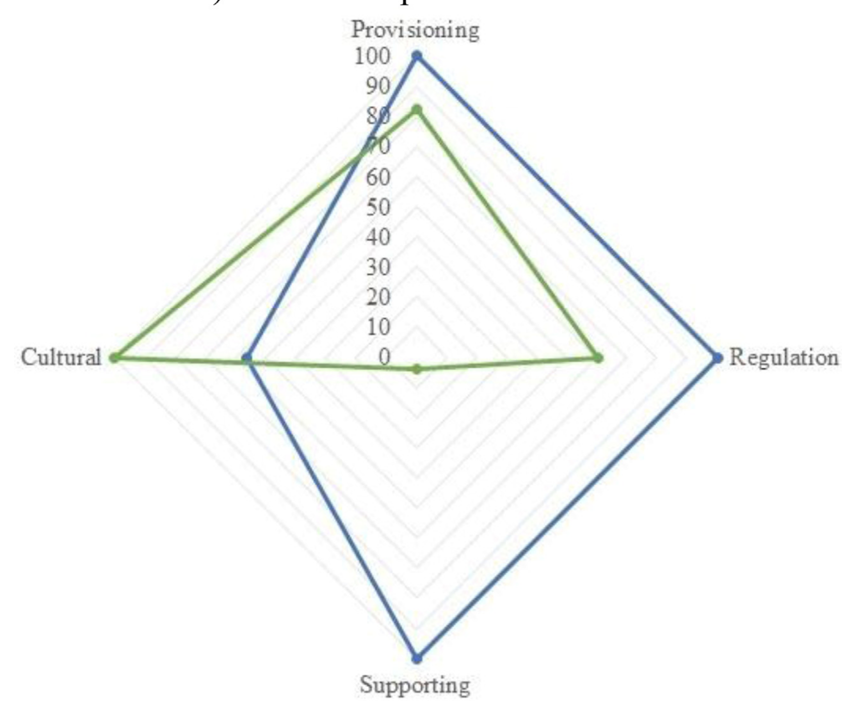
2.2. Regulation services

2.2.1. Soil carbon sequestration

Below-ground carbon sequestered on focal land over 20 years (Mg ha^{-1}) was calculated as the sum of soil organic carbon in the top 30 cm of soil and the carbon in below-ground live plant biomass. The model starts with a baseline soil carbon estimate, resulting from the USDA-SSURGO soil Geo-database, and uses empirical rates of soil carbon change that are dependent upon both baseline soil carbon estimates and crop rotation. Regarding uncertainty, the baseline soil carbon estimates have unknown spatial variation and measurement error. Soil carbon change factors have standard devi-



a) Perennial replacement scenario



b) Annual replacement scenario

Fig. 3. Comparing the current and future land change scenarios including (a) perennial replacement scenario and (b) annual replacement scenario using spider graph for 4 ecosystem services according to the Millennium Ecosystem Assessment (2003). For each metric in the spider graph, the scenario with the higher outcome value is set to a value of 100%, and the lower value from the other scenario is divided by the maximum value and expressed as a value of 100% or lower.

ations ranging from 6 to 20%. The equation that adjusts soil carbon change based on initial carbon has unreported error (West et al., 2008).

2.2.2. Nitrous oxide emissions

The N_2O estimation is a statistical model that predicts N_2O estimation (Mg ha^{-1} per year) using environmental and management-related factors. The inputs of N_2O model are climate, soil organic carbon content, soil texture, drainage, soil pH, nitrogen application rate per fertilizer type, and type of crop. Soil organic carbon content, soil texture, drainage, and soil pH are extracted from the USDA-SSURGO soil Geo-database. While climate data comes from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Geo-database, land cover data comes from

Table 1
Output summary of perennial replacement scenario for the current landscape, the transformed landscape, and the difference between both scenarios in absolute values.

Models	Current scenario	Transform scenario	Delta
Gross biofuel (Gal)	128,814,733	168,456,661	39641928
Net-income ($Million)	66.39	93.88	27.48
Net-energy (MBtu)	9,582,143	5,487,819	−4094324
Soil carbon sequestration (ton)	19,057,186	19,022,287	−34899
Nitrous oxide emission (ton)	369.07	1449.2	1080.13
Phosphorous loading (lb)	40,369.30	164,046	123676.70
Soil loss (ton)	4,053,403	6,801,041	2747638
Pollinator abundance	0.233	0.151	−0.082
Biocontrol	0.631	0.365	−0.266
Grassland bird	0.314	0.064	−0.250

the cropland data layer. The development of the statistical models is outlined in Bouwman et al. (2002), who estimate the prediction uncertainty between −40% to +70%.

2.3. Supporting services

2.3.1. Phosphorus loading

The phosphorus loading model estimates the amount of phosphorus loaded into surface water each year for each pixel within study area. Phosphorus loss estimates for each pixel under the four cropping systems (i.e., corn, soy, grass and alfalfa) are generated in advance using the Environmental Policy Integrated Climate (EPIC) agro-ecosystem model (Zhang et al., 2010). In these pre-computed simulations, corn and soybean production uses conventional tillage and optimal amounts of synthetic fertilizer, while alfalfa and grassland simulations assume no tillage and optimal amounts of fertilizer. Pre-computed estimates of phosphorus loss are further modified with an exponential decay function (Soranno et al., 1996) from the nearest stream and the type of crop at a given location. Uncertainty of phosphorus loading estimates depends on uncertainties in the many assumptions and parameter estimates in the EPIC agro-ecosystem model. Validations studies have shown that EPIC simulations capture 59–87% of the variation in observed phosphorus losses from fields (Jenkins et al., 2010). Additional uncertainty arises from model inherent assumptions (i.e., exponential decay).

2.3.2. Soil loss

The Revised Universal Soil Loss Equation (RUSLE) is used to estimate annual soil loss for each pixel of land. This model grounds on factors such as annual rainfall, runoff erosivity, soil erodibility, slope length, slope steepness, crop and management, and conservation practices to quantify average annual soil loss in tons per year (Khanal et al., 2013). Rainfall data is available from the PRISM Geo-database and land cover data comes from the cropland data layer. Slope steepness and slope length are derived from a digital elevation model. Soil erodibility information comes from the USDA-SSURGO soil Geo-database. The accuracy of this estimate depends on the accuracy of the input layers and management specifications. Previous studies have shown that RUSLE describes approximately 75% of the variation in average annual soil loss across sites (Risse et al., 1993).

2.4. Cultural services

2.4.1. Pollinator abundance

The pollination potential model estimates an index of flower visitation by bees that varies from 0 (few flower visitors) to 1 (many visitors). The index is derived from a statistical model (Bennett and Isaacs, 2014). The inputs are the proportions of grassland and forest within a 1 km radius of focal location. The model was derived from Bennett and Isaacs (2014), who measured bee visitation to soybean fields along a landscape gradient in Michigan. This pollination potential model explained 64% of the variation in bee visitation observations.

2.4.2. Biocontrol

The biocontrol potential model results in an index of crop-pest removal by arthropod natural enemies that varies from 0, for little pest removal, to 1, for a lot of pest removal. The index is derived from a statistical model. The inputs to the model are the land cover at a given cell and the proportion of grassland within a 1 km radius of a given cell. The model was derived from studies by Meehan et al. (2013) and Skevas et al. (2014), who measured removal of sentinel crop pests in corn, soybean, and different grassland habitats in Wisconsin and Michigan. The bio-control model explained roughly 80% of the variation in observations of pest removal.

2.4.3. Grassland bird

The grassland bird habitat model produces an index ranging from 0 to 1. While a value of 0 refers to poor grassland bird habitat, a value of 1 indicates better grassland bird habitat. The index is derived from a statistical model, where the amount of grassland and row crops within a 400 m radius of a given cell are the inputs. The model is introduced by Meehan et al. (2013) which assess the effects of landscape characteristics on the presence of grassland birds of management concern, using data from the North American Breeding Bird Survey conducted in northern Illinois, eastern Iowa, and southern Wisconsin. The grassland bird model only explains 16% of the variation in observations of rare grassland bird occurrence.

3. SmartScape™ implementation and study area

In order to implement the SmartScape™ effectively, a set of crop change scenarios for a selected study area was defined. Introduction of energy crops into agricultural lands could promote sustainability if they foster multiple ecosystem services and mitigate ecosystem disservices from existing crops. The introduction of potential dedicated perennial energy crops such as grasslands into this region has been suggested as one way to promote alternative energy sources as well as support multiple ecosystem services and mitigate ecosystem disservices (Meehan et al., 2013). Therefore, in this study, we investigated both crop change cases, (1) introduction of grasslands as well as (2) the loss of grasslands to quantify how these changes affect a variety of ecosystem services. The study area is Dane county in Wisconsin that is dominated by high rate of agriculture lands. Dane county is located in the southern of Wisconsin (Fig. 2). SmartScape™ includes perennial energy crops (i.e., grass and alfalfa) and annual energy crops (i.e., corn and soy) in agriculture landscape.

We specifically investigated the replacement of perennial energy crops with annual energy crops (called perennial replacement scenario after here) as well as replacement of annual energy crops with perennial energy crops (called annual replacement sce-

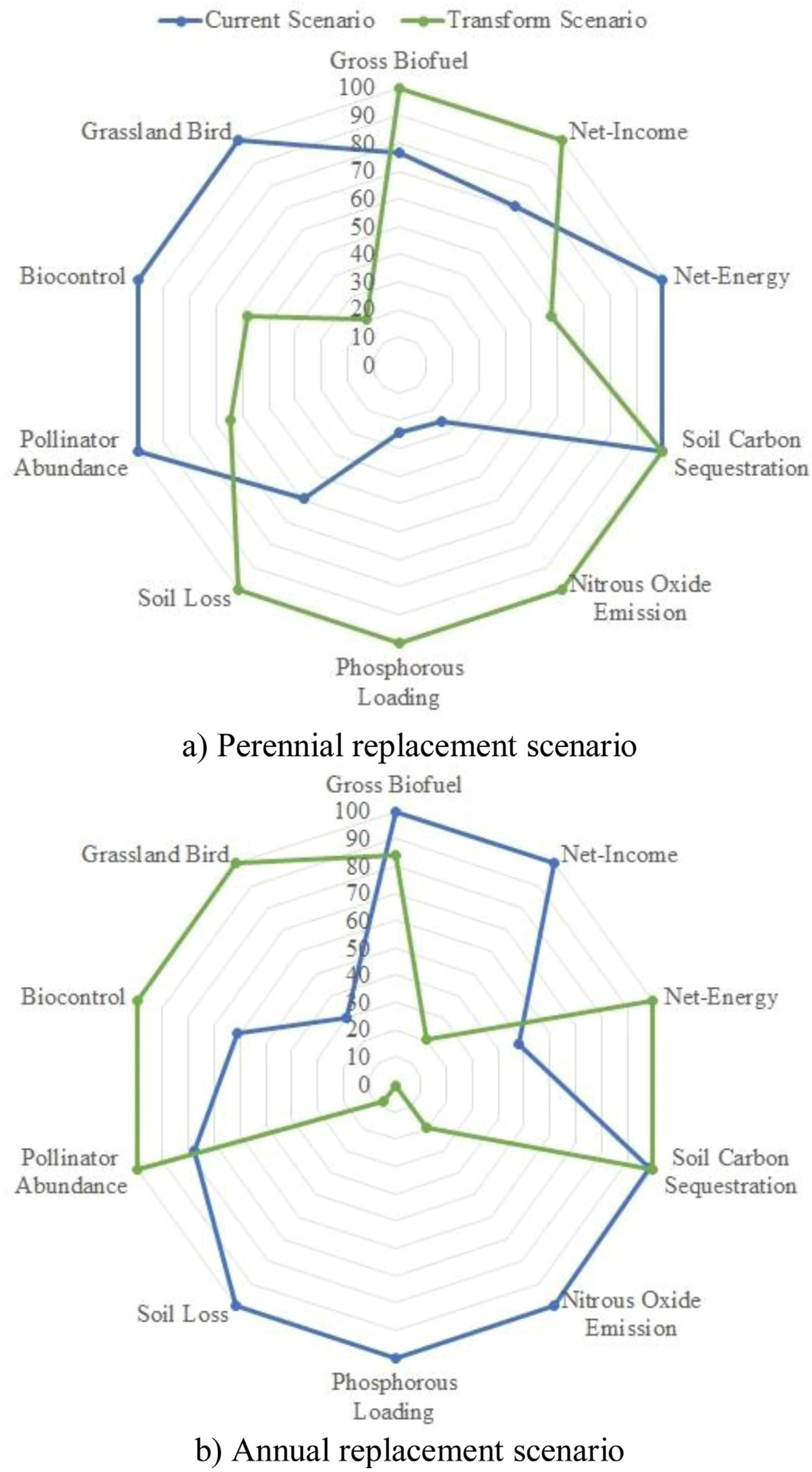


Fig. 4. Comparing the current and future land change scenarios including (a) perennial replacement scenario and (b) annual replacement scenario using spider graph for 10 ecosystem services. For each metric in the spider graph, the scenario with the higher outcome value is set to a value of 100%, and the lower value from the other scenario is divided by the maximum value and expressed as a value of 100% or lower.

nario thereafter). For perennial replacement scenario, areas under grass and alfalfa production that were located on high quality soil and flat slope (less than 5°) were selected and converted to corn. The SmartScape™ indicated that these conditions matched 5.47% of the current landscape (Fig. 2a). For the annual replacement scenario, areas under corn and soy production that were located on high slope (higher than 10°) were selected and converted to grass. The SmartScape™ indicated that these conditions matched 2.98% of the current landscape (Fig. 2b). We ran the SmartScape™ which launches various environmental models for the selected landscape before and after transformation. Besides, SmartScape™ also provides options to modify management options for the transformation as well as global assumptions of the environmental models. Examples of management options include conventional

Table 2
Output summary of annual replacement scenario for the current landscape, the transformed landscape, and the difference between both scenarios in absolute values.

Models	Current scenario	Transform scenario	Delta
Gross biofuel (Gal)	66,341,068	55,724,250	−10,616,819
Net-income ($Million)	44.527	8.984	−35.543
Net-energy (MBtu)	1,950,848	4,061,320	2,110,472
Soil carbon sequestration (ton)	5,786,647	5,874,341	87,694
Nitrous oxide emission (ton)	553.56	107.76	−445.80
Phosphorous loading (lb)	275,702	1,519.90	−274,182
Soil loss (ton)	12,722,340	940,665	−11,831,675
Pollinator abundance	0.302	0.388	0.086
Biocontrol	0.445	0.730	0.285
Grassland bird	0.100	0.334	0.234

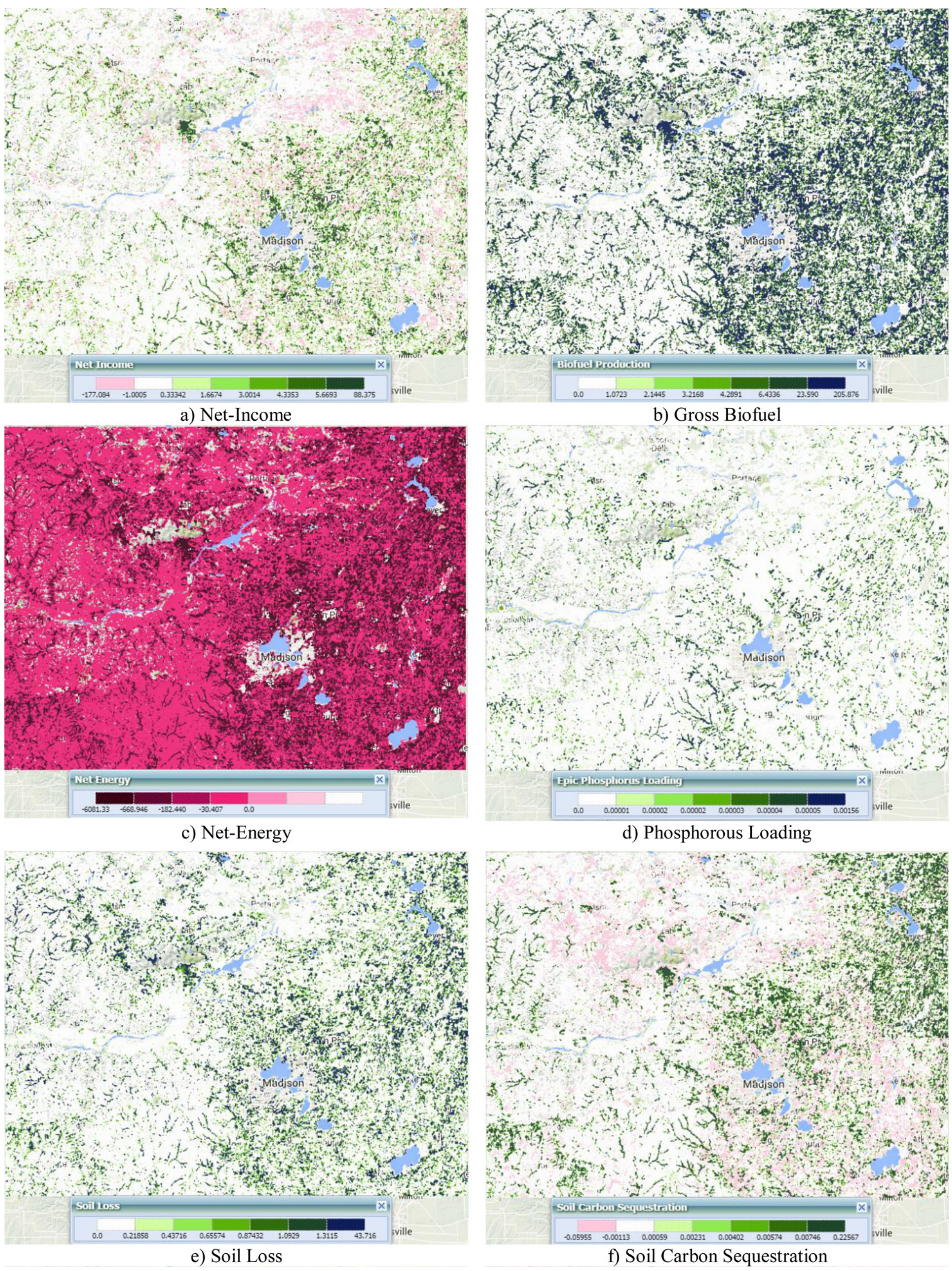
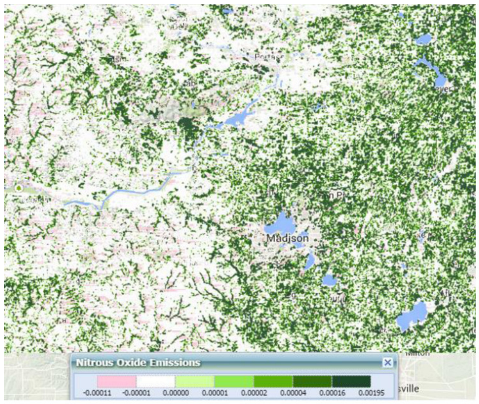
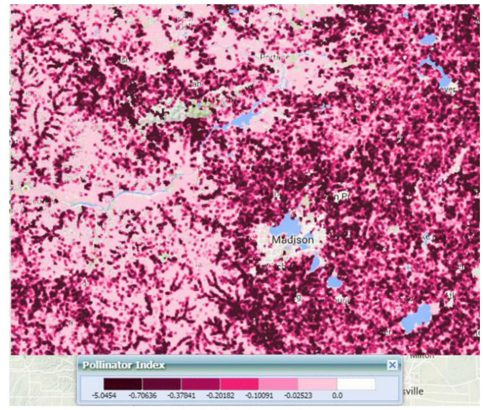


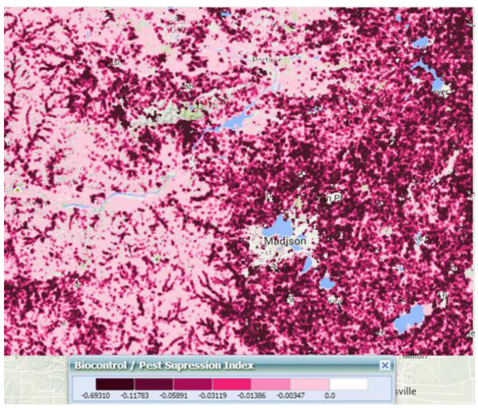
Fig. 5. Mapping the difference of ecosystem services between current and future landscape for perennial replacement scenario. Each map is color coded from dark pink (low values) to white (zero values) and dark green (high values). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



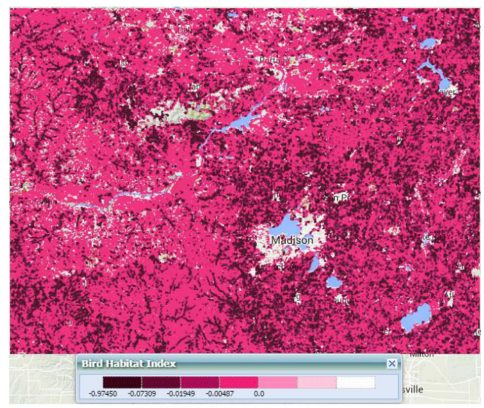
g) Nitrous Oxide Emissions



h) Pollinator Index



i) Biocontrol



j) Bird Habitat Index

Fig. 5. (*continued*)

tillage versus no-till management and manure based fertilizer versus synthetic fertilizer. Model assumptions include, for instance, crop prices and multiplicative factors associated with management options.

4. Results

4.1. Tradeoff analysis according to millennium ecosystem

For the perennial replacement scenario, the provisioning, regulation, and supportive services for the future annual energy crop were 4%, 38%, and 58% higher than current perennial energy crop (Fig. 3a). However, the cultural services for the future annual energy crop were 52% lower than the current perennial energy crop (Fig. 3a). For the annual replacement scenario, the provisioning, regulation, and supportive services for the future perennial energy crop were 18%, 40%, and 96% lower than the current annual energy crop (Fig. 3b). However, the cultural services for the future perennial energy crop were 44% higher than the current annual energy crop (Fig. 3b).

4.2. Tradeoff analysis among individual ecosystem services

4.2.1. Gross biofuel

For the perennial replacement scenario, total gross biofuel produced from the hypothetical annual energy crop was approximately 24% higher than that of the current perennial cover (Table 1 and Fig. 4a). In contrast, for the annual replacement scenario, total gross biofuel produced from the hypothetical perennial cover was approximately 16% lower than that of the current annual cover (Table 2 and Fig. 4b). The differences in both scenarios occurred due to the fact that annual biofuel production is higher than perennial biofuel production (Hill et al., 2006).

4.2.2. Net-income

At the time of writing (i.e., early 2015), the default dry metric tonne price for various crops in the global assumptions panel were as follows: corn = $240, corn stover = $50, grass = $100, soy = $400, and alfalfa = $254. For the perennial replacement scenario, the total net-income generated for the future annual cover was 29% higher than that of the current perennial cover (Table 1 and Fig. 4a). In contrast, for the annual replacement scenario, the total net-income generated for the future perennial cover was 80% lower than that of the current annual cover (Table 2 and Fig. 4b). The differences in both scenarios highlighted the difference between the selling price of a perennial energy crop (e.g., grass and alfalfa) and an annual energy crop (e.g., corn, corn stover; Meehan et al., 2013).

4.2.3. Net-energy

For the perennial replacement scenario, total annual net-energy produced from the hypothetical annual energy crop was approximately 43% lower than that of the current perennial cover, assuming that the current perennial biomass was converted to cellulosic ethanol (Table 1 and Fig. 4a). In contrast, for the annual replacement scenario, total annual net-energy produced from the hypothetical perennial energy crop was approximately 52% higher than that of the current annual cover (Table 2 and Fig. 4b). These differences occurred due to the fact that that the energy production is lower for annual energy crops than for perennial energy crops (Farrell et al., 2006).

4.2.4. *Soil carbon storage*

Given that soil carbon changes at decadal scales, the crop change associated with the both scenarios did not result in a large change (<2%, Tables 1 and 2; Fig. 4a and b). These changes were negative, −0.18%, for perennial replacement scenario, however, they were positive, 1.52%, for annual replacement scenario. The differences in both scenarios demonstrated that annual crops hold less carbon than perennial crops (West et al., 2008).

4.2.5. *N_2O emissions*

After switching from perennial crops to conventional annual crops, nitrous oxide emissions increased by 75% (Table 1 and Fig. 4a). In contrast, switching from conventional annual crops to perennial crops, results in a decline of nitrous oxide emissions by 81% (Table 2 and Fig. 4b). These differences highlighted that perennial crops emit less nitrous oxide than annual crops (Bouwman et al., 2002).

4.2.6. *Phosphorus loading*

For the perennial replacement scenario, phosphorus loading increased by 75% (Table 1 and Fig. 4a) after switching from perennial crops to conventional annual crops production. However, for the annual replacement scenario, phosphorus loading decreased by 99% (Table 2 and Fig. 4b) after changing from annual crops to perennial crops. These differences occurred due to the fact that annual crops hold less phosphorus than perennial crops (Soranno et al., 1996; Zhang et al., 2010).

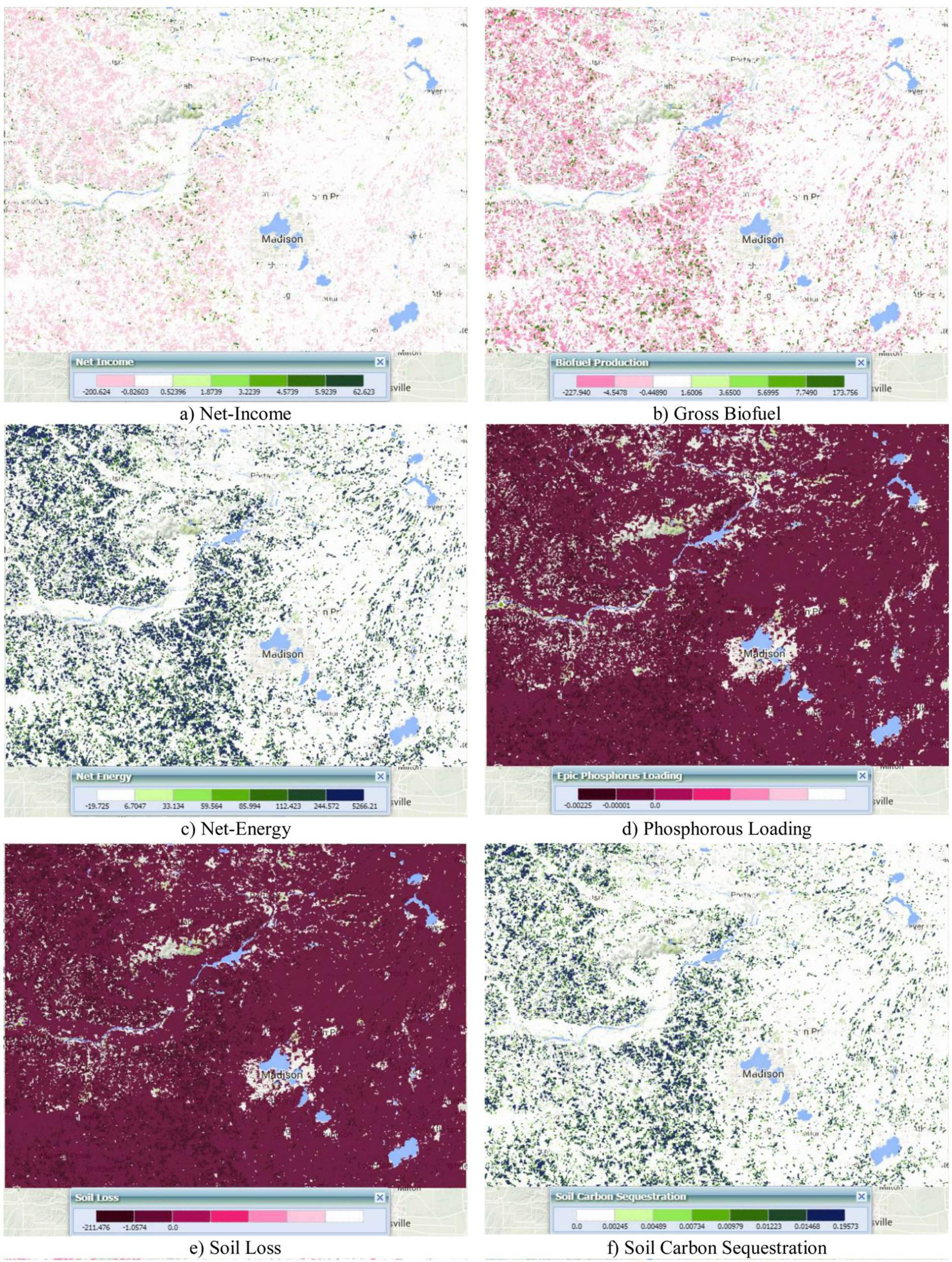
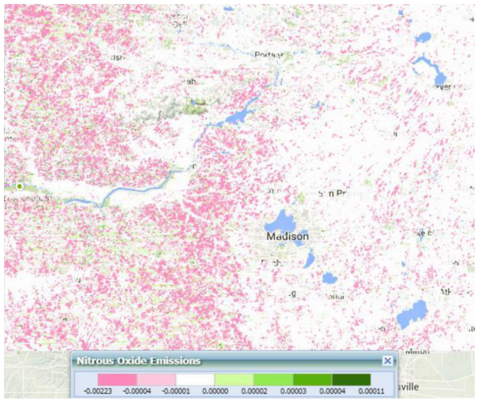
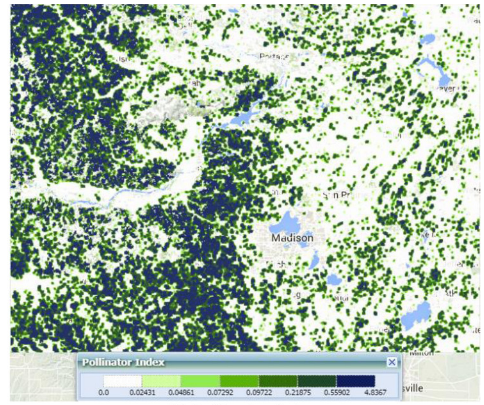


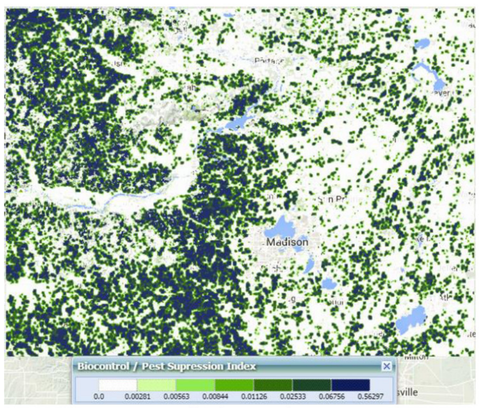
Fig. 6. Mapping the difference of ecosystem services between current and future landscape for annual replacement scenario. Each map is color coded from dark pink (low values) to white (zero values) and dark green (high values). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



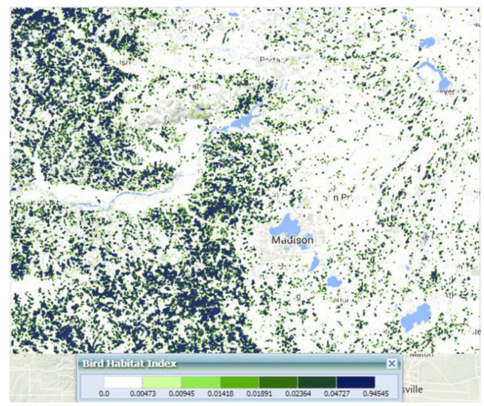
g) Nitrous Oxide Emissions



h) Pollinator Index



i) Biocontrol



j) Bird Habitat Index

Fig. 6. (*continued*)

4.2.7. Soil loss

Once perennial crops are converted to conventional annual crops, soil loss was estimated to increase by 40% (Table 1 and Fig. 4a). On the contrary, a switch from conventional annual crops to perennial crops provoked a decrease of soil loss by 93% (Table 1 and Fig. 4b). The differences in both scenarios demonstrated that conventional annual crops production typically leads to considerably higher soil loss than perennial crops production (Khanal et al., 2013).

4.2.8. Biodiversity

For the perennial replacement scenario, the average pollinator abundance index, biocontrol index, and grassland bird index were 35%, 42%, and 80% lower, respectively (Table 1 and Fig. 4a). However, for the annual replacement scenario, the average pollinator abundance index, biocontrol index, and grassland bird index were 22%, 39%, and 70% higher, respectively (Table 1 and Fig. 4b). These changes provide evidence that biodiversity are higher in agricultural areas with perennial energy crops (Meehan et al., 2012).

4.3. Mapping ecosystem services tradeoff

We subtracted the corresponding map of current ecosystem services from future ecosystem services for both crop change scenarios (the resulting map called heat map thereafter) to compare the ecosystem services before and after crop transformation. Cells with positive (gradient of green colors) or negative (gradient of pink colors) values in the heat map imply the cells within the transform scenario have larger or lower values than current scenario, respectively. The results showed (Fig. 5) that the heat maps of perennial replacement scenario for the net-energy, pollinator index, biocontrol, and bird habitat index models include more cells with negative values. In contrast, the heat maps of annual replacement scenario (Fig. 6) for the net-income, gross biofuel, soil loss, phosphorus loading, and nitrous oxide emission models include more cells with negative values.

5. Discussion

In this study, we illustrated how policymakers can take advantage of SmartScape^{TM} to produce effective crop change decisions using tradeoff analysis. Users are able to use SmartScape^{TM} individually as well as in a group. They can define their crop change scenario by answering "what-if" type questions and evaluate it. In a trial-and-error process, they modify and change their initial land selection criteria as well as crop change scenario to find suitable scenario. While developing a crop change policy is very straightforward individually, developing a crop change policy in a group or among groups of people are always challenging since there are always conflicting interest among groups of people with different area of expertise (e.g., economists, ecologists, climatologists and etc.). SmartScape^{TM} as an effective tool provides a platform to develop crop change policies among groups of people by debating conflicting viewpoints and providing solution strategies (Groot et al., 2007). SmartScape^{TM} facilitates a tradeoff analysis between multiple ecosystem services at a time to ensure that policies have outcomes that are agreeable to a diversity of stakeholders.

There are also other SDSSs that have been developed for planning and policy impact assessment dealing with a couple of ecosystem services. We briefly compared SmartScape^{TM} with other existing SDSSs. SDSSs operate at various spatial and temporal scales. For example, SmartScape^{TM} have been primarily designed to develop effective crop change policy at regional scale such as county scale, while MANUELA (von Haaren et al., 2012) assesses the influence of land use at local scale such as farm lands. SDSSs can be effective in short-term as well as long-term for policymakers. For instance, SmartScape™ provides insights on the short-term impacts of crop changes on multiple ecosystem services and on potential strategic crop change, while LandCaRe (Wenkel et al., 2013) provides information on the long-term impacts of climate change on potential management options for adaptation. SDSSs also developed to assess the consequence of land use changes such as forest and agriculture on multiple ecosystem services. For example, Frank et al. (2015) recently developed an online SDSSs called GISCAME which assesses how forest management options affect the provision of biomass and other ecosystem services. While SmartScape™ assesses how agricultural management options affect multiple ecosystem services with an integrative modeling and assessment approach.

The models implemented in SmartScape™ have several merits. First, since the SmartScape™ utilized a pixel-based approach, the value of ecosystem services for different crop types is more detailed than ever. However, even for the same crop type, the value of ecosystem services may vary due to the contribution of other factors and due to the form of ecosystem functions. For example, the values of the soil loss model for annual energy crops such as corn in areas with higher slopes are significantly higher from the areas in lower slopes. Second, the values of ecosystem services estimated in this study are a dynamic result that takes multiple factors expected for the crop change into account. Third, the models used in the SmartScape™ contribute to the development of ecosystem maps. Such maps can be useful for the policy formulation, conservation planning, and environmental impact assessment, since they have spatial attributes at the pixel level. Lastly, SmartScape™ makes the results of complex models accessible to non-technical users in a web-based format. The SmartScape™ is easy to use, expandable to other regions for which data inputs are available, and can be customized to accommodate modeling activities that meet specialized user needs.

Other studies suggest that replacement of perennial energy crops with annual energy crops result in rise of income (Meehan et al., 2013), higher biofuel production (Hill et al., 2006), lower energy production (Farrell et al., 2006), higher phosphorus loading (Zhang et al., 2010), higher soil loss (Khanal et al., 2013), less carbon sequestration (West et al., 2008), higher nitrous oxide emission (Bouwman et al., 2002), and lower in biodiversity (Bennett and Isaacs, 2014). Our findings are in line with the exiting literature (Song et al., 2015a,b; Meehan et al., 2013; Hill et al., 2006; Farrell et al., 2006; Zhang et al., 2010, Khanal et al., 2013; West et al., 2008 and Bouwman et al., 2002). We found that the perennial replacement scenario affected net-energy, phosphorus loading, soil loss, soil carbon sequestration, nitrous oxide emission, grassland bird habitat, pollinator abundance, and biocontrol negatively. However, other ecosystem services such as net-income and gross biofuel were enhanced by such transformation. On the other hand, perennial replacement scenario affected net-income and gross biofuel negatively. However, other ecosystem services such as net-energy, phosphorus loading, soil loss, soil carbon sequestration, nitrous oxide emission, grassland bird habitat, pollinator abundance, and biocontrol were enhanced by such transformation.

SmartScape™ has limitations as well to be addressed. First, while Costanza et al. (1997) divide ecosystem service functions into 17 categories, SmartScape™ assesses 11 ecosystem services due to the lack of suitable data and defensible models. Therefore, taking more categories into consideration will provide better insights to the sustainability. Second, the resolution of the data used in this study is 30 m and more accurate results can be obtained by acquiring data with higher resolution. Third, in the current version of SmartScape™, policymakers must define their own initial crop change scenario and evaluate it. Finding suitable crop change scenario is a trial-and-error process which is time consuming. Future improvements might involve modifying SmartScape™ so that it can find the best crop change scenario among all possible crop change scenarios automatically. Finally, SmartScape™ is currently developed for crop policy assessment at regional scale and is not able to assist farmers or land owners at parcel scale. Future improvements to incorporate farm lands as a separate layer for further assessment at farm scale are necessary.

6. Conclusion

We illustrated how SmartScape™ can benefit policymakers to evaluate the consequences of crop change scenarios on various ecosystem services in agricultural landscape. In this study, we evaluated two agricultural crop change scenarios (i.e., perennial replacement scenario and annual replacement scenario) with the aim of maximizing benefits through crop practices associated with a variety of ecosystem services in a Dane county of Wisconsin, United States. We found that replacing perennial energy crops with annual energy crops promoted net-income and gross biofuel. In contrast, replacing annual energy crops with perennial energy crops promoted net-energy, phosphorus loading, soil loss, soil carbon sequestration, nitrous oxide emission, grassland bird habitat, pollinator abundance, and biocontrol. The evaluation of SmartScape™ by policymakers showed that it has large potential to be used for assessing and choosing the best crop change policy by comparing the tradeoff analysis among multiple ecosystem services simultaneously. The nature of SmartScape™ brings additional advantages on dealing with complex crop transitions for sustainable development from a spatially-explicit perspective.

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