LOCAL ENVIRONMENTAL BENEFITS OF SOLAR FARMING IN WISCONSIN

APPENDIX C: MAPPING POTENTIAL ENVIRONMENTAL CO-BENEFITS FROM SOLAR DEVELOPMENT

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1. *Introduction*

In order to meet Wisconsin's carbon-free goals and to help avoid the worst impacts of climate change, there will need to be a significant increase in carbon-free energy generation in Wisconsin. As part of this transition, prior analyses indicate that Wisconsin may need 20 to 30 GW of utility-scale solar electricity generation. Perhaps the largest environmental concern with solar energy development is the land area footprint required, which is much larger than for fossil gas facilities. When sited on undeveloped land, solar facilities can cause habitat loss and fragmentation.

In Wisconsin, utility-scale solar facilities are typically sited on farm fields. This minimizes habitat loss or fragmentation concerns, but leads to concerns of taking too much good farmland out of production. Furthermore, areas with high densities of livestock require sufficient agricultural land on which to spread manure in a responsible manner. Solar arrays on land needed for manure disposal could cause manure to be overapplied onto a smaller area and/or shift the spreading to other land less suitable for receiving manure.

However, converting row crops to solar arrays can provide some local environmental co-benefits in addition to the climate and air quality benefits of solar energy production displacing fossil fuel energy generation. Annual row cropping is a leading contributor to nitrate, phosphorus, sediment and pesticide contamination of drinking water and surface waters in Wisconsin. Replacing row crops with solar arrays maintained with perennial vegetation in and around the arrays will substantially reduce pollutant runoff from the land.

With appropriate vegetation management, solar facilities can also provide wildlife habitat for grassland species, including pollinators whose numbers have declined due to habitat loss and pesticide use. Increased pollinator abundance can also provide a benefit to nearby crops that are dependent on pollinators such as fruit trees, cranberries, or squashes.

Finally, solar facilities themselves can provide opportunities for co-locating agricultural activity and electricity generation (agrivoltaics). Some crops can be grown under and around solar panels, and sheep can graze around the arrays.

Thoughtful and intentional siting of solar facilities in locations that maximize co-benefit and minimize adverse impacts should be an important aspect of Wisconsin's transition to renewable energy. Here, we illustrate how agricultural land can be ranked on the basis of relative potential to provide environmental co-benefits and minimize adverse impacts. We score agricultural land based on the following characteristics that would indicate land where siting solar could produce local environmental benefits:

- Potential to contribute phosphorus loading to nearby waterways
- Potential to contribute to groundwater nitrate contamination
- Nearby area of crops highly dependent on pollinators

Spatial analyses of co-benefit potential like this can be combined with technical site requirements (e.g., proximity to electric infrastructure like distribution lines; acceptable slope) and other siting considerations such as minimizing wildlife conflict[1] to guide deliberate, intentional siting of solar facilities.

[1] The Nature Conservancy: Site Renewables Right. Available at: https://www.nature.org/en-us/what-we-do/our-priorities/tackle-climate-change/climate-change-stories/site-wind-right/?vu=siterenewablesright

2. Methods

2.1 Data Sources

We created a 1 km^2 grid across the state and used the 30m resolution Wiscland 2.0 land cover dataset[2] to remove cells where agricultural land cover comprised less than half of grid cell, leaving only cells where the dominant land cover was agricultural.

To identify areas that are potentially contributing to nitrate groundwater contamination, we used the terrestrial nitrogen surplus estimated at the HUC8 watershed level by Sabo et al.[3], combined with a groundwater contamination susceptibility model developed by the Wisconsin Department of Natural Resources and the Wisconsin Geologic and Natural History Survey at 500m resolution.[4] The nitrogen surplus dataset uses total nitrogen inputs (e.g., fertilizer, manure, biosolids, natural and crop N fixation) and total nonhydrologic outputs (N_2O, N_2, and NH_3 emissions; harvested crop N content) to estimate terrestrial surplus that can contaminate waterways (i.e., inputs-outputs). The groundwater contamination susceptibility model uses substrate properties and depth to water table to identify areas of the state that are more and less susceptibility to groundwater contamination.

We used three different datasets to quantify phosphorus loading potential in each grid cell. First, we used the USGS's SPARROW dataset[5] to assign a catchment-level incremental phosphorus yield from agriculture to each cell. This dataset estimates the phosphorus contribution to waterways originating in each catchment area within the state. Where grid cells overlapped multiple catchment areas, a composite yield for the cell was calculated based on the area of the grid cell in each catchment area it overlapped with. For each cell, we assigned an incremental yield from fertilizer only.

The cell's incremental yield was then combined with proximity to impaired waterways. Impaired waterways are most in need of input reductions, and land closer to waterways is assumed to generally contribute more inputs than land farther away. Shapefiles of waterways

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[2] Available at: https://dnr.wisconsin.gov/maps/WISCLAND
[3] Sabo RD, Clark CM, Bash J et al. 2019. Decadal shift in nitrogen inputs and fluxes across the contiguous United States: 2002-2021. Journal of Geophysical Research: Biogeosciences 124: 3104-3124.
[4] Kessler K and Schmidt R. 1989. Groundwater Contamination Susceptibility in Wisconsin. Available at: https://data-wi-dnr.opendata.arcgis.com/datasets/groundwater-contamination-susceptibility-model
[5] Robertson DM and Saad DA. 2019. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in streams of the Midwestern United States. USGS Scientific Investigations Report 2019-5114.

impaired from phosphorus or sedimentation were obtained from the Wisconsin Department of Natural Resources' GIS Open Data Portal.[6] The distance between each cell's center to the nearest impaired waterway was calculated in ArcGIS.

Second, we used surplus and legacy phosphorus estimated at the HUC8 watershed level by Sabo et al.[7] Because phosphorus is largely carried to waterways bound to soil particles, we combined the surplus and legacy phosphorus with the RK product from the Revised Universal Soil Loss Equation. The R factor is the rainfall-runoff erosivity factor, quantifying the intensity of storms in a given area with higher R factors indicating climate conditions that can lead to more soil erosion and runoff. The K factor represents the susceptibility of soil to erosion and runoff based on the soil's physical properties. Soils where particles more easily detach and/or have lower water infiltration rates have higher K factors.

R factors for each grid cell were assigned from the National Oceanic and Atmospheric Administration.[8] K factors for each grid cell were obtained from gSSURGO. Aggregated values for each cell were calculated by weighting the k factor of each soil type within each grid cell by the proportion of the cell covered by that soil type. For each cell, an RK product was calculated by multiplying the R factor and K factor. Phosphorus input was combined with RK product and proximity to an impaired waterbody to assign each grid cell as relative phosphorus contribution score.

Third, we used county-level phosphorus application rates from NuGIS.[9] Cells were assigned application rates of either phosphorus from fertilizer or nitrogen from fertilizer and manure, depending on whether a cell is penalized for being needed for manure landspreading (see below for more details). Phosphorus application rates were then combined with RK product and proximity to impaired waterbodies for an overall score for potential to contribute phosphorus runoff to nearby waterways.

[6] https://dnr.wisconsin.gov/maps/GetGISData
[7] Sabo RD, Clark CM, Gibbs DA et al. 2021. Phosphorus inventory for the conterminous United States (2002-2012). Journal of Geophysical Research: Biogeosciences 126: e2020JG005684
[8] NOAA Office for Coastal Management. 2022. R-Factor for the Coterminous United States. Available at: https://www.fisheries.noaa.gov/inport/item/48224
[9] Nutrient Use Geographic Information System. Available at: https://nugis.tfi.org/

We note that we also considered using county-level phosphorus application data from Falcone.[10] However, there was a high degree of correlation with the NuGIS dataset (R^2=0.86), and thus there will be little change in relative scoring of the cells.

We calculated the area of crops highly dependent on pollinators following Walston et al.[11] We obtained the 2019, 2020, and 2021 cropland data layers from the United States Department of Agriculture.[12]Total area of crops highly dependent on pollinators[13] within 2 km of a solar facility assumed to have a circular, 2,000-acre footprint centered on each grid cell was calculated for each year, and then averaged across the three years to account for crop rotation. We note that Walton et al. also calculated areas of low- and moderately-dependent crops, which includes crops like soybeans and alfalfa. However, in Wisconsin, a large percentage of all agricultural land includes soy or alfalfa in its rotation. Thus, the ability to distinguish where a relatively higher benefit would be obtained would be muted if considering proximity to all pollinator-dependent crops.

2.2 Assigning Relative Co-Benefit Potential Score

For each characteristic, each grid cell was assigned a score based on the percentile for that characteristic. For nitrate contribution potential, phosphorus contribution potential and pollinator-dependent crop benefit potential, a higher cell value indicates greater co-benefit potential. Thus, cells in the 80-100th percentiles were assigned a score of 5; cells in the 60-80th percentile were assigned a score of 4; cells in the 40-60th percentile were assigned a score of 3; cells in the 20-40th percentile were assigned a score of 2; cells in the 0-20th percentile were assigned a score of 1.

To combine SPARROW phosphorus loading with proximity to impaired waterways, each cell was assigned a relative score for incremental phosphorus load: cells in the 80-100th percentile of surplus and legacy phosphorus were assigned a score of 5; cells in the 60-80th percentile of surplus and legacy phosphorus were assigned of a score of 4; cells in the 40-60th percentile were assigned a score of 3; cells in the 20-40th percentile were assigned a score of 2;

[10] Falcone JA. 2020. Estimates of county-level nitrogen and phosphorus form fertilizer and manure from 1950 through 2017 in the conterminous United States. USGS Open-File Report 2020-1153
[11] Walston, L. J., et al. 2018. Examining the Potential for Agricultural Benefits from Pollinator Habitat at Solar Facilities in the United States. Environmental Science & Technology 52: 7566–7576.
[12] Available at: https://www.nass.usda.gov/Research_and_Science/Cropland/Release/index.php
[13] As defined by Walston et al. 2018, highly dependent crops include: buckwheat, watermelons, cucumbers, caneberries, cherries, peaches, apples, almonds, pears, cantaloupes, honeydew melons, nectarines, plums, squash, pumpkins, blueberries, gourds, and cranberries.

cells in the 0-20th percentile were assigned a score of 1. Similarly, cells were assigned a relative proximity to impaired water score based on percentile. Because a closer proximity to an impaired water indicates a greater co-benefit potential, cells in the 0-20th percentile were assigned a score of 5; cells in the 20-40th percentile were assigned a score of 4; cells in the 40-60th percentile were assigned a score of 3; cells in the 60-80th percentile were assigned a score of 2; cells in the 80-100th percentile were assigned a score of 1.

The relative phosphorus loading and impaired water proximity scores were summed, and cells were then assigned a relative phosphorus loading + impaired water proximity score based on percentile (score of 5 in the 80-100th percentile; score of 1 in the 0-20th percentile).

To combine phosphorus input data with RK factor and impaired water proximity to get an overall phosphorus contribution score, each cell was assigned a relative score for surplus and legacy phosphorus (Sabo et al. dataset) or phosphorus application (NuGIS dataset) based on percentile of all cells. Cells in the 80-100th percentile of phosphorus were assigned a score of 5; cells in the 60-80th percentile were assigned of a score of 4; cells in the 40-60th percentile were assigned a score of 3; cells in the 20-40th percentile were assigned a score of 2; cells in the 0-20th percentile were assigned a score of 1. Similarly, cells were assigned relative RK product and impaired water proximity score based on percentile. The relative phosphorus, RK product and impaired water proximity scores were summed, and cells were then assigned a relative phosphorus + RK product + impaired water proximity score based on percentile (score of 5 in the 80-100th percentile; score of 1 in the 0-20th percentile).

3. Limitations

We emphasize that this mapping represents a high-level screening of where solar development may provide the most environmental co-benefits throughout the state. Each input represents a best estimate based on data available on a statewide basis and has its own associated error or limitation. For example, some model input data are only available statewide at a county or watershed level, but can be unevenly distributed throughout the county or watershed. This can lead to inaccurate results when applying the same county-level characteristic to all fields within the county.[14] More detailed analyses using more detailed information will more accurately quantify the co-benefit potential within a given area of interest. For example, incorporating soil phosphorus field measurements and cropping practices would improve estimates of potential phosphorus export. Such data may be available within a smaller area of interest but are not available to our knowledge at a statewide level.

Using different datasets as proxies for co-benefits helps to minimize errors associated with any one dataset. There is greater confidence in co-benefit potential for cells where all multiple datasets agree and less confidence where there is disagreement. All three phosphorous inputs, for example, indicate relatively high co-benefit potential in Racine county, northern Walworth county, and the Central Sands region. However, only the Sabo dataset indicates relatively high co-benefit potential in Barron county and only the SPARROW dataset indicates relatively high co-benefit potential in Marinette and Oconto counties.

[14] See, e.g., Booth EG and Kucharik CJ. 2021. Data inaccessibility at sub-county scale limits implementation of manuresheds. Journal of Environmental Quality 51: 614-621.