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Modeling the ecosystem services of native vegetation management practices at solar energy facilities in the Midwestern United States

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ABSTRACT

The increasing pressure on land resources for food and energy production along with efforts to maintain natural systems necessitates the development of compatible land uses that maximize the co-benefits of multiple ecosystem services. One such land sharing opportunity is the restoration and management of native grassland vegetation beneath ground-mounted solar energy facilities, which can both protect biodiversity and restore related ecosystem services. In this paper, we applied the InVEST modeling framework to investigate the potential response of four ecosystem services (carbon storage, pollinator supply, sediment retention, and water retention) to native grassland habitat restoration at 30 solar facilities across the Midwest United States. Compared to pre-solar agricultural land uses, solar-native grassland habitat produced a 3-fold increase in pollinator supply and a 65% increase in carbon storage potential. We also observed increases in sediment and water retention of over 95% and 19%, respectively. We applied these results to project the potential benefits of adoption of native grassland management practices in current and future solar energy buildout scenarios. Our study demonstrates how multifunctional land uses in agriculture-dominated landscapes may improve the provision of a variety of ecosystem services and improve the landscape compatibility of renewable energy and food production.

1. Introduction

Solar photovoltaic (PV) energy technologies have exponentially increased across the globe over the past decade (Kabir et al., 2018; Irsyad et al., 2019). Currently, there are over 33 gigawatts (GW) of ground-based large-scale (>1 MW) solar PV energy production in the U. S. (EIA, 2019a), representing about 1.5% of total U.S. electricity generation in 2018 (EIA, 2019b). The proliferation of large-scale solar energy developments is expected to continue across the U.S. over the next decade. For example, the U.S. Department of Energy's National Renewable Energy Laboratory, through its Standard Scenarios Report, estimates around 200 GW of installed electric capacity among ground-mounted solar facilities by 2040 under its Mid-Case scenario, and more than 500 GW of ground-mounted solar facilities by 2040 under its Low-PV Cost scenario (Cole et al., 2019). Like other forms of energy development, land use represents a major challenge for future solar energy deployment. Ground-based solar energy developments require between 2.5 and 3.5 ha per megawatt (MW) (Ong et al., 2013; Hernandez et al., 2014), and approximately 7500 km^2 of total land will be needed to meet 2030 projected solar energy production (Hartmann et al., 2016), roughly the combined size of the states of Delaware and Rhode Island.

Given their large land requirements, questions about the sustainability of solar energy developments have emerged in terms of their compatibility with other land uses such as agriculture (Moore-O'Leary et al., 2017; Hernandez et al., 2019). Ground-based solar energy developments are increasing in agricultural landscapes, due in large part to the siting of utility-scale solar energy developments on former agricultural fields (Adelaja et al., 2010; Adeh et al., 2019). Croplands are generally flat, open, and relatively undeveloped, making them ideal locations for solar energy development (Adeh et al., 2019). This pattern of conversion from agriculture to solar energy development can represent a land use tradeoff between food production and renewable energy production (e.g., Krishnan and Pearce, 2018). As the pressure intensifies on land resources for energy and food production, greater emphasis has been placed on solutions that maximize mutual benefits of multiple

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ecosystem services. Recent approaches have suggested the integration of solar energy with food production, biodiversity conservation, and other ecosystem services (i.e., the energy-food-ecology nexus; Moore-O'Leary et al., 2017; Hernandez et al., 2019). For example, the co-location of solar energy and agriculture, often termed as "agrivoltaic systems", could improve the land-use potential of solar sites for energy and food production (Ravi et al., 2016; Dinesh and Pearce, 2016; Hoffacker et al., 2017; Barron-Gafford et al., 2019). In one study, Barron-Gafford et al. (2019) found that shading by solar PV arrays benefitted the production of crops such as Chiltepin peppers (*Capsicum annuum var. glabriusculum*), jalapenos (*C. annuum* var. *annuum*), and tomatoes (*Solanum lycopersicum var. cerasiforme*) by increasing yields and reducing water requirements while also creating cooler microclimate conditions that improved solar energy production.

Other research surrounding the energy-food-ecology nexus of solar energy has focused on the restoration of native grassland vegetation at ground-mounted solar facilities ("solar-native vegetation") to improve biodiversity and other ecosystem services such as pollination of adjacent croplands (Moore-O'Leary et al., 2017; Walston et al., 2018; Hernandez et al., 2019). In the United States, this approach has focused on vegetation management efforts at solar facilities aimed at establishing native grassland vegetation, such as milkweed (*Asclepias* spp.), native forbs and wildflowers, and other pollinator-friendly vegetation, either among the solar PV arrays or elsewhere within the solar facility footprint area, that attract and support native insect pollinators and other beneficial insect predators by providing food resources, refugia, and nesting habitat. Highlighting the potential significance of this approach, recent research found that over 3500 km^2 of agricultural land near existing solar energy facilities in the U.S. may benefit from increased pollination services through the establishment of solar-native vegetation (Walston et al., 2018).

Conventional ground management approaches at solar facilities often involve the establishment and management of low-growing turfgrass (Walston et al., 2018). While turfgrass provides some ecosystem service value for biodiversity and soil and water control, shifting to native grassland management practices at these locations has the potential to improve the ecosystem services potential of solar energy facilities. Compared to conventional turfgrass approaches, native grassland vegetation may improve ecosystem services related to biodiversity, carbon storage, water conservation, soil retention, and pollination of nearby croplands. Favorable microclimate conditions created by solar PV arrays, such as lower temperatures and greater soil moisture, can improve the performance of native grasses, which increases above-ground biomass and related carbon sequestration (Armstrong et al., 2016; Adeh et al., 2018). In addition, native grasses and forbs typically have deeper root systems than row crop agriculture and turfgrass (Schenk and Jackson, 2002), with root depths of some native grassland species exceeding 2–5 m (Packard and Mutel, 1997). Deeper root systems create the potential for improved soil stabilization and reduced water runoff (Hernandez-Santana et al., 2013). To date, however, these solar-native vegetation ecosystem service benefits have not been adequately quantified or evaluated in a common framework that allows for an understanding of a suite of ecosystem services. Thus, to build upon the previous efforts to understand the ecosystem service benefits of solar-native vegetation, this paper focuses on modeling the potential supply of ecosystem services resulting from different vegetation management approaches at solar energy facilities. Specifically, we were interested in addressing the following question: *What are the multiple ecosystem service benefits of solar-native vegetation compared to pre-existing land uses and other types of vegetation management practices at solar facilities*? To address this question, we conducted a geospatial land use change assessment for solar energy facilities in the Midwest and we developed spatially-explicit models at a regional scale aimed at quantifying differences in the following ecosystem services associated with solar-vegetation management options: pollinator supply, carbon storage, soil retention, and water yield. We then project these results to examine ecosystem service implications of future solar energy development within the region.

2. Methods

2.1. Study area

We examined ecosystem services associated with vegetation management practices at solar energy facilities within the Midwestern region of the United States (Fig. 1). This region is approximately 1.1 million km^2 in size and includes the states of Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, and Wisconsin. The predominant land use in this region is agriculture (37% of the study area), followed by forest (33%) and grasslands and other herbaceous land cover types (17%). The climate is humid temperate, with an average annual precipitation of 725 to 1100 mm (USDA, 2019). Average annual minimum and maximum temperatures in the region are −9 degrees Celsius (°C) and 29 °C, respectively (USDA, 2019).

Euro-American settlement and associated agricultural intensification has resulted in the decline of the region's grasslands, a diverse vegetation system that was much more dominant and widespread throughout the region prior to the mid-1800s. For example, over 99% of the tallgrass prairie in Illinois, Indiana, Iowa, Minnesota, and Missouri have been lost primarily due to agricultural expansion (Samson and Knopf, 1994). As such, many of the current terrestrial ecological restoration objectives within the region focus on restoration of native grassland and prairie systems. For solar sites in the Midwest, increasing emphasis has been placed on native grassland restoration among the PV arrays (Clean Energy States Alliance, 2020), which is a more compatible habitat type for solar energy development than other habitat types such as forests or wetlands.

2.2. Identification of solar energy facilities and data preparation

We identified the location of large-scale ground-based solar energy facilities (>1 MW) from the U.S. Energy Information Administration (EIA) for the year 2018 (EIA, 2019). The EIA reports generator-level specific information on electricity production facilities, including latitude and longitude information for facility locations and nameplate electricity capacity (MW). We queried the EIA database to only those sectors that were utility or industrial ground-based facilities (sectors 1 and 2). By doing so, we omitted large commercial rooftop facilities from our study. We then used a Geographic Information System (GIS; ArcGIS version 10.6.1) to map the approximate point location of each facility using the latitude and longitude coordinates reported by the EIA. We overlaid these points with the latest online World Imagery basemap within ArcGIS (ESRI, 2019) and digitized the footprint boundaries of all solar sites observable in the imagery. Solar facility polygons were drawn to include the PV panel area plus other areas observable within the fenced area of the facility (e.g., disturbed soil, laydown areas, operations facilities). Most of the World Imagery available for the region was obtained in 2018. We then calculated the size (ha) of each digitized solar facility's footprint polygon. For these facilities, we correlated facility electric capacity (MW) and footprint size (ha) and we used this relationship to estimate the footprint size for solar facilities that were not observed or incomplete in the satellite imagery. The 2018 list of all solar energy facilities in the Midwest, along with corresponding footprint sizes, is provided in Supplement 1.

We conducted a land use change assessment to determine what percentage of solar facilities in the Midwest were developed on former agricultural fields or other land use-land cover (LULC) types. We performed this assessment only for those solar facility footprints that could be delineated in a GIS. Because large-scale solar energy development largely did not appear in the Midwest until 2012, we used 2010 LANDFIRE Existing Vegetation Types (http://www.landfire.gov/evt.php) as the pre-solar land use dataset and determined the composition

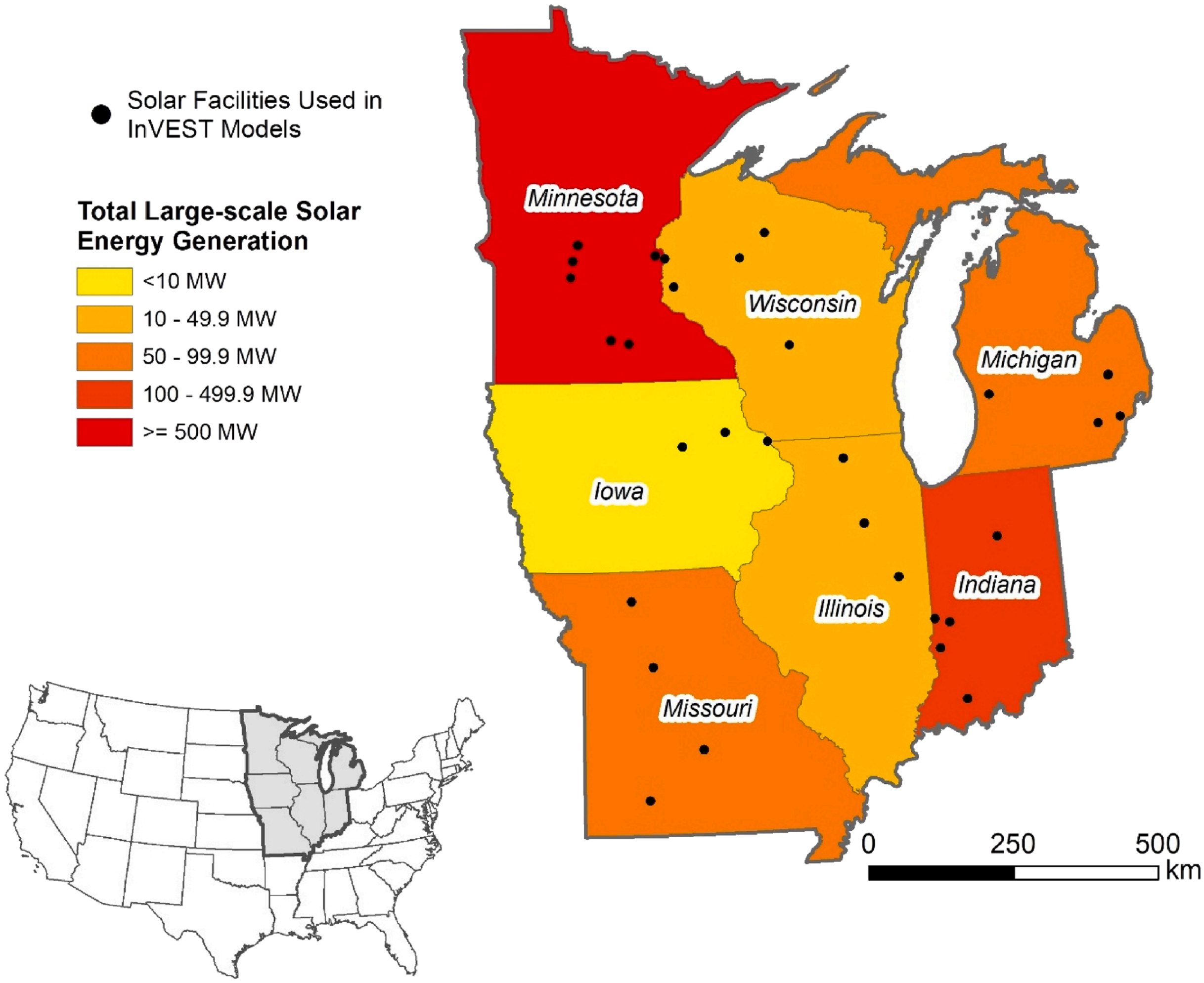

Fig. 1. Total 2018 large-scale (>1 MW) solar energy generation in States of the Midwest region of the United States (source: EIA, 2019). Locations of the thirty solar energy facilities used in InVEST modeling are shown in black.

of 2010 land use types intersecting the solar facility footprints as the measure of LULC change (see Supplement 1).

2.3. Scenarios

To determine the ecosystem services among vegetation management activities at mapped solar energy facilities, we designed three land use scenarios for the solar energy facility footprints: an agriculture scenario (the baseline “pre-solar development” land use) and two solar energy development scenarios – a solar-turfgrass scenario and a solar-native grassland scenario (Fig. 2). Because we assumed the majority of solar facilities in the region were previously under corn-soybean agricultural production (Supplement 1), we replaced all land uses in the solar footprint polygons with agriculture to represent the pre-solar land use. We considered this scenario to be the baseline scenario for comparison. The second scenario we evaluated was a solar-turfgrass vegetation scenario in which we assumed the sodding of cool-season turfgrass within the solar facility. This scenario also involves regular vegetation maintenance at the solar facility such as active mowing and herbicide applications to minimize or prohibit the growth of vegetation (<0.3 m high) within the solar facility footprint. Turfgrass is a common vegetation management practice at solar facilities and this scenario was considered to be the business as usual (“BAU”) scenario for operating solar facilities. The third scenario we evaluated was a solar-native grassland scenario in which we assumed the intentional establishment of native prairie grasses and forbs in the solar facility footprint that provide forage and nesting habitat for native insect pollinators. Compared to the turfgrass scenario, the solar-native grassland scenario involves management activities that allow the vegetation to flower and reach heights up to 1 m within the solar PV arrays (the maximum height typically allowed at solar PV arrays to avoid shading of the panels). Because native grasses and forbs typically have deeper root systems than turfgrass (Schenk and Jackson, 2002), we assumed greater above- and below-ground vegetation biomass under the solar-native grassland scenario compared to the solar-turfgrass scenario.

2.4. Modeling framework

We used a multiple service model called Integrated Valuation of Environmental Services and Tradeoffs (InVEST, version 3.6; Sharp et al., 2018) to evaluate ecosystem services under each of the three land use scenarios at the Midwest solar energy facilities. The InVEST suite of tools has been developed to assist decision makers in comparing the impacts of different land use scenarios on the provision of ecosystem services. To our knowledge, this is the first application of InVEST to examine ecosystem service response to solar energy land uses. We used the following four existing InVEST models: Pollinator Model (for pollinator habitat quality), Carbon Storage Model, Sediment Delivery Ratio (SDR) Model (for soil retention), and Water Yield Model (for water retention). A detailed description of our modeling methods and parameters can be found in Supplement 2. Each of these InVEST models incorporate spatial datasets on land use-land cover (LULC) and some of them use elevation,

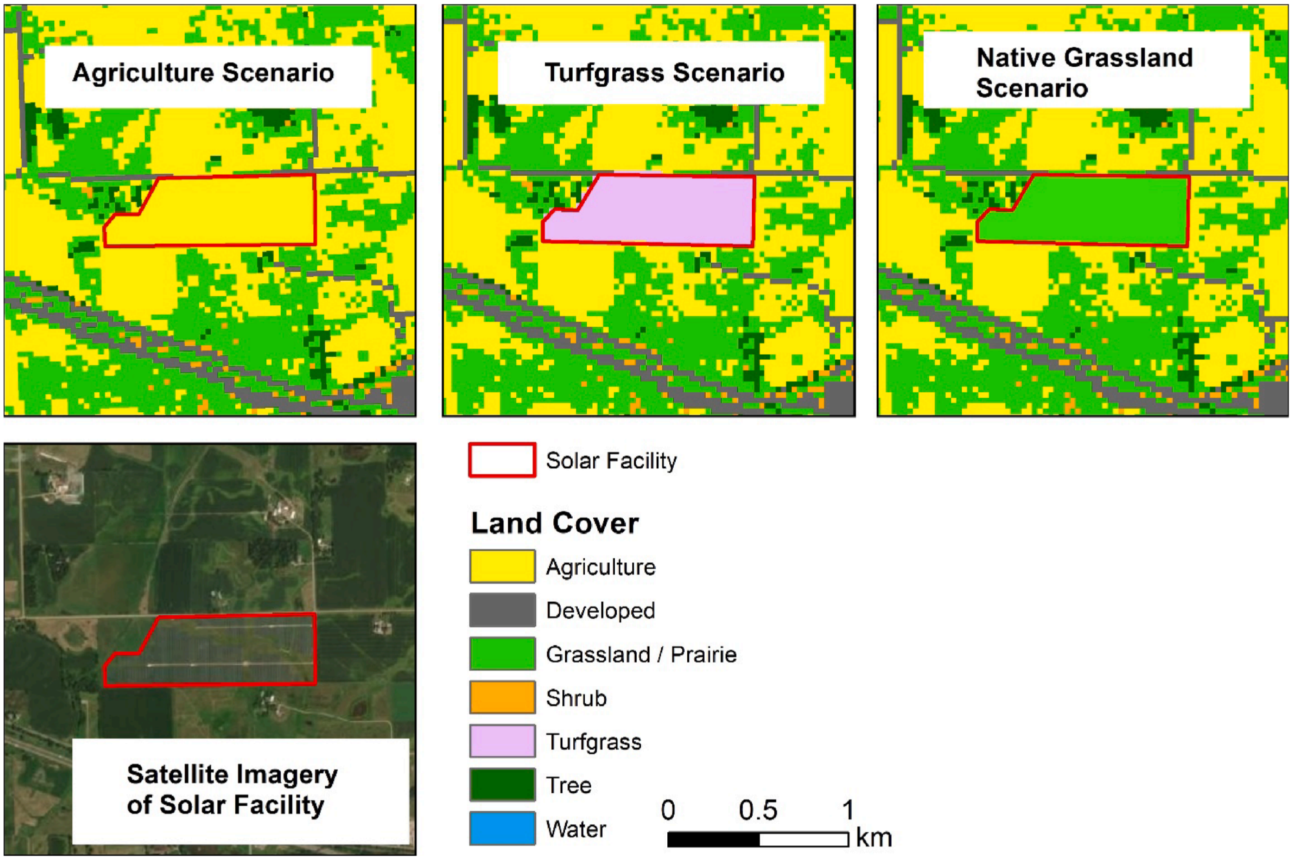

Fig. 2. Vegetation scenarios evaluated in this study. The agriculture scenario represents the pre-solar land use.

rainfall, and soil and vegetation properties, along with tabular biophysical parameters, to conduct spatially-explicit assessments of ecosystem services. The spatial datasets used in the models are also described in Supplement 2.

For this LULC dataset, we used a 30 m raster dataset of vegetated land cover from the 2014 LandFire Program (Existing Vegetation Types; http://www.landfire.gov/evt.php). We initially summarized the LULC map across the entire Midwest region into seven broad LULC classifications based on vegetation life form: developed, agriculture, barren or sparsely vegetated, grassland, shrubland, forested, and water and wetlands. We then updated the LULC map to create an eighth LULC classification representing solar energy facility developments using the footprint polygons delineated from satellite imagery. We selected a total of 30 solar facility footprint polygons, with a minimum of 3 footprints in each state, to update the LULC raster dataset (Fig. 1). This LULC update was performed by overlaying the facility footprint polygons on the initial LULC map and reclassifying the underlying pixels of the LULC map to a unique solar-specific LULC code.

All of the InVEST models also require tabular biophysical parameters to relate land cover types from the LULC map to the individual ecosystem service processes. We reviewed the existing literature to identify studies utilizing these InVEST models in the United States to parameterize each model. Surrogate vegetation and LULC types were used to identify the biophysical parameters to include in each scenario (Table 1).

We used the surrogate LULC types to review existing literature from previous InVEST modeling studies in the United States and summarize the biophysical parameters for each model (Table 2). We ran each model using upper- and lower-bound parameter values based on the 25% and 75% quartile range of values reported in the literature. We used this range to estimate the uncertainty in models and we used the midpoint (average) values in comparing ecosystem services across scenarios. For all ecosystem service estimates, we focused on the change in the service delivery for the solar-native grassland scenario compared with the solar-turfgrass scenario and the baseline agriculture scenario. For each scenario, we assumed the surrogate vegetation (Table 1) was consistently and uniformly distributed across all solar facilities. We were not able to use InVEST to model the effect of solar panels on these ecosystem services so we assumed this effect to be constant across all three land use scenarios.

Table 1
Land use-land cover (LULC) surrogates for the three land use scenarios modeled in this study.

Scenario	Surrogate LULC types
Agriculture (baseline pre-solar land use)	Row crop agriculture LULC types (e.g., corn-soybeans).
Solar-turfgrass	Residential, suburban, and turfgrass LULC types.
Solar-native grassland	Native grassland and prairie LULC types.

The InVEST Carbon Storage Model is a carbon stock estimation model that is explicitly connected to land cover type. This model calculates total carbon storage (Mg C/ha) for each land cover type based on the aggregation of four carbon pools: aboveground carbon density, belowground carbon density, soil organic carbon density, and dead organic matter carbon density (Sharp et al., 2018). We used this model to examine differences in total carbon storage associated with each scenario.

The InVEST Pollinator Model was designed to model and map patterns of pollinator habitat quality and potential pollination service values across landscapes (Sharp et al., 2018). This model utilizes information on floral resource availability (associated with each LULC type), along with tabular inputs on nesting and foraging parameters for individual pollinator species or species groups, to estimate the supply,

Table 2
Biophysical parameters used in the InVEST Models. The range represents the upper- and lower-bound parameter values used in the models

	Carbon storage model[a]	Pollinator model[b]		Sediment (SDR) model[c]	Water yield model[d]	
Scenario	Total carbon storage (Mg C/ha)	Ground nest availability	Floral resource availability	USLE C-factor	Root restricting layer (mm)	Kc
Agriculture	68.0–88.6	0.137–0.213	0.270–0.400	0.30–0.43	775–925	0.55–0.60
Solar-turfgrass	87.0–104.4	0.310–0.530	0.460–0.580	0.03–0.08	775–925	0.65–0.75
Solar-native grassland	108.0–148.1	0.430–0.570	0.675–0.825	0.01–0.03	1250–1750	0.75–0.85

[a] Sources: Grafius et al. (2016); Johnson et al. (2012); Kovacs et al. (2013); Liebman et al. (2013); Polasky et al. (2011); Sharp et al. (2018); Sun et al. (2018).
[b] Sources: Davis et al. (2017); Kennedy et al. (2013); Zhao et al. (2019). Cavity nest availability assumed to be 0 in all scenarios.
[c] Sources: Bai et al. (2019); Chaplin-Kramer et al. (2016); Grafius et al. (2016) Sharp et al. (2018); Sun et al. (2018).
[d] Sources: Bai et al. (2019); Redhead et al. (2016); Sharp et al. (2018). Kc = Plant Evaporation Coefficient.

abundance, and service value of insect pollinators across the landscape. In this study, we used the pollinator supply InVEST output to assess the ability of each scenario vegetation type to support insect pollinators. As described by the InVEST model (Sharp et al., 2018), pollinator supply is a unitless index (between 0 and 1) indicating where pollinators originate on the landscape. For the purpose of comparing the different vegetation scenarios, we used native bumblebees (Family Apidae) and native sweat bees (Family Halictidae) as the modeled guilds (Supplement 2).

The InVEST Sediment Delivery Ratio (SDR) Model estimates the overland movement of sediment based on topography, climate, soil, and land cover properties. The SDR model is a spatially-explicit model working at the spatial resolution of the input digital elevation model raster (Sharp et al., 2018). For each pixel, the model computes the amount of annual soil loss from that pixel based on a revised Universal Soil Loss Equation (USLE). It then calculates the SDR, which is the proportion of soil loss that reaches the catchment. Finally, the model uses the USLE and SDR to calculate erosion as total catchment sediment export (tons/ha). Inputs for the SDR model include raster maps for LULC, elevation, rainfall, and soil erodibility, along with tabular biophysical attributes related to sediment retention based on land cover type (Supplement 2). We used this model to estimate the amount of surface soil erosion associated with each vegetation scenario. Because sediment erosion represents a negative impact on the landscape, we considered erosion to be the inverse of a positive ecosystem service – soil retention, or the ability of a modeled vegetation type to retain soil.

The InVEST Water Yield Model calculates the net water yield at pixel-based and watershed scales based on the difference between precipitation and actual evapotranspiration. Actual evapotranspiration is a function of reference evapotranspiration, root restricting layer depth, plant available water content, and land cover type (Sharp et al., 2018). Following the methods described by Bai et al. (2019), we used the Water Yield model as an interim step in quantifying water retention: the ability of the modeled land cover type to intercept water from runoff. Water retention is calculated by subtracting runoff from water yield as follows:

$$WR_{ij} = WY_{ij} - Runoff_{ij}$$

where WR_i is the annual water retention (mm/yr) for pixel i on LULC type j, WY_{ij} is the annual water yield (mm/yr) for pixel i on LULC type j (calculated from InVEST), and $Runoff_{ij}$ is the annual surface runoff (mm/yr) for pixel i on LULC type j. Runoff is a product of annual precipitation and a runoff coefficient for each LULC type based on slope and soil type (Supplement 2). Because most solar energy developments are constructed on low slopes (<10%; Hartmann et al., 2016) and most agricultural areas in the region are loamy soils (Hollinger, 1995), we calculated LULC-specific erosion coefficients based on assumed slope of <10% and loamy soil properties.

2.5. Synthesis

We compared the output from the four InVEST models among the three vegetation scenarios. These comparisons were made on a unit-area basis for the 30 modeled solar energy developments and projected to the current amount of large-scale solar energy development in the Midwest region. We also explored the future potential for these ecosystem services by projecting these results to a future solar energy development scenario. Based on solar energy targets identified from state legislation and energy websites (e.g., Illinois Future Energy Jobs Act [S.B. 2814, 2016]; SEIA, 2019; MISO, 2019), we estimated the total foreseeable potential large-scale solar energy development within the Midwest region in the next 10–15 years (2030–2034). Using a solar land use-MW relationship calculated from delineated existing solar footprints in the region (Supplement 1), we estimated the future aggregate solar footprint size and projected our InVEST model results to this scenario.

3. Results

3.1. Solar energy development

We identified 276 large-scale solar facilities in the Midwest region that were operating in 2018, representing a total nameplate electricity capacity of 1183.8 MW (Supplement 1). The state of Minnesota contained most of the region's solar energy development both in terms of the number of facilities and total electricity capacity (Fig. 1; Table 3). Approximately 59% of the solar facilities and over 62% of the region's solar electricity capacity occurred in Minnesota. The state of Iowa contained the fewest number of solar facilities (n = 5) and the lowest amount of large-scale solar electricity generation (9.2 MW).

We identified and mapped the facility footprints of 192 solar facilities from the ESRI World Imagery. The remaining 84 solar facilities were either incomplete or not yet constructed at the time the satellite imagery was collected. We determined a land use-MW relationship of 3.0 ha per MW for all 192 delineated solar facilities (Supplement 1) and applied this relationship to estimate the footprint sizes for the remaining 84 solar facilities. Using the GIS-derived and estimated solar footprint sizes, we determined the total current footprint size among all solar facilities in the Midwest to be approximately 3416 ha (34.2 km^2).

Table 3
Summary of current (2018) large-scale solar energy development in the Midwest region.[a]

State	Current number of solar facilities	Current total nameplate capacity (MW)	Total current estimated footprint size (ha)[b]
Illinois	6	38.5	86.7
Indiana	60	214.3	574.2
Iowa	5	9.2	15.9
Michigan	13	98.3	250.1
Minnesota	163	741.5	2252.7
Missouri	17	61.1	173.2
Wisconsin	14	20.9	63.2
Regional total	276	1183.8	3416.0

[a] Sources: Data for 2018 solar facility development obtained from EIA (2019).
[b] Estimated total footprint size was based on solar footprint polygons digitized in GIS (for those facilities that could be mapped and located with satellite imagery) a land use relationship of 3.0 ha per MW of nameplate capacity for those facilities that could not be located within satellite imagery (Supplement 1).

We determined the pre-solar construction land uses by identifying and quantifying the amount of 2010 LULC types within the 192 delineated solar facility footprints. By far, the dominant pre-construction LULC type converted to solar energy was row crop agriculture, comprising 70% of the 2010 LULC types within the solar footprint polygons (Supplement 1). This represents a conversion of approximately 2391 ha (23.9 km^2) of row crop agriculture to current ground-based solar energy development. Other forms of LULC conversion included developed areas (15.0%, 512.4 ha), pasture and hay fields (5.4%, 184.5 ha), and forest and riparian areas (4.5%, 153.7 ha).

3.2. InVEST model results

Ecosystem service model results for the 30 Midwest solar facilities, averaged by state, are presented in Table 4 (see Supplement 2 for more detailed results). Differences in modeled ecosystem service results among scenarios were primarily related to LULC changes. We used the variability in reported biophysical parameter values (Table 2) to calculate the range (and midpoint average) of ecosystem service results under each scenario. We found the patterns of ecosystem service provision among scenarios were consistent for the entire Midwest (Fig. 3). For example, the solar-native grassland scenario retained more water than the solar-turfgrass scenario, which retained more water than the agriculture scenario (solar-native grassland > solar-turfgrass > agriculture). We therefore present remaining results using the regional averages of modeled ecosystem services.

Carbon Storage. On average for the entire Midwest region, the solar-native grassland scenario had a potential carbon storage capacity of 129.3 Mg C/ha, which was 65% and 35% greater than the agriculture and solar-turfgrass scenarios, respectively (Table 4; Fig. 3).

Pollinator Supply. On average, the solar-native grassland scenario improved pollinator supply by 3-fold and 30% compared to the agriculture and solar-turfgrass scenarios, respectively (Table 4; Fig. 3).

Table 4
State and Midwest regional average ecosystem service results.

State	Agriculture scenario	Turfgrass scenario	Native grassland scenario
Carbon storage (Mg C*ha^{-1})			
All States	78.3	95.7	129.3
Pollinator supply (unitless index)			
Illinois	0.032	0.071	0.094
Indiana	0.032	0.072	0.094
Iowa	0.032	0.074	0.093
Michigan	0.032	0.076	0.095
Minnesota	0.033	0.074	0.098
Missouri	0.034	0.076	0.101
Wisconsin	0.034	0.079	0.100
Regional average	0.033	0.074	0.096
Sediment export (tons*ha^{-1}*yr^{-1})			
Illinois	7.084	0.536	0.131
Indiana	2.935	0.237	0.062
Iowa	2.165	0.168	0.041
Michigan	0.837	0.065	0.017
Minnesota	3.449	0.258	0.063
Missouri	10.252	1.061	0.263
Wisconsin	0.528	0.039	0.009
Regional average	0.327	0.030	0.007
Water retention (mm*ha^{-1}*yr^{-1})			
Illinois	832.3	910.0	1007.4
Indiana	740.3	812.6	900.1
Iowa	666.8	725.0	791.5
Michigan	733.0	783.2	842.4
Minnesota	748.3	803.2	869.3
Missouri	748.9	820.5	907.3
Wisconsin	762.2	824.7	904.1
Regional average	744.3	808.0	885.0

Sediment Export. On average, sediment export under the solar-native grassland scenario was 0.007 tons/ha/year, which was a reduction of over 95% and 77% compared to the agriculture and solar-turfgrass scenarios, respectively (Table 4; Fig. 3).

Water Retention. On average, water retention under the solar-native grassland scenario was 885.0 mm/yr, which was 19% and 9.5% greater than the agriculture and solar-turfgrass scenarios, respectively (Table 4; Fig. 3).

3.3. Projections to current and future energy scenarios

Using the Midwest regional averages for all calculations, the solar-native grassland scenario for all existing solar facilities (3416 ha) had the potential above- and below-ground carbon storage capacity of 267,473 Mg C, which was 174,216 Mg and 114,778 Mg greater than the agriculture and solar-turfgrass scenarios, respectively (Table 5). The solar-native grassland scenario conserved over 1000 tons more sediment from erosion than the agriculture scenario and 79 tons more sediment than the solar-turfgrass scenario. For existing solar energy developments, the solar-native grassland scenario retained over 4,800,000 m^3 and 2,600,000 m^3 more water than the agriculture and solar-turfgrass scenarios, respectively (Table 5). Because InVEST calculates pollinator supply as a unitless index value, we did not make future projections for pollinator habitat quality.

Based on solar energy targets identified from state legislation and energy websites (e.g., Illinois Future Energy Jobs Act [S.B. 2814, 2016]; SEIA, 2019; MISO, 2019), we conservatively estimated the amount of large-scale solar energy development for a future 2030–2034 time period to be approximately 10,000 MW (10 GW). This represents about 5% of the national 2030 goal for ground-mounted solar set forth by the U.S. Department of Energy (U.S. Department of Energy, 2012). Several Midwestern states such as Minnesota, Illinois, Indiana, and Wisconsin already have a queue of expected solar projects that would collectively reach this level of development in the next 5 years. Based on our calculated regional solar land use estimate of 3.0 ha per MW (Supplement 1), we estimated this future regional solar development footprint to occupy approximately 30,000 ha (300 km^2). If all solar facilities incorporated native grassland vegetation management strategies under this future energy scenario, the total above- and below-ground carbon storage potential of these facilities could exceed 3,800,000 Mg C, which would represent 1,500,000 Mg C and 1000,000 Mg C greater storage potential than agriculture and solar-turfgrass scenarios, respectively (Table 5). Under this future energy scenario, region-wide adoption of solar-native grassland management strategies has the potential to conserve over 9000 tons of sediment loss from erosion annually and retain over 40,000,000 m^3 of water from runoff annually (Table 5).

4. Discussion

Ecosystem services of vegetation management options at solar energy facilities are an emerging field of study. Our study demonstrates how multifunctional land uses in agricultural-dominated landscapes have the potential to improve the provision of a variety of ecosystem services. Numerous studies have demonstrated the effectiveness of native grassland restoration in agricultural landscapes in conserving insect pollinators and restoring important ecosystem services (e.g., Hernandez-Santana et al., 2013; Blaauw and Isaacs, 2014; Schulte et al., 2017). While field studies at solar facilities are currently under way to measure the ecosystem services of different vegetation management options, it will take several years for these field data to become available. To obtain initial estimates, we focused on examining the potential ecosystem services in a spatially-explicit manner using secondary data sources and scaled our model results to regional estimates. Our models included input parameters from previous studies in the U.S. that evaluated ecosystem service tradeoffs among various land uses, including

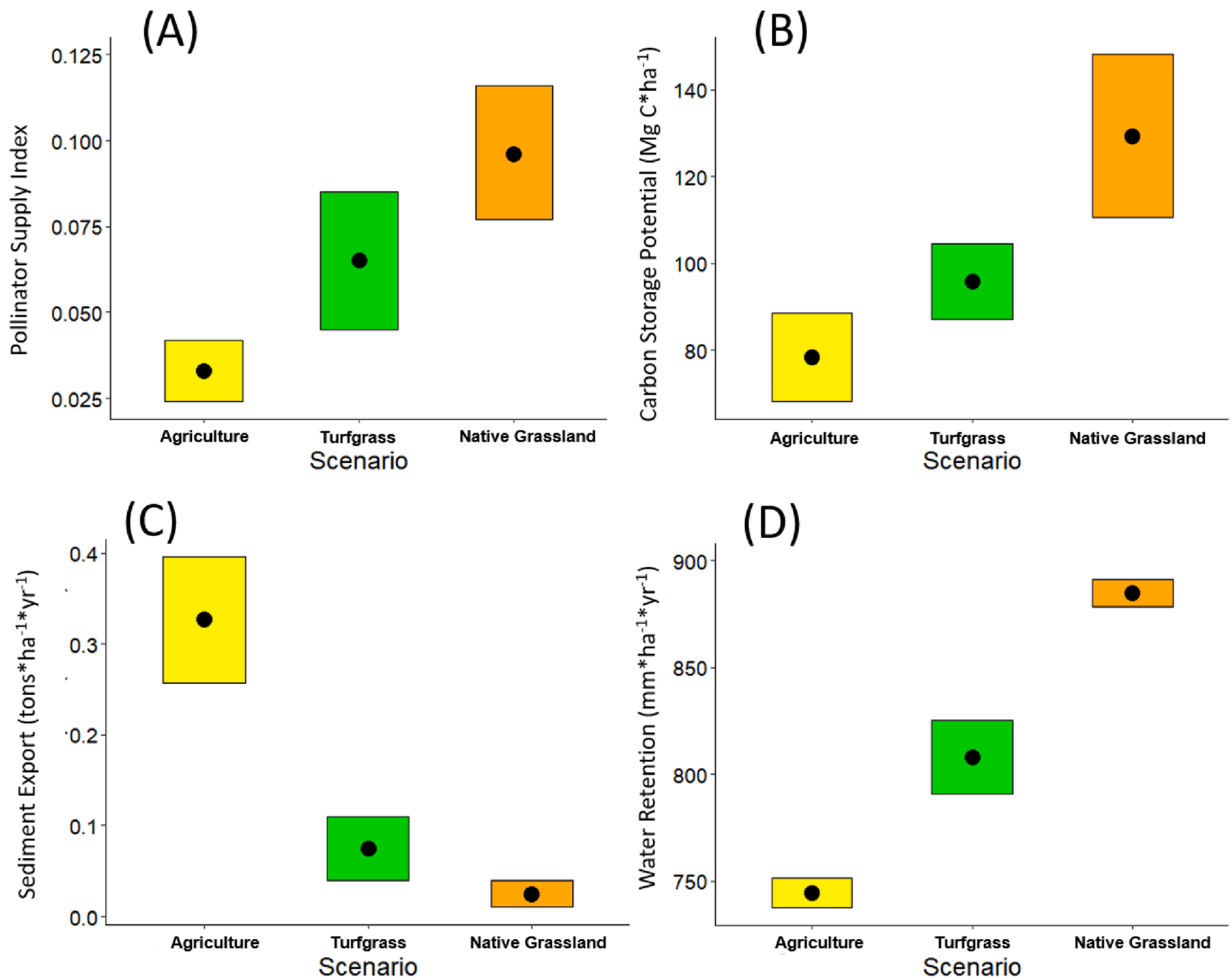

Fig. 3. Average ecosystem service values for the thirty Midwest solar facilities modeled with InVEST: (A) pollinator supply, (B) carbon storage, (C) sediment export, and (D) water retention. Tiles represent the upper- and lower-bound estimates based on the 25% and 75% quartiles. Points represent the midpoint average values.

Table 5
Ecosystem services projected to the entire current and future solar energy development footprints in the Midwestern U.S.

Solar development time peirod[a]	Agriculture scenario	Turfgrass scenario	Pollinator scenario
Carbon storage (Mg C)			
Current	267,473	326,911	441,689
Future	2,349,000	2,871,000	3,879,000
Sediment export (tons*yr^{-1})			
Current	1117.0	102.5	23.9
Future	9810.0	900.0	210.0
Water retention (m^3*yr^{-1})			
Current	25,425,300	27,601,300	30,231,600
Future	223,290,000	242,400,000	265,500,000

[a] Current time period refers to existing solar energy facilities in the Midwest as of 2018 (1.2 total GW), with a total estimated footprint size of 3416 ha (34.2 km^2) (EIA, 2019). Future time period refers to a future solar energy development scenario (10 GW), with an estimated footprint size of 30,000 ha (300 km^2).

our land use surrogates (agriculture, native grassland and prairie, and turfgrass/suburban land use types). This approach allowed us to examine the potential tradeoffs in vegetation management land uses at solar energy facilities.

There is ample research supporting the InVEST ecosystem service model parameters and output related to our surrogate land cover types (see Table 2 and Supplemental 2). For example, in a study of land use impacts on ecosystem services in Minnesota, Johnson et al. (2012) examined tradeoffs in total carbon storage using estimates of 108 Mg C * ha^{-1}, 100 Mg C * ha^{-1}, and 67.7 Mg C * ha^{-1} for native grassland, developed, and agricultural land use types, respectively. In Wisconsin, Meehan et al. (2013) used the InVEST pollinator model with biophysical parameters similar to ours to associate pollinator habitat with LULC types. They found that switching from annual row crop agriculture (corn) to perennial grasses in Wisconsin would increase pollinator abundance by an average of 11%. In Iowa, Schulte et al. (2017) discovered that prairie strips in corn-soybean dominated agricultural settings reduced total water runoff from catchments by 37%, resulting in the retention of 20 times more soil as compared to an agricultural baseline scenario.

As expected, our models suggest that solar-native grassland improves habitat for local insect pollinators. Overall, we detected a 3-fold increase in pollinator supply under the solar-native grassland scenario compared to the pre-solar development land use scenario (agriculture) and a 30% increase in pollinator supply compared to the solar-turfgrass scenario. The implementation of pollinator-friendly vegetation at current and future solar energy facilities has the potential to benefit biodiversity by providing habitat for insect pollinators and other wildlife (e.g., birds; Clean Energy States Alliance, 2020). In addition, increased abundance and diversity of native pollinators associated with solar-native grassland could improve the services these organisms provide for pollination of nearby agriculture. A number of studies have found direct correlations between pollinator habitat enhancements in agricultural settings and improved agricultural production associated with beneficial increases in pollinator services (Blaauw and Isaacs, 2014; Pywell et al., 2015; Venturini et al., 2017). In the Midwest, dominant crops such as soybeans may benefit from the presence of native pollinators. For example, pollinator habitat enhancement around soybean fields in Ohio increased native pollinator visitation to soybean flowers and increased soybean yields by up to 23% (Cunningham-Minnick et al., 2019). There are nearly 400 km^2 of soybean fields within 1.5 km of existing solar facilities across the seven Midwest states in this study (Walston et al., 2018), highlighting the potential agricultural pollinator service implications of solar-native grassland.

Compared to baseline agricultural land uses, our models suggest that solar-native grassland has the potential to increase the total carbon storage capacity of all current and future solar energy sites in the Midwest by over 170,000 Mg C and 1,500,000 Mg C, respectively. Putting these estimates into context, compared to the agricultural baseline scenario, the potential total future solar-native grassland carbon storage benefit is equivalent to offsetting the CO_2 emissions from over 5000 GWh of electricity generated from coal-fired power plants (World Nuclear Association, 2011). There are also future implications of solar-native grassland for sediment and water retention. The future solar-native grassland scenario has the potential to reduce over 9000 tons of sediment loss as a result of surface erosion annually and retain over 40,000,000 m^3 of surface water runoff annually from future solar sites. These increases in ecosystem services are equivalent to offsetting the amount of erosion and runoff of over 1000 ha (10 km^2) of row crop agriculture in the Midwest annually (NRCS, 2010).

It is important to clarify that the full ecosystem service benefits modeled in our study may not be immediately observed after the establishment of solar-native grassland. Rather, ecosystem services may gradually increase over time as the native grassland community matures. For example, soil organic carbon accumulates at former row-crop agricultural fields that have been restored to native prairie grasses at a rate of approximately 0.68 Mg $C*ha^{-1}*yr^{-1}$ (McLauchlan et al., 2006). At this rate, an average 10 MW solar facility (30 ha) situated on land formerly used for agriculture that has been planted with native grassland vegetation will accumulate over 200 Mg of soil organic carbon after 10 years of operation. Over the timeframe of a solar energy facility lease period (which may be 20–30 years), therefore, we expect the site's ecosystem service potential to increase and more closely resemble modeled outcomes. Nevertheless, some ecosystem service benefits of solar-native grassland may be more quickly realized. For example, in as little as 3 years post-seeding, newly established native grasslands in Iowa are capable of reducing erosion and runoff in agricultural landscapes (Hernandez-Santana et al., 2013). In another study in Michigan, the establishment of native wildflowers in agricultural systems doubled the abundance of native bees and increased their visitation to nearby blueberry crops by 25% in less than 3 years after wildflower planting (Blaauw and Isaacs, 2014).

Our study focused on comparing the potential ecosystem services of different land management scenarios at solar energy facilities. We recognize some practical considerations in our study that warrant further investigation. First, the InVEST models we used have unique assumptions that relate land use classifications to ecosystem services (Sharp et al., 2018). Therefore, our modeling results were limited by the accuracy of the 30 m land use raster dataset we used and the general ecosystem service relationships that have been developed for those land use classifications. Second, our models did not incorporate sensitivity analyses or field-based validation efforts with primary data collected at solar facilities. Instead, we focused on examining a range of possible ecosystem service outcomes based on secondary sources of data from previous InVEST studies that examined surrogate land use types. This approach allowed us to understand the uncertainty in model results and we used average values to compare scenarios. Validation of our models consisted of comparisons to other InVEST studies that evaluated our land use surrogates. As discussed above, the relative differences in our model results were consistent with these previous studies. Third, we were not able to measure how solar panels may influence the modeled ecosystem services so we assumed the influence of solar panels to be constant. However, the presence of solar panels may influence ecosystem processes. For example, soil evapotranspiration processes may decline by 10–30% under solar panels compared to open sites (Marrou et al., 2013). For these reasons, greater emphasis should be placed on interpreting the relative implications of our results rather than the actual ecosystem service value calculations. Additional work is needed to collect the primary data on ecosystem services at solar energy facilities, collect data on the temporal patterns of these ecosystem services in relation to habitat establishment, and examine the effects of solar panels on processes such as runoff, erosion, and carbon storage.

5. Conclusions

The establishment of native grassland vegetation at solar energy facilities is a strategic land use practice to improve the landscape compatibility of solar energy development (Walston et al., 2018; Hernandez et al., 2019). Recent attention on this strategy from the solar industry, natural resource agencies, conservation organizations, and state governments underscores the amount of multidisciplinary coordination involved in implementing solar-native grassland (EPRI, 2019; Clean Energy States Alliance, 2020). In regions where native grasslands have been lost to other human activities such as agriculture, native grassland restoration at solar energy facilities represents a win-win solution for energy and the environment through the improved ecosystem services provided by the native habitat that may encourage future solar energy adoption. While several states have passed legislation and scorecards to guide the implementation of solar-native vegetation habitat standards, decisions regarding establishment of solar-native grassland also consider the costs of particular seed mixes and costs of seedling establishment, vegetation height restrictions, and long-term maintenance needs (Clean Energy States Alliance, 2020).

This paper is the first to compare the potential ecosystem services related to vegetation management practices at solar energy facilities. Since none of the calculated ecosystem service benefits of solar-native grassland accrue solely to the solar industry or any other group of stakeholders, the calculated values may be better considered as benefits for society-as-a-whole. These findings may be used to build cooperative relationships between the solar industry and surrounding communities to better integrate solar energy into agricultural landscapes. We focused on the potential non-monetary aspects of these ecosystem services in this study. Additional work is needed to collect the primary data that would support economic evaluations to inform solar-native grassland business decisions for the solar industry and quantify the economic benefits of services provided to nearby farmers, landowners, and other stakeholders.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to have influenced the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecoser.2020.101227.

References

[EIA] Energy Information Administration, 2019a. Form EIA-860 detailed data for 2018. Available at. https://www.eia.gov/electricity/data/eia860/ (Accessed 25 October 2019).
[EIA] Energy Information Administration, 2019b. Electric power monthly. Available at. https://www.eia.gov/electricity/monthly/.
[EPRI] Electric Power Research Institute, 2019. Overview of Pollinator-Friendly Solar Energy. Report 3002014869. December.
[MISO] Midcontinent Independent System Operator, 2019. Generator interconnection queue. Available at. https://www.misoenergy.org/planning/generator-interconnection/GI_Queue/. (Accessed 25 February 2020).
[NRCS] Natural Resources Conservation Service, 2010. 2007 National Resources Inventory: Soil Erosion on Cropland (April).
[SEIA] Solar Energy Industries Association, 2019. Solar state by state. Available at. https://www.seia.org/states-map. (Accessed 25 February 2020).
[USDA] US Department of Agriculture, Natural resources conservation service, 2019. National geospatial management center. Available at. http://datagateway.nrcs.usda.gov/.
Adeh, E.H., Selker, J.S., Higgins, C.W., 2018. Remarkable agrivoltaic influence on soil moisture, micrometeorology and water-use efficiency. PLoS One 13, e0203256. https://doi.org/10.1371/journal.pone.0203256.
Adeh, E.H., Good, S.P., Calaf, M., Higgins, C.W., 2019. Solar PV power potential is greatest over croplands. Sci. Rep. 9, 11442. https://doi.org/10.1038/s41598-019-47803-3.
Adelaja, S., Shaw, J., Beyea, W., McKeown, J.D.C., 2010. Renewable energy potential on brownfield sites: a case study of Michigan. Energy Policy 38, 7021–7030. https://doi.org/10.1016/j.enpol.2010.07.021.
Armstrong, A., Ostle, N.J., Whitaker, J., 2016. Solar park microclimate and vegetation management effects on grassland carbon cycling. Environ. Res. Lett. 11, 074016 https://doi.org/10.1088/1748-9326/11/7/074016.
Bai, Y., Ochuodho, T.O., Yang, J., 2019. Impact of land use and climate change on water-related ecosystem services in Kentucky, USA. Ecol. Indic. 102, 51–64. https://doi.org/10.1016/j.ecolind.2019.01.079.
Barron-Gafford, G.A., Pavao-Zuckerman, M.A., Minor, R.L., Sutter, L.F., Barnett-Moreno, I., Blackett, D.T., Thompson, M., Kimond, K., Gerlak, A.K., Nabhan, G.P., Macknick, J.E., 2019. Agrivoltaics provide mutual benefits across the food-energy-water nexus in drylands. Nature Sustainability 2, 848–855. https://doi.org/10.1038/s41893-019-0364-5.
Blaauw, B.R., Isaacs, R., 2014. Flower plantings increase wild bee abundance and the pollination services provided to a pollination-dependent crop. J. Appl. Ecol. 51, 890–898.
Chaplin-Kramer, R., Hamel, P., Sharp, R., Kowal, V., Wolny, S., Sim, S., Mueller, C., 2016. Landscape configuration is the primary driver of impacts on water quality associated with agricultural expansion. Environ. Res. Lett. 11, 074012 https://doi.org/10.1088/1748-9326/11/7/074012.
Clean Energy States Alliance, 2020. State pollinator-friendly solar initiatives. Available at. https://www.cesa.org/assets/State-Pollinator-Friendly-Solar-Initiatives.pdf. (Accessed 30 January 2020).
Cole, W., Gates, N., Mai, T., Greer, D., Das, P., 2019. 2019 Standard Scenarios Report: A U.S. Electricity Sector Outlook, Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-74110. https://www.nrel.gov/docs/fy20osti/74110.pdf.
Cunningham-Minnick, M.J., Peters, V.E., Crist, T.O., 2019. Nesting habitat enhancement for wild bees within soybean fields increases crop production. Apidologie 50, 833–844.
Davis, A.Y., Lonsdorf, E.V., Shierk, C.R., Matteson, K.C., Taylor, J.R., Lovell, S.T., Minor, E.S., 2017. Enhancing pollination supply in an urban ecosystem through landscape modifications. Landsc. Urban Plan. 162, 157–166. https://doi.org/10.1016/j.landurbplan.2017.02.011.
Dinesh, H., Pearce, J.M., 2016. The potential of agrivoltaic systems. Renewable Sustainable Energy Reviews 54, 299–308.
ESRI, 2019. ArcGIS online standard service: world imagery collection, map server. Available at. http://goto.arcgisonline.com/maps/World_Imagery. (Accessed 25 October 2019).
Grafius, D.R., Corstanje, R., Warren, P.H., Evans, K.L., Hancock, S., Harris, J.A., 2016. The impact of land use/land cover scale on modelling urban ecosystem services. Landsc. Ecol. 31, 1509–1522. https://doi.org/10.1007/s10980-015-0337-7.
Hartmann, H.M., Grippo, M.A., Heath, G.A., Macknick, J., Smith, K.P., Sullivan, R.G., Walston, L.J., Wescott, K.L., 2016. Understanding Emerging Impacts and Requirements Related to Utility-scale Solar Development; ANL/EVS-16/9; Argonne National Laboratory: Lemont, IL.
Hernandez, R.R., Hoffacker, M.K., Field, C.B., 2014. Land-use efficiency of big solar. Environ. Sci. Technol. 48, 1315–1323.
Hernandez, R.R., Armstrong, A., Burney, J., Ryan, G., Moore-O'Leary, K., Diédhiou, I., Grodsky, S.M., Saul-Gershenz, L., Davis, R., Macknick, J., Mulvaney, D., Heath, G.A., Easter, S.B., Hoffacker, M.K., Allen, M.F., Kammen, D.M., 2019. Techno-ecological synergies of solar energy for global sustainability. Nature Sustainability 2, 560–568.
Hernandez-Santana, V., Zhou, X., Helmers, M.J., Asbjornsen, H., Kolka, R., Tomer, M., 2013. Native prairie filter strips reduce runoff from hillslopes under annual row-crop systems in Iowa, USA. J. Hydrol. 477, 94–103.
Hoffacker, M.K., Allen, M.F., Hernandez, R.R., 2017. Land-sparing opportunities for solar energy development in agricultural landscapes: a case study of the Great Central Valley, CA, United States. Environmental Science & Technology 51, 14472–14482.
Hollinger, S.E., 1995. Midwestern climate center soils atlas and database. Illinois state water survey. Champaign, IL. Circular 179.
Irsyad, M.I., Halog, A., Nepal, R., 2019. Renewable energy projections for climate change mitigation: an analysis of uncertainty and errors. Renew. Energy 130, 536–546. https://doi.org/10.1016/j.renene.2018.06.082.
Johnson, K.A., Polasky, S., Nelson, E., Pennington, D., 2012. Uncertainty in ecosystem services valuation and implications for assessing land use tradeoffs: an agricultural case study in the Minnesota River Basin. Ecol. Econ. 79, 71–79.
Kabir, E., Kumar, P., Kumar, S., Adelodun, A.A., Kim, K., 2018. Solar energy: potential and future prospects. Renew. Sust. Energ. Rev. 82, 894–900. https://doi.org/10.1016/j.rser.2017.09.094.
Kennedy, C.M., Lonsdorf, E., Neel, M.C., Williams, N.M., et al., 2013. A global quantitative synthesis of local and landscape effects on wild bee pollinators in agroecosystems. Ecol. Lett. 16, 584–599.
Kovacs, K., Polasky, S., Nelson, E., Keeler, B.L., Pennington, D., Plantinga, A.J., Taff, S.J., 2013. Evaluating the return in ecosystem services from investment in public land acquisitions. PLoS One 8, e62202.
Krishnan, R., Pearce, J.M., 2018. Economic impact of substituting solar photovoltaic electric production for tobacco farming. Land Use Policy 72, 503–509.
Liebman, M., Helmers, M.J., Schulte, L.A., Chase, C.A., 2013. Using biodiversity to link agricultural productivity with environmental quality: results from three field experiments in Iowa. Renewable Agriculture and Food Systems 28, 115–128.
Marrou, H., Dufour, L., Wery, J., 2013. How does a shelter of solar panels influence water flows in a soil-crop system? Eur. J. Agron. 50, 38–51.
McLauchlan, K.K., Hobbie, S.E., Post, W.M., 2006. Conversion from agriculture to grassland builds soil organic matter on decadal timescales. Ecol. Appl. 16, 143–153.
Meehan, T.D., Gratton, C., Diehl, E., Hunt, N.D., Mooney, D.F., Ventura, S.J., Barham, B. L., Jackson, R.D., 2013. Ecosystem-service tradeoffs associated with switching from annual to perennial energy crops in riparian zones of the US Midwest. PLoS One 8, e80093. https://doi.org/10.1371/journal.pone.0080093.
Moore-O'Leary, K.A., Hernandez, R.R., Johnston, D.S., Abella, S.R., Tanner, K.E., Swanson, A.C., Kreitler, J., Lovich, J.E., 2017. Sustainability of utility-scale solar energy – critical ecological concepts. Front. Ecol. Environ. 15, 385–394.
Ong, S., Campbell, C., Denholm, P., Margolis, R., Heath, G., 2013. Land-Use Requirements for Solar Power Plants in the United States, NREL/TP-6A20-56290. June, National Renewable Energy Laboratory, Golden, Colo.
Packard, S., Mutel, C.F., 1997. The Tallgrass Restoration Handbook: For Prairies, Savannas and Woodlands. Island Press, Washington, DC, USA.
Polasky, S., Nelson, E., Pennington, D., Johnson, K.A., 2011. The impact of land-use change on ecosystem services, biodiversity and returns to landowners: a case study in the state of Minnesota. Environ. Resour. Econ. 48, 219–242. https://doi.org/10.1007/s10640-010-9407-0, 2011.
Pywell, R.F., Heard, M.S., Woodcock, B.A., Hinsley, S., Ridding, L., Nowakowski, M., Bullock, J.M., 2015. Wildlife-friendly farming increases crop yield: evidence for ecological intensification. Proc. R. Soc. B 282, 20151740. https://doi.org/10.1098/rspb.2015.1740.
Ravi, S., Macknick, J., Lobell, D., Field, C., Ganesan, K., Jain, R., Elchinger, M., Stoltenberg, B., 2016. Colocation opportunities for large solar infrastructure and agriculture in drylands. Appl. Energy 165, 383–392.
Redhead, J.W., Stratford, C., Sharps, K., Jones, L., Ziv, G., Clarke, D., Oliver, T.H., Bullock, J.M., 2016. Emperical validation of the InVEST water yield ecosystem service model at a national scale. Sci. Total Environ. 569–570, 1418–1426.
Samson, F., Knopf, F., 1994. Prairie conservation in North America. Bioscience 44, 418–421. https://doi.org/10.2307/1312365.
Schenk, H.J., Jackson, R.B., 2002. Rooting depths, lateral root spreads and below-ground/above-ground allometries of plants in water-limited ecosystems. J. Ecol. 90, 480–494. https://doi.org/10.1046/j.1365-2745.2002.00682.x.
Schulte, L.A., Niemi, J., Helmers, M.J., Liebman, M., Arbuckle, J.G., James, D.E., Kolka, R.K., O'Neal, M.E., Tomer, M.D., Tyndall, J.C., Asbjornsen, H., Drobney, P., Neal, J., Van Ryswyk, G., Witte, C., 2017. Prairie strips improve biodiversity and the delivery of multiple ecosystem services from corn–soybean croplands. Proc. Natl. Acad. Sci. 114, 11247–11252.
Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., et al., 2018. InVEST 3.7. The Nature Conservancy, and World Wildlife Fund, User's Guide. The Natural Capital Project, Stanford University, University of Minnesota, p. 0.
Sun, X., Crittenden, J.C., Li, F., Lu, Z., Dou, X., 2018. Urban expansion simulation and the spatio-temporal changes of ecosystem services, a case study in Atlanta Metropolitan area, USA. Science of the Total Environment 622, 974–987.
U.S. Department of Energy, 2012. Sunshot vision study. February 2012. https://www.energy.gov/sites/prod/files/2014/01/f7/47927.pdf.
Venturini, E.M., Drummond, F.A., Hoshide, A.K., Dibble, A.C., Stack, L.B., 2017. Pollination reservoirs in lowbush blueberry (Ericales: Ericaceae). J. Econ. Entomol. 110, 333–346.
Walston, L.J., Mishra, S.K., Hartmann, H.M., Hlohowskyj, I., McCall, J., Macknick, J., 2018. Examining the potential for agricultural benefits from pollinator habitat at solar facilities in the United States. Environmental Science & Technology 52, 7566–7576.
World Nuclear Association, 2011. Comparison of Lifecycle Greenhouse Gas Emissions of Various Electricity Generation Sources. WNA Report, July.
Zhao, C., Sander, H.A., Hendrix, S.D., 2019. Wild bees and urban agriculture: assessing pollinator supply and demand across urban landscapes. Urban Ecosyst. 22, 455–470.