



The interplay of future solar energy, land cover change, and their projected impacts on natural lands and croplands in the US

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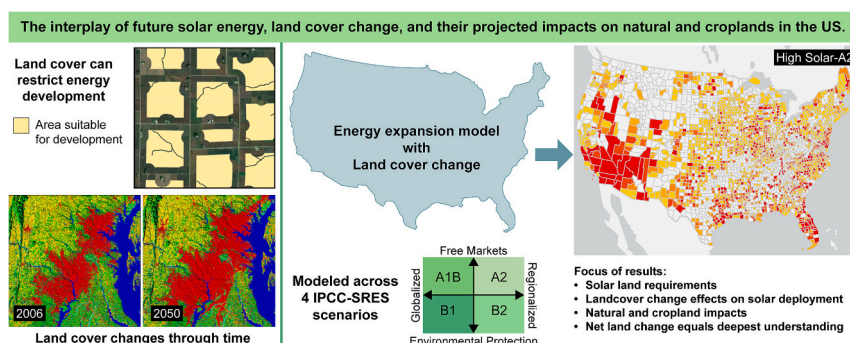
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HIGHLIGHTS

- Future land cover change dynamics had minimal impacts on solar PV potential and cost.
- Increases and decreases in PV capacity depended on the land change scenario.
- Solar may be a small part of total land cover change in the future.
- Individual counties may experience significant solar PV deployment.
- Land requirements of energy should be put in context with land use change from other sources.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Jacopo Bacenetti

Keywords:

Energy capacity expansion
Energy impacts
Habitat loss
Land, water, energy

ABSTRACT

Projections for deep decarbonization require large amounts of solar energy, which may compete with other land uses such as agriculture, urbanization, and conservation of natural lands. Existing capacity expansion models do not integrate land use land cover change (LULC) dynamics into projections. We explored the interaction between projected LULC, solar photovoltaic (PV) deployment, and solar impacts on natural lands and croplands by integrating projections of LULC with a model that can project future deployment of solar PV with high spatial resolution for the conterminous United States. We used scenarios of LULC projections from the Intergovernmental Panel on Climate Change Special Report on Emission Scenarios from 2010 to 2050 and two electricity grid scenarios to model future PV deployment and compared those results against a baseline that held 2010 land cover constant through 2050. Though solar PV's overall technical potential was minimally impacted by LULC scenarios, deployed PV varied by -16.5 to 11.6 % in 2050 from the baseline scenario. Total land requirements for projected PV were similar to other studies, but measures of PV impacts on natural systems depended on the underlying land change dynamics occurring in a scenario. The solar PV deployed through 2050 resulted in 1.1 %– 2.4 % of croplands and 0.3 %– 0.7 % of natural lands being converted to PV. However, the deepest understanding of PV impacts and interactions with land cover emerged when the complete net gains and losses from all land cover change dynamics, including PV, were integrated. For example, one of the four LULC projections allows for high solar development *and* a net gain in natural lands, even though PV drives a larger percentage of

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natural land conversion. This paper shows that integrating land cover change dynamics with energy expansion models generates new insights into trade offs between decarbonization, impacts of renewables, and ongoing land cover change.

1. Introduction

Electricity production and transmission require space, and the estimated area requirements of wind and solar energy for deep decarbonization are significant, raising concerns about the loss of both natural land and croplands (Agha et al., 2020; Brown and Botterud, 2021; Denholm et al., 2022; Hernandez et al., 2015; Larson et al., 2021). Investigations of such energy-environment interactions have a long history and include wide ranging topics such as the Water-Energy-Food nexus (Albrecht et al., 2018; Keairns et al., 2016) and the climate, land, energy, and water systems (CLEW) framework (Howells et al., 2013; Ramos et al., 2021). Within this scope of research, sophisticated capacity expansion models now allow researchers to study future energy infrastructure and its environmental impacts at national and regional scales (Cook et al., 2022; Deshmukh et al., 2023; Wu et al., 2023).

Capacity expansion models simulate, project, and analyze the dynamics of electricity systems (Koltsaklis and Dagoumas, 2018; Ringkjøb et al., 2018). These computational tools have transformed our ability to understand the complexities of electricity production, distribution, consumption, and demand and are used in a wide array of problems—from scenario analyses to grid planning and operation, to equity and energy justice—and to assess a variety of energy-related policies and their economic impacts (Bistline et al., 2023; DeAngelo et al., 2021; Goforth et al., 2023).

When investigating electricity futures, capacity expansion models project grid evolution out several decades or more (Craig et al., 2018). Over these time scales, land use and land cover change (LULC)—when anthropogenic and natural processes alter landscapes—may result in transitions to land use or land cover types that are not compatible with electricity production, especially for wind and solar technologies (Chen et al., 2022; Jägermeyr et al., 2021).

Future land cover change will influence where new generators might be located, but electricity development will impact current land cover and influence future land use. For example, urban expansion can either make utility-scale solar facilities impossible in areas dominated with homes and commercial buildings or grow around an existing solar facility. Ultimately, this issue involves competition for space. A convincing body of science suggests such competition is already affecting renewable energy development (Segreto et al., 2020; Turner et al., 2023; Weber et al., 2023). In addition, constraints on renewable energy deployment driven by environmental and social concerns can alter the amount and location of available renewable energy resources, and the total amounts of infrastructure needed to meet decarbonization objectives (Lopez et al., 2023; Mai et al., 2021; Wu et al., 2020, 2023).

Natural lands (grasslands, forests, wetlands, and shrublands) and croplands interact with PV development in many ways. In some places, laws designed to protect agricultural land may inhibit PV deployment (Owley and Morris, 2019). Concerns and opposition about losing croplands to PV can be motivated for many reasons, including the perception that rural areas must “bear the burden” of PV development more than urban (Nilson and Stedman, 2023). Natural lands also impact, and are impacted by, PV. Natural lands set aside for conservation or recreation are often off-limits to energy development. PV development on natural lands may generate environmental conflicts if they impact species of concern or alter ecological processes that support biodiversity and/or recreational opportunities, though the opposite can be true when PV is installed in already disturbed lands (Evans et al., 2023).

Similar to capacity expansion models, geographers use a variety of computational approaches to forecast future LULC at scales from individual cities and regions to the globe (De Rosa et al., 2016; National

Research Council, 2014; Verburg et al., 2019). Some approaches focus on specific types of change, such as urbanization (Chang et al., 2020) while others model change across an ensemble of land cover classes (Marvin et al., 2023). Given the breadth of work on LULC modeling, many countries have projected LULC futures, and global models—typically run at broader spatial resolutions and with fewer land cover classes—also exist (Chen et al., 2020; van Asselen and Verburg, 2013).

Given the ubiquity of both capacity expansion and LULC models, the growing interest in the land-energy-water nexus, and calls for more integrated approaches (Hamiche et al., 2016; Tudose et al., 2023; Verburg et al., 2019), we were surprised to find few examples where these models were used to explore interactions between future electricity development and future LULC. LULC and capacity expansion models have been, separately, integrated with climate models (Bühne et al., 2021; Cohen et al., 2020; Craig et al., 2018). We are not aware of studies that integrate capacity expansion models and LULC dynamics when projecting the future electricity system and its potential impacts, though studies have incorporated constraints on capacity expansion based on LULC designations—such as restricting capacity expansion in national parks, near wetlands, within distances to roads, and so on (Lopez et al., 2023; Wu et al., 2023). Similarly, some studies have looked at one aspect of power sector change, such as biomass with carbon capture, but focus on that one aspect rather than looking at the broader power sector as a whole (Fajardy et al., 2018; Powell and Lenton, 2012).

How future electricity impacts land cover will depend on both the total levels of electricity generation, storage, and transmission installed and where it is placed relative to different land cover types. Similarly, the extent to which LULC might impact electricity development will depend on the amount and types of land that experience change as well as the renewable energy resource potential of those lands.

In this paper, we explored interactions between projected land cover change and projected solar energy development and how impacts on croplands and natural lands from future solar energy depend on broader land cover change dynamics. We integrated forecasts of LULC across the conterminous United States developed by the United States Geological Survey (USGS) under different climate change storylines, into long-term solar energy deployment projections from the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory (NREL).

2. Materials and methods

We integrated four LULC scenarios across 2 solar deployment scenarios into the ReEDS capacity expansion model and compared the outputs to analyze how future LULC affects solar PV development and estimate the area of croplands and natural lands required for this new solar energy. Doing so required several steps, detailed next.

2.1. Land cover projections and PV potential

Sohl et al. (2014) projected land cover across the conterminous United States annually from 1992 to 2100 using the forecasting scenarios of land use change (FORE-SCE) model (Sohl et al., 2007). The projections were designed to match Scenarios A1B, A2, B1, and B2 (Fig. 1) from the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES). The IPCC scenarios were described in (Nakicenovic and Swart, 2000) while Sleeter et al. (2012) described how the IPCC-SRES storylines were downscaled and used in FORE-SCE. The four IPCC-SRES scenarios span futures representing differences in human population growth, energy and materials intensity,

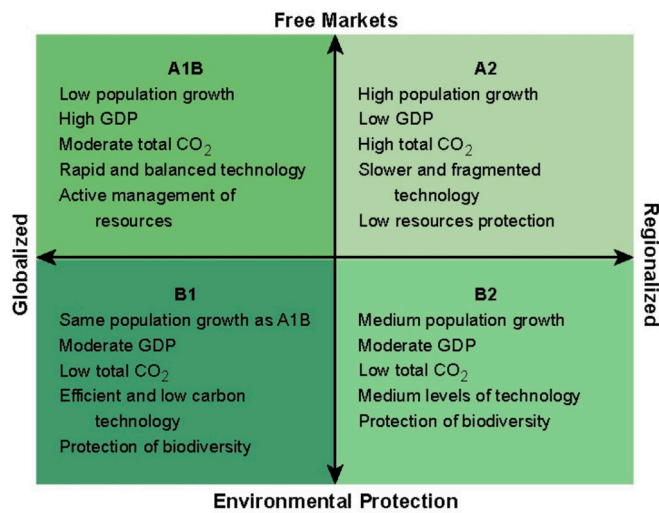


Fig. 1. Graphic diagram illustrating some of the key differences among the four IPCC-SRES scenarios used in this work.

greenhouse gas emissions, and global vs. regional solutions to economic and environmental issues (Fig. 1). Scenarios A1B and A2 focus less on climate change reduction and environmental sustainability than B1 and B2. The IPCC now uses Representative Concentration Pathways (RCP), instead of the SRES, but LULC projections for the US have not been created using RCP. SRES A2 is similar to RCP8.5, B1 to RCP4.5, B2 to RCP6.0, while A1B is between RCP 6.0 and RCP 8.5 in terms of radiative forcing and mean surface temperature (van Vuuren and Carter, 2014).

We resampled the spatial resolution from the FORE-SCE projections (250 m) to match those used in Renewable Energy Potential (reV) model (90 m, described next) using the gdalwarp utility (GDAL, <https://gdal.org>). We maintained the current projection (Albers Equal-Area Conic, EPSG: 42303) and resampled the original raster data from 250 m to 90 m with the nearest neighbor method. To check the downscaled data, we performed two QA/QC analyses. First, we successfully matched Table 1 from (Sohl et al., 2014) using the downscaled data and compared total area for each land cover class as well as rates of estimated change from 2005 to 2100 between the original (250 m) and downscaled (90 m) data. Next, we found similar spatial patterns of LULC between the two original and downscaled after we selected two forecasted years from each scenario (two forecasts for four scenarios = eight rasters) and visually compared outputs between the 90 and 250 m data by randomly selecting locations with expected change (urban growth around a city, climate change induced changes in agriculture, and so on).

The downscaled land cover data were used as an input in the Renewable Energy Potential (reV) model (Maclaurin et al., 2019), (Fig. 2), which is an open-source model (<https://nrel.github.io/reV/>) developed by NREL to conduct detailed assessments of renewable energy resources and technology performance while considering the intersection of grid infrastructure and location-dependent siting,

Table 1
Summary of the 10 scenarios used in this analysis.

Scenario Name	Solar Deployment	Land Cover
BAU-Baseline	Business as Usual	B2 2010
BAU-A1B	Business as Usual	A1B 2050
BAU-A2	Business as Usual	A2 2050
BAU-B1	Business as Usual	B1 2050
BAU-B2	Business as Usual	B2 2050
High Solar-Baseline	High Solar	B2 2010
High Solar-A1B	High Solar	A1B 2050
High Solar-A2	High Solar	A2 2050
High Solar-B1	High Solar	B1 2050
High Solar-B2	High Solar	B2 2050

including land cover. The reV model is a spatially discrete model evaluating constraints on development at 90 m resolution, aggregated into 67,000 individual 11.5×11.5 km “sites” across the United States. At each site, the quantity (megawatts), quality (capacity factor), cost (site and transmission), and hourly energy profiles are estimated. Across a user-defined geographic region, these collective sites represent a “supply curve”—the foundational input into a capacity expansion model. The supply curve specifies the amount of resource available at each location, the hourly energy production profile of that resource, and the cost to develop the resource at that location.

2.2. Capacity expansion modeling

The capacity expansion modeling was performed using the ReEDS model (Ho et al., 2021). ReEDS is an open-source (<https://github.com/NREL/ReEDS-2.0>) optimization model developed by NREL that simulates electricity sector investment decisions and operations based on system constraints, policy, and demands for electricity (Ho et al., 2021). ReEDS has a wide range of technology options and has been used for a variety of land use and decarbonization studies (Ho et al., 2021). ReEDS projects generation, storage, and transmission builds and operations from current day through 2050 for the conterminous United States (Denholm et al., 2022; Wisner et al., 2016). The model outputs electricity price, system cost, electricity flows, CO₂ emissions, and a variety of other metrics based on sensitivities such as fuel prices, demand growth, retirements, policy, technology and financing costs, and renewable resource restrictions. Key for our analyses, ReEDS inputs information about PV supply curves generated by reV. ReEDS also include projections for new rooftop PV, based on a customer adoption submodel, that includes state policies and tax credits).

We ran ReEDS on the NREL high-performance computer (Kestrel) at a county-level resolution. By modeling each of the 3000+ counties, we allow the model to represent variation in the cost and quality of developing renewable energy because each county had a unique supply curve for wind and solar resources. In addition, county-level resolution enabled us to more easily downscale ReEDS’ solar deployment projections back to the 11.5×11.5 km sites from reV. To build the ReEDS supply curve, individual sites from reV are aggregated into categories by county, resource class, and interconnection cost. ReEDS determines how much solar capacity is deployed in each county, class, and cost category. To downscale, we then take the buildouts from ReEDS and allocate them to any reV sites that correspond to that supply curve category. We assume capacity is distributed evenly across all reV sites that correspond to the combination of county, class, and cost from the ReEDS supply curve buildout.

Because each reV site was 11.5×11.5 km yet the land cover data were 90×90 m, we could not directly relate new PV development to specific land cover types. Instead, we calculated the area of each land cover type in a site. When PV capacity was built at a reV site, we assumed it was distributed across different land types in proportion to their total. For example, a site with 10 MW of PV that was 40 % forested and 60 % crops would have 4 MW of PV on forested land and 6 MW on cropland.

2.3. Simulations and analysis

We ran 10 scenarios in ReEDS using combinations of solar deployment and land cover (Table 1). For solar deployment, we included a “business as usual” (BAU) scenario that used reference assumptions consistent with the no-new-policy Mid-case from NREL’s 2023 Standard Scenarios (Gagnon et al., 2023) and a high solar deployment scenario that used low solar and battery costs and high wind costs and included a 100 % CO₂ emission reduction requirement. For land cover change, we used four projections out to 2050 from (Sohl et al., 2014) based on the IPCC-SRES scenarios (Fig. 1). The fifth was the 2010 land cover from Scenario B2. The 2010 scenario represented a “baseline” starting

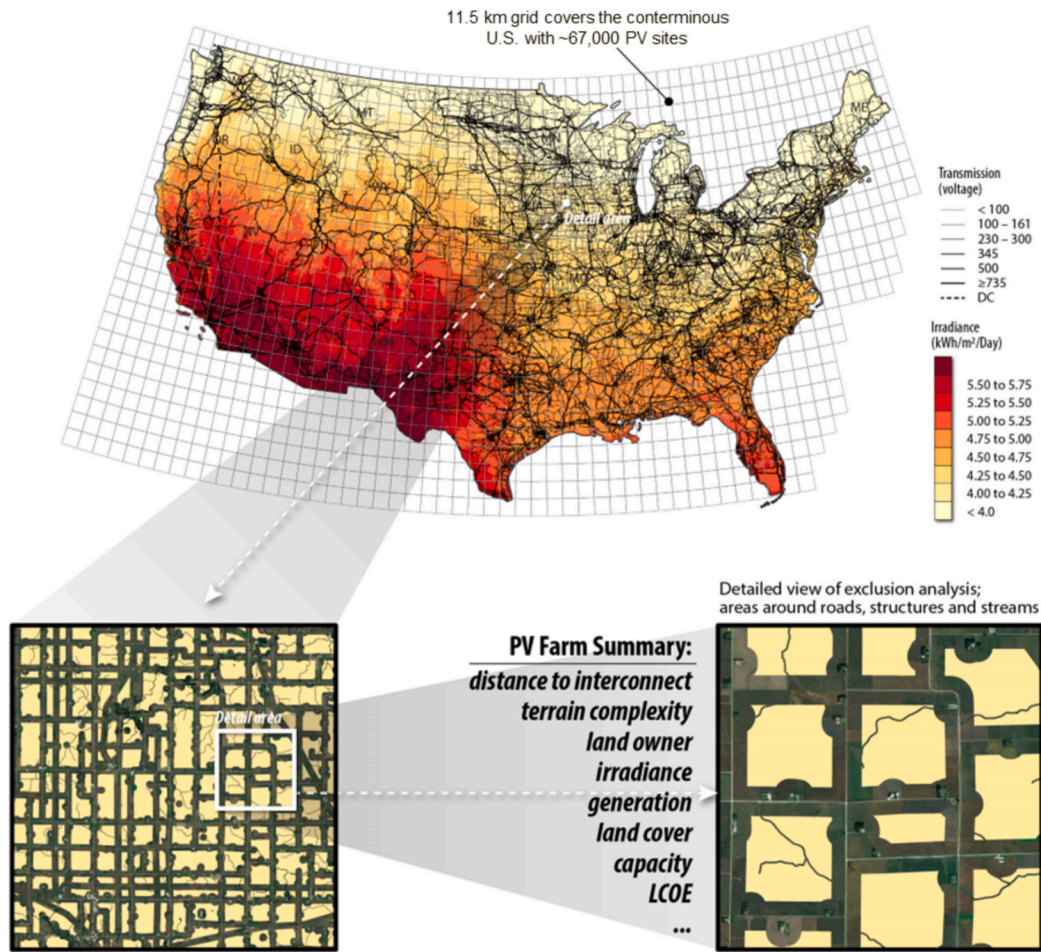


Fig. 2. Summary of the method applied in the reV model to exclude land based on setbacks, protected areas, or other criteria.

condition. Though [Sohl et al. \(2014\)](#) started their simulations in 1992, differences across scenarios in any land cover class were <2 % in 2010—and 2010 corresponds with meaningful solar PV deployment in the United States. We selected Scenario B2 for the baseline because it was most like the average land cover area across the four scenarios.

Given our main objective of studying how incorporating land cover dynamics alters outputs from energy expansion models, we opted to reduce complexity in our scenarios. Though ReEDS simulates capacity expansion annually, we used static supply curves from reV within each scenario. For example, scenarios with “A1B” in their name ([Table 1](#)) used the 2050 A1B land cover projected by [Sohl et al. \(2014\)](#) to generate the supply curve. The single supply curve was used in each year of the ReEDS simulation. Calculating a unique annual supply curve for each year of projected land cover and incorporating these curves into ReEDS would increase our computational time ~ 400× (40 years × 10 scenarios) while adding only nuanced results relative to our approach of contrasting the 2010 vs. 2050 endpoints.

In our simulations, we used simple rules to link land cover to potential PV capacities for each reV site. Though many factors can impact PV development, we excluded PV from water, wetlands, and developed land cover classes. These exclusions are well supported because utility-scale PV (of sizes ~ ≥ 1 MW) are often too large for the remaining patches of open space within developed/urbanized areas, wetlands are protected from development in most locations, and we are not modeling “floating” PV on water bodies. As these land cover classes changed across the land cover scenarios, reV generated different supply curves.

We did not attempt to align the underlying economic and population growth assumptions from IPCC-SRES scenarios used in [Sohl et al. \(2014\)](#)

with the ReEDS modeling assumptions. Therefore, the only change implemented in ReEDS across the land-use scenarios was the solar and wind resource availability due to the land-cover classification. Aligning the underlying assumptions and scenarios in the LULC model and the ReEDS model would be ideal, but was outside of the scope of this work. Instead, the four scenarios selected from [Sohl et al. \(2014\)](#) are intended to capture a wide range of futures that might exist as large amounts of solar are deployed.

Solving the ReEDS model at county-level resolution was computationally expensive, so we ran each of the three U.S. interconnection regions independently and then pieced together the solutions. Because of the limited amount of transmission capacity across interconnections and limited electricity demand near interconnection seams, this single-interconnection approximation is unlikely to impact the broader solution.

In both 2010 and 2050, we extracted the MW of installed PV capacity and the area of land required for the installed capacity for each reV site. Based on analysis by [Lopez et al. \(2024\)](#), we used a capacity density of 43 MW/km² to convert MW of capacity to area. We do not assume this density changes over time, though that could happen if PV module efficiencies continue to increase.

Before performing analyses, we simplified the land cover classification used by [Sohl et al. \(2014\)](#) and the outputs from ReEDS/reV by combining all wetland classes into a single wetland class and by combining all forest and mechanically disturbed forest classes into a single forest class, resulting in 10 classes ([Table S1](#))—in which perennial ice/snow was not included.

For each year and scenario, we summarized the ReEDS outputs

nationally and for each county in the United States. At the national scale, we estimated the total amount of installed capacity and surface area required for each scenario and compared scenarios with land cover change to the baseline “2010” scenario. We also estimated the new amount of land required for PV by subtracting 2010 land requirements from those of 2050.

To place the estimates of land requirements for new PV in context within the geography of land cover change dynamics in the United States, we performed two analyses. First, we compared the area required for new PV against the projected land cover change caused by all processes, such as increases in developed lands or croplands. Using annual raster maps from Sohl et al. (2014) we estimated both positive and negative changes to each land cover class from 2010 to 2050—the same time periods as the energy simulations. To add nuance to these analyses, we combined forests, grasslands, shrublands, and wetlands into a single “natural” land class and estimated the amount of loss in natural lands to land cover classes dominated by human activities (“anthropogenic,” which included developed, croplands, hay/pasture, barren, and mining). We then compared area change from natural to anthropogenic to the area requirements of new PV.

Second, for 2050, we calculated the percent of natural lands and croplands that would be used if all the land required by new PV occurred on these lands. Because the reV supply curves were created using an 11.5 × 11.5 km grid, we could not directly measure how much PV went on specific land cover classes. As an alternative, we assumed all new PV may go on natural lands or croplands, essentially measuring the maximum possible amount of each land cover type impacted by projected new PV nationally.

We used the county-level summations of installed capacity and required area to build county-based maps of forecasted PV deployment and visually compared patterns across scenarios. The maps included both installed capacity in each county and the percent of the total area in each county required by new PV.

3. Results and discussion

Including land cover change dynamics into ReEDS had small effects on national projections of installed solar capacity, the spatial pattern of

development, and the cost of the electricity system. However, projections of installed capacity changed across the SRES scenarios. Though the area required for new PV was a relatively large proportion of all transitions out of natural lands, projected PV in 2050—regardless of scenario—required a maximum of 1.1 %–2.4 % of croplands or 0.3–0.7 % of all natural lands in the conterminous United States.

3.1. National summaries

Land cover change had minimal impacts on the total technical potential for solar (Fig. 3). The technical potential in each of the future scenarios was 1.3–1.7 TW (1.0–1.4 %) lower than the baseline, largely driven by the increase in developed area, which excluded solar deployment. The total technical potential for wind also decreased slightly in the 2050 scenarios relative to the baseline (Fig. S1).

Unlike technical potential, the SRES scenarios of land cover change affected total installed PV capacity under both High and BAU PV deployment scenarios (Table 2, Fig. S2). Under high PV deployment, Scenarios A1B and A2 had increased PV deployment in 2050 (~3 and 12 % respectively) relative to the baseline scenarios while B1 and B2 had 6–7 % less deployment. Under BAU deployment, all scenarios except A2 had reduced PV deployment. The largest declines occurred in the B1 (–16.5 %) and B2 (–8.7 %) SRES scenarios with BAU deployment.

Table 2

Installed solar PV capacity (GW) in 2050 for the 10 scenarios. “Baseline” is the SRES B2 scenario using land cover from 2010, but with solar deployment for 2050. A1B, A2, B1, and B2, are 2050 projections using the 2050 land cover for that scenario. “High” and “BAU” refer to the PV deployment scenarios. Values in parentheses are the percent difference from the baseline 2010 values for each PV deployment scenario.

PV Deployment	2010	Land Cover Change Scenario			
	Baseline	A1B	A2	B1	B2
High	1039	1068 (2.8)	1160 (11.6)	977 (–5.9)	966 (–7.0)
BAU	588	542 (–7.9)	604 (2.6)	491 (–16.5)	537 (–8.7)

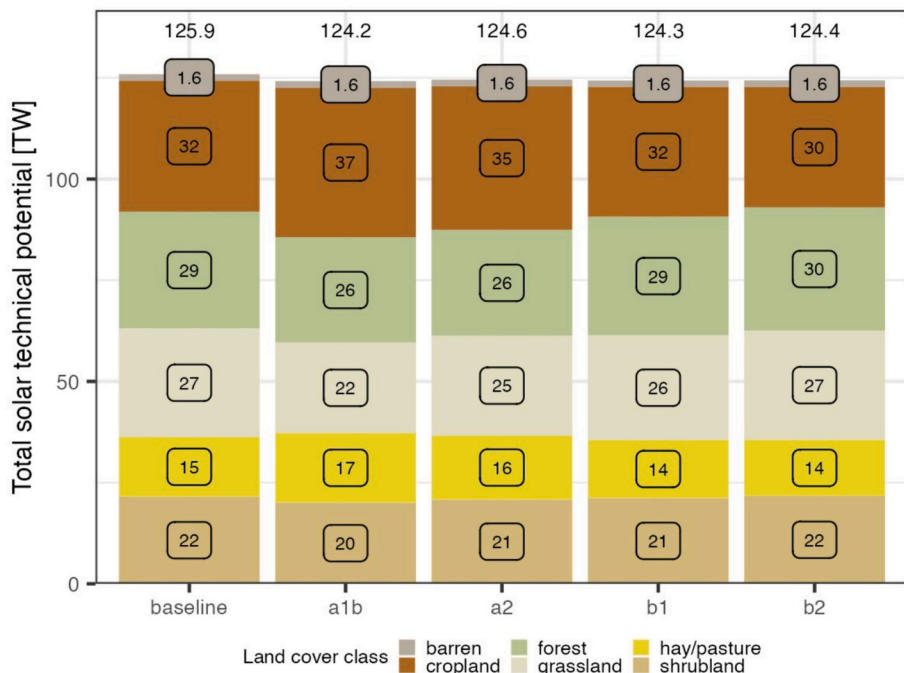


Fig. 3. Total solar technical potential by land cover class for the 5 scenarios. Values inside of rectangles are the technical potential for that land cover class.

Interestingly, the scenarios with the highest PV deployment (A1B and A2, Table 2) had the largest areas of excluded land cover classes (water+wetlands+developed; A1B = 891,471 km², A2 = 864,903 km², B1 = 863,422 km², B2 = 848,930 km²). The total land excluded from PV deployment in 2050 varied across scenarios by ~42,450 km², representing 1829 GW of potential PV given the capacity density used (43 W/km²)—far more than the total PV capacities deployed in any scenario.

This suggests the spatial pattern of excluded lands relative to the quality of the solar resource and development costs may drive the differences in results across scenarios more than the total amounts of excluded land. These results highlight the trade-offs in wind and solar capacity. Wind resource is excluded due to LULC change, and there is far less wind technical potential than solar technical potential in the United States (Fig. S1). Therefore, locations that have lower wind buildouts due to reduced wind technical potential are likely to see increases in solar capacity to offset the lower amount of wind.

Overall, the changes to the electricity system from incorporating LULC are relatively minor (Fig. S2) for the total generation mix across scenarios. Capturing the LULC increased the cost of building and operating the electricity system by 0.1–2.1 % across the scenarios (Fig. S3), meaning U.S. models of the electricity system are likely underestimating costs by approximately that amount when using renewable energy resource representations that do not account for LULC. Wu et al. (2023) estimated an ~3 % increase in systems costs for meeting net-zero targets with enhanced land and ocean protections in the western United States.

3.2. Future solar energy and land cover change

3.2.1. PV land requirements

Our simulations suggest new solar development will require ~14,000 to 35,000 km² of land (Table 3). These values are similar to those from (Denholm et al., 2022) (~15,000–29,000 km²) and (Larson et al., 2021) (~14,000–64,000 km²). Differences among the studies are likely caused by the capacity density for PV used and the levels of deployment modeled relative to other technology options such as nuclear or carbon capture. Denholm et al. (2022) used a capacity density of 32 MW/km², while Larson et al. (2021) used a value similar to our own (45 vs. our 43 MW/km²). The higher maximum area from value of Larson et al. (2021) was likely driven by their E + RE+ scenario, which deployed >2.5× more PV than our highest scenario (Table 2).

Future PV, relative to all other drivers of land cover change, will likely play a minor role in gross land cover change (any change in a pixel between 2010 and 2050) at the national scale. The area of gross land cover change was 13 to 43 (BAU) and 7 to 23 (High) times larger than the area required by future PV in 2050 across SRES scenarios (see Table 3, gross land cover change vs. area required by PV).

3.2.2. PV interactions with croplands and natural lands

The area requirements of forecasted solar ranged from 1.1 to 2.4 % of the area of croplands and from 0.26 to 0.69 % of the area of natural lands in 2050 (Table 3). These estimates suggest deep decarbonization strategies that include solar may be feasible with real, but relatively small, impacts to natural systems and agriculture. These percentages are upper bounds because they assume all the new solar within a ReEDS 11.5 × 11.5 km site would use natural lands or croplands while it will actually be built on a variety of LULC classes.

The relatively small percentage of croplands and natural lands required by new solar does not mean concerns about potential impacts to wildlife or agriculture are unfounded. Though the percentage is low nationally, the area we and others (Denholm et al., 2022; Larson et al., 2021) have estimated is large and could result in losses to areas supporting sensitive natural resources and/or high-quality agriculture lands if solar is sited in these locations. The small percentage of both croplands and natural lands required by future solar suggests potential flexibility exists so that solar could be sited in locations that remain cost-effective yet have minimized impacts on agriculture and natural systems. An

Table 3

Land cover change results by SRES scenarios. Gross change refers to the sum of all changes (gains + losses), while net change is gains – losses. “Natural lands” refers to forests, grasslands, shrublands, and wetlands, while “anthropogenic lands” refers to developed, cropland, mining, barren, and hay/pasture. Values in the table are km², except where units are provided. BAU refers to the “Business as Usual” PV deployment scenario. The range in the last to rows represents the value under the BAU (lower, first value) and the High (larger, second value) PV deployments.

Metric	A1B	A2	B1	B2
Gross land cover change	856,319	517,362	192,708	343,073
Change from natural to anthropogenic lands	329,194	149,573	127,035	45,443
Total amount of croplands in 2050	1,497,871	1,445,547	1,298,113	1,202,584
Net Change in natural lands	–428,008	–258,681	–60,238	113,279
Net change in natural lands if all new PV (High) occurred on them	–459,858	–1,293,367	–89,235	84,626
Total amount of natural lands in 2050	4,866,914	4,993,914	5,253,048	5,397,740
Percent of natural lands used if all 2050 PV (High) occurred on 2050 natural lands (BAU-High)	0.35–0.65	0.35–0.69	0.26–0.55	0.28–0.53
Percent of all natural to anthropogenic land change relative to PV surface area requirements (BAU-High)	5–10	12–23	11–23	34–63
Percent of croplands used if all 2050 PV (High) occurred on 2050 croplands (BAU-High)	1.13–2.12	1.2–2.4	1.1–2.2	1.3–2.4
Area required by PV (BAU) - (High)	16,934 - 31,850	17,363 - 34,686	13,853 - 28,997	15,284 - 28,653

analysis of net-zero energy strategies in the western United States reached similar conclusions (Wu et al., 2022, 2023). Furthermore, future developments in agrivoltaics (Barron-Gafford et al., 2019), siting PV arrays (Stid et al., 2022; Stoms et al., 2013), and land management at facilities (Sinha et al., 2018; Walston et al., 2023) may allow some types of farming and/or further minimize impacts to natural systems. Our results may be unique to the United States and other countries that have large regions with low population densities and large amounts of natural land cover. Countries with high population densities and more intense land use may not have the ability to optimize siting as easily.

3.2.3. PV and other land change dynamics

When we place the land cover change from PV in the context of overall future land cover change dynamic, a more nuanced understanding of PV’s potential consequences and the broader geographic future of land cover emerges. For example, the area required by PV varied from ~29,000 to 35,000 km² in the high deployment scenarios (Table 3), yet the net change in natural lands, independent of PV, varied much more—from –429,000 to +113,000 km². As the underlying land cover dynamics resulted in more natural lands (going left to right across scenarios in Table 3), net land change from natural to anthropogenic land cover decreased and became positive. Given less transition from natural lands to anthropogenic, PV accounted for a higher percentage of conversions from natural lands, up to 63 % in Scenario B2. We note the large differences across scenarios depend on both how much solar is built and, more importantly, how much land changed from natural to anthropogenic.

Scenario B2 is worth further consideration. Scenario B2 represented a net gain of ~113,000 km² of natural land alongside relatively high

levels of solar development. Of the IPCC scenarios, it depicts a future with high levels of conserved lands, fewer croplands, and low levels of development. Because of this, a much smaller area of natural land was converted to anthropogenic land use than in the other scenarios, while forecasted PV remained relatively high—resulting in the large percentage of natural to anthropogenic land change relative to PV surface requirements. Despite the seemingly high impacts of PV on natural land conversion, B2 represents a scenario with high solar deployment and an overall gain in natural land cover.

In contrast, Scenario A1B had the largest increase in developed land and croplands, causing the largest decline in natural land cover—which reduced the contribution of solar to possible losses of natural lands. A key message from this analysis is that projected impacts of land cover change from energy infrastructure must be placed in a broader geographic context of land change dynamics to fully understand the overall net gains or losses to land cover types of interest.

3.3. Spatial patterns of development and land cover change

County-based maps of PV build out for the conterminous US using either total installed capacity or the percent of a county's total area required for PV, showed surprising consistencies, and only subtle changes in spatial patterns across SRES scenarios (Figs. 4, 5 and Fig. S4, S5) and illustrated that some counties may have relatively large amounts of area utilized by solar. Starting from 2023 current conditions, ReEDS projected future PV to generally occur primarily in the southwestern US, Florida, along the Gulf and Atlantic coasts and in the Midwest in all scenarios. Development patterns in the Midwest and central US varied across scenarios as did levels of development in northern California and Oregon.

Across most scenarios, relatively large areas of the US had sparse PV deployment. One of these areas spanned the Prairie Potholes and North-western states, such as Wyoming, Montana, and eastern Washington. The region spanning central Texas near the US-Mexico border northeast through Oklahoma and into Pennsylvania, including southern states, also had sparse PV development in the High-solar B1 and B2 scenarios and most of the BAU scenarios. The lack of PV deployment in these regions was likely caused by low electricity demand and/or limited grid infrastructure for interconnecting new solar resources. These 'lower developed' regions indicate the socio-economic and land use changes caused by new PV may not occur in some parts of the US, while the national level values of change we estimated will be concentrated in a smaller area.

The spatial pattern of land required to support projected PV also shows differences in what regions may, or may not, have PV deployment. Counties with >10 % of their land area used to support projected PV occurred almost exclusively in Midwest and eastern US, particularly in Florida across many scenarios. Because counties in the western US are often large, very few had >10 % of their land area required for PV, despite generally larger amounts of capacity installed. Depending on the scenario, maximum percentages of land required to support PV ranged from ~22 to 34 % in the High Solar scenarios and 11–16 % in the BAU scenarios. These are relatively large percentages of some counties and how communities will respond to these levels of deployment remains to be seen.

The mapping results also suggest counties with large amounts (>1600 MW) of the modeled PV buildouts are somewhat rare. The ReEDS model did not allocate PV deployment equally across the US, but instead often selected the same county for deployment regardless of scenario, suggesting these areas may present the greatest opportunities for deployment due to resource quality, transmission infrastructure, or other factors. We note that these county level projections result from our least-cost buildout simulations. They may have high levels of uncertainty, particularly in later time periods if policies such as tax credits, levels of social acceptance, and zone rules that affect PV deployment change.

4. Conclusions

The interplay between energy, land, air, water, and climate has been recognized and studied for some time (Committee on Health et al., 2010; Harte and Jassby, 1978; Ramos et al., 2021). The energy to air nexus is typically unidirectional, with energy mixes affecting air quality and having consequence for human and natural systems (Crooks et al., 2021; Driscoll et al., 2015; International Energy Agency, 2016). However, the energy-land nexus is bi-directional as land is required by energy but also for a wide array of human activities and for supporting natural resources. We know of few capacity expansion models that integrate land-energy dynamics to allow the investigation of these interactions and potential trade-offs they may illuminate (Lopez et al., 2023; Mai et al., 2021; Wu et al., 2020, 2023).

This work examined the interaction between LULC, the buildout of the electricity system, and its impacts on natural lands and croplands. We focused on solar PV because it is projected to be a major part of a decarbonized U.S. electricity system and because it is a driver of land-use change. We observed that the total solar resource potential in the US is so large that capturing LULC change results in minimal changes to the overall technical potential of solar PV. These changes in technical potential results in differences in solar buildout in 2050 of -17 % to 12 % for the US. The total system cost of these buildouts only changes by 0.1–2.1 %, indicating that by not capturing land-cover change, planning models will be slightly underestimating the cost of building out a future electricity system.

Solar PV is likely to become a small but meaningful source of land-use change, with 0.3–0.7 % of natural lands being converted to PV by 2050. This level of LULC change for PV could represent up to 5–63 % of the total natural land conversion that occurs for any reason among the scenarios we examined. These results highlight the importance of considering the interactions between PV land requirements, other drivers of land change, and competition for land. We note that more rooftop/parking lot PV will reduce the amount of utility-scale PV and the land use requirements we simulated. However, rooftop space is limited and more expensive than utility-scale solar (Gagnon et al., 2016). Continued work on understanding competing interests and needs for land, especially in the context of energy system models that are projecting major changes to the energy system over the coming decades will help inform and prepare for future energy transitions.

CRedit authorship contribution statement

Jay E. Diffendorfer: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Investigation, Formal analysis, Conceptualization. **Brian Sergi:** Writing – review & editing, Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Anthony Lopez:** Writing – review & editing, Software, Investigation, Conceptualization. **Travis Williams:** Writing – review & editing, Software, Investigation, Formal analysis. **Michael Gleason:** Writing – review & editing, Software, Investigation. **Zach Ancona:** Writing – review & editing, Visualization, Investigation, Data curation. **Wesley Cole:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization.

Declaration of competing interest

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

Data availability

The ReEDS supply curves and model version are available at https://github.com/NREL/ReEDS-2.0/tree/LULC_supply_curves. The

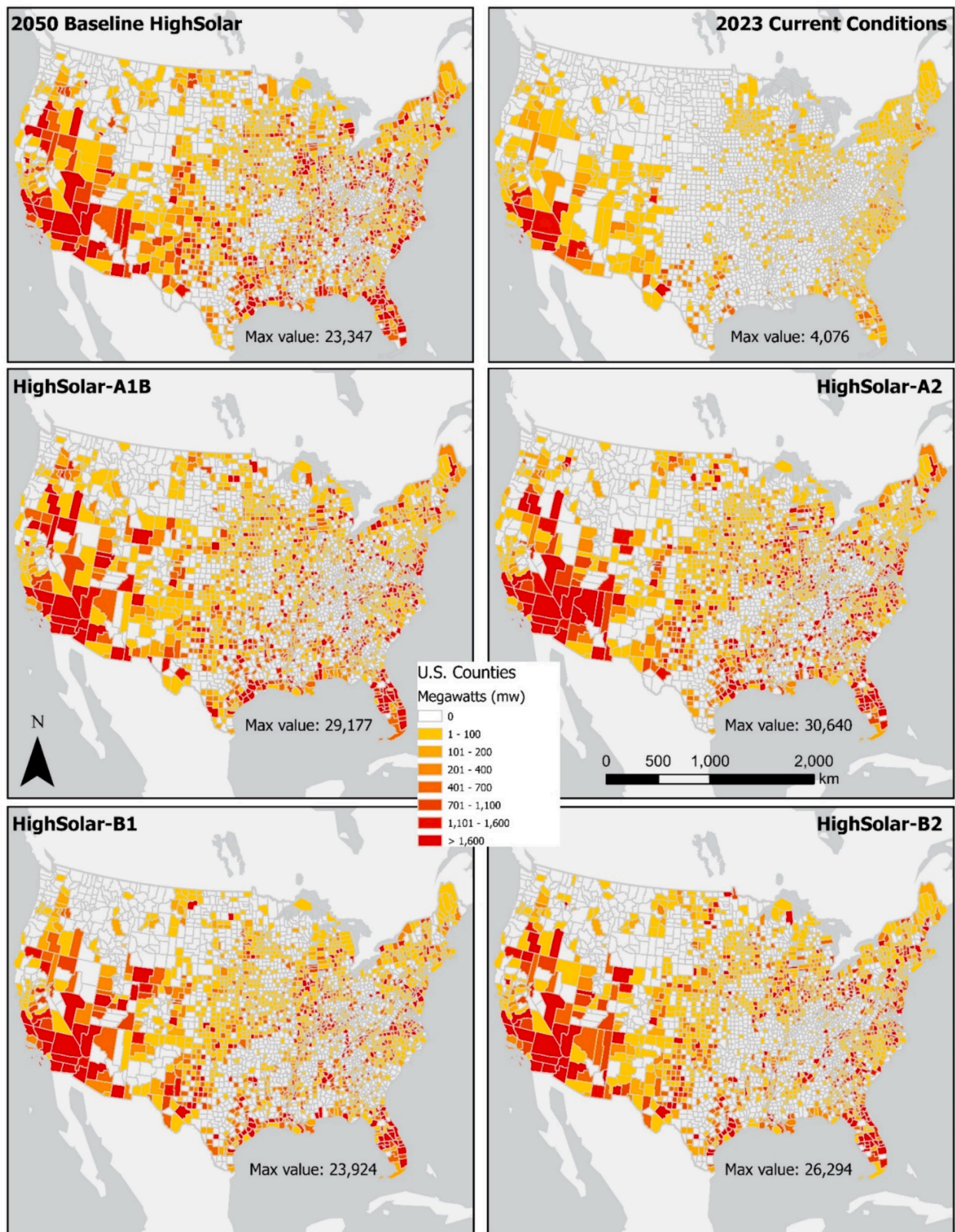


Fig. 4. Maps of photovoltaic capacity deployed (MW) across US counties in the High Solar scenarios. “2023 Current Capacity” is the installed capacity of PV from Energy Information Administration, “Baseline”, A1B, A2, B1 and B2 show outputs in 2050.

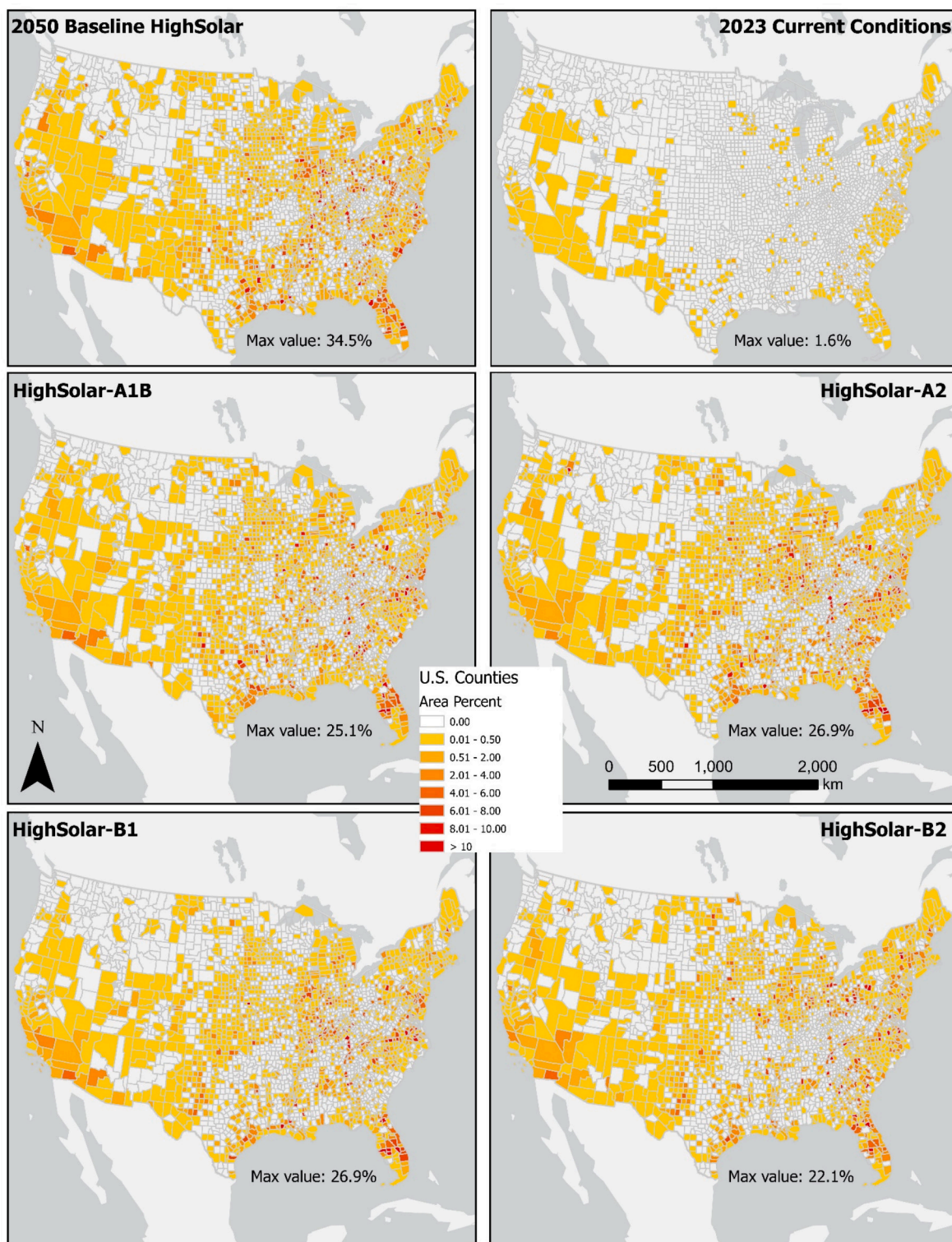


Fig. 5. Maps of the percent of a counties’ land area required by the projected photovoltaic capacity across US counties in the High Solar deployment scenarios. “2023 Current Conditions” is the installed capacity of PV from Energy Information Administration, “Baseline”, A1B, A2, B1 and B2 show outputs in 2050.

data used in the analysis, R code, and shapefiles used in the maps are available at doi:<https://doi.org/10.5066/P13S7MXU>.

Acknowledgements

Mary Straka (U.S. Geological Survey [USGS]) assisted with geospatial analyses of NLCD data. This work was authored in part by

researchers from the National Renewable Energy Laboratory (NREL), operated by Alliance for Sustainable Energy, LLC, for the US Department of Energy under contract no. DE-AC36-08GO28308. Funding was provided by US Department of Energy’s Office of Energy Efficiency and Renewable Energy (EERE) Solar Energy Technologies Office (award number 38421) and by the USGS Climate and Land Use Change, and Land Change Science Programs. The views expressed herein do not

necessarily represent the views of the US Department of Energy or the United States Government (except USGS). Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. The USGS Powell Center provided the opportunity for initial ideas and collaborations between USGS and NREL to develop.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2024.173872>.

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