Description of the approach, data and analytical methods used for *Farms Under Threat 2040* projections of solar energy facilities

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<u>Introduction:</u>
During the next few decades, millions of acres of solar energy installations will be installed in the U.S. as the country transitions to renewable energy (Cole et al. 2020). To better understand the potential impacts of rapid solar expansion on U.S. farmlands and ranchlands, American Farmland Trust, as part of the *Farms Under Threat* initiative, developed a model to illustrate future patterns of solar siting and inform solar siting policies and practices. The predictive analysis uses state-level 2040 solar demand data for the contiguous U.S. from the National Renewable Energy Laboratory's Regional Energy Deployment System (ReEDS) model Mid-case Scenario dataset (Cole et al. 2020, Brown et al. 2020).

The resulting projection model places new solar development based on a technical suitability/conditional transition probabilities map and other land-use characteristics derived from historical use patterns. It determines demand, spatial suitability, spatial attributes (size, shape, and density), and transition rates (how likely a given land use is to be developed) for solar development on a per-pixel basis within seven distinct regions throughout the contiguous United States. We inputted the demand, suitability, spatial attributes, and transition rates into a coupled Markov-cellular automata spatial allocation procedure using Dinamica EGO.

We integrated the solar projection with the *Farms Under Threat 2040* (*FUT2040*) future urban development modeling, which projects new urban and highly developed (UHD) and low- density residential (LDR) land uses from 2016-2040 (Xie et al. 2022). An estimate of projected UHD and LDR areas was used to mask the landscape. We then applied the solar model to determine areas for new solar development. While this does not perfectly reflect the way that these three land uses interact in the real world, it simplifies the modeling process and avoids potential conflicts that could result in unrealistic landscape patterns. The resulting maps illustrate likely patterns for the future deployment of large-scale solar. They allowed us to quantify the agricultural lands under these installations and determine how much is Nationally Significant farmland (Freedgood et al. 2020), the nation's best land for long-term production.

<u>Regional Framework for Modeling:</u>
Predictive land-use models are most useful when their parameters are reflective of the unique characteristics of landscapes within ecologically and/or geographically similar regions. In the context of solar development, it is important to capture the variation observed in the types, quantities, patterns, and locations of solar development among different areas of the country. Since past solar development is somewhat limited, we aggregated the lower 48 states into seven larger geographical regions to adequately project solar suitability characteristics in areas where there is currently limited – or no – solar development (Table 1). Deploying these models at regional scales helps to capture localized development *patterns* that might otherwise be missed if modeled at the national level. However, state-level demand from the ReEDS model was used to determine the *amount* of solar projected in each state.

Table 1: Solar Model Regional Framework

Region	*States*
Appalachia	KY, NC, TN, VA, WV
Great Lakes	IA, IL, IN, OH, MI, MN, MO, WI
Mountain Plains	AZ, CO, ID, KS, MT, ND, NE, NM, NV, SD, UT, WY
Northeast	CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT
Pacific	CA, OR, WA
Southeast	AL, FL, GA, SC
Southern Delta	AR, LA, OK, TX, MS

Detailed Modeling Methods:

Solar Siting Markov-Cellular Automata Model Schema:
Markov chains are commonly used to forecast future land-use change (e.g. Keshtkar & Voigt 2016). Typically, multiple years of static historical land-use data are used as inputs to compute past land-use transitions and transition rates. These observed transitions are then extrapolated to simulate *likely* future land-use transitions within a specified time interval (e.g. 1-year, 5-year, or 10-year intervals) based on conversion probabilities and rates for each unique land-use type. While Markov chain models can predict the amount of land-use change that is likely to occur through time, they do not capture the complex and heterogeneous patterns that are inherent in human-dominated environments (see Cadenasso et al 2007 for a primer on land cover heterogeneity). To address the issue of pattern, Markov models are often coupled with patch-based cellular automata (CA) models, which are fundamentally spatially explicit and do account for the complexities of land-use spatial patterns (Meentemeyer et al. 2013). In essence, coupled Markov-CA models account for both amounts through time (Markov chain transition probabilities) and spatial patterns (patch-CA) and are meant to be a holistic method for forecasting future land change.

To build a national-scale predictive solar model, we applied coupled Markov-CA modeling methods that predict and allocate new patches of the two main categories of solar development—larger utility-scale photovoltaics (UPV) and smaller distribution-side utility-scale photovoltaics (DUPV)—to simulated landscapes in 2040 (Figure 1). We parameterized and calibrated this Markov-CA solar siting and development model using four distinct sub-models that are intended to represent ground-level components of solar development. These sub-model components include: (1) Demand; (2) Suitability; (3) Transition Rates; and (4) Spatial Attributes. Sub-model components are described in detail below.

Demand Component (How Much):
We derived the demand component from the National Renewable Energy Laboratory (NREL) Regional Energy Deployment System (ReEDS) 2020 Model (Brown et al. 2020). Our model leverages the NREL ReEDS Mid-case Scenario data on solar demand by state in 2040 (Cole et al. 2020). The ReEDS Mid-case Scenario extrapolates future renewable energy capacity/generation based on current economic and renewable energy development conditions, as well as federal and state policies. Demand is expressed at the state level in terms of annual generation capacity in megawatts (MW).

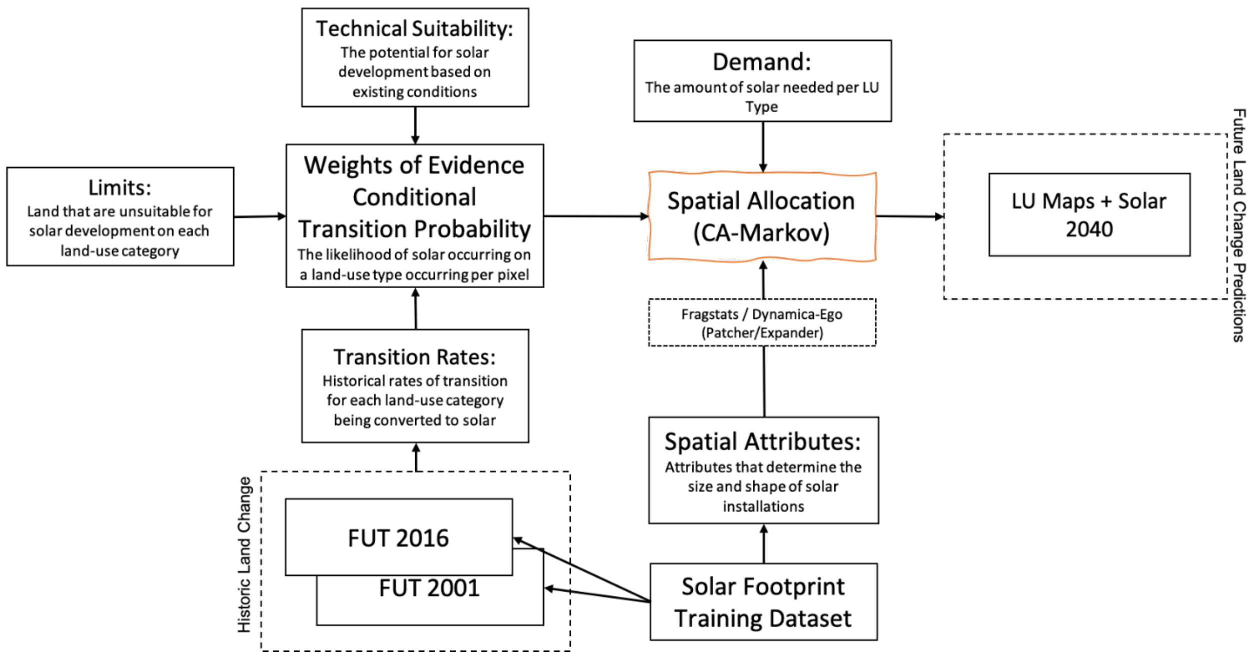

Figure 1: *Markov-CA Solar-Siting Development Model Schema. Demand, suitability, transition, and spatial attribute sub-model components are computed to parameterize a Markov-CA land-use model designed to predict where and how much solar development will occur in 2040.*

Our modeling only focused on utility-scale solar energy installations. We focus on two categories from the ReEDS data: utility-scale photovoltaics (UPV) and distribution-side utility-scale photovoltaics (DUPV). The ReEDS model defines UPV as being large (~600 acres) and likely to be sited in rural areas (Brown et al. 2020). Their size makes it viable to build grid interconnections, so it is possible to site them farther from existing substation or transmission nodes than DUPV facilities, but proximity to transmission lines is still important. In contrast, the ReEDS model defines DUPV as being small (~6 acres) and situated closer to urban areas where they can be directly connected to existing grid-nodes. The model reflects these distinctions in array size and infrastructure requirements.

We did not include concentrating solar power (CSP) since it is largely restricted to the desert southwest and is also much less common than UPV and DUPV. We also did not include rooftop solar development since it is most likely deployed in areas that are already designated as urban and highly developed (UHD) and low-density residential (LDR) and does not directly threaten farmland.

The amount of land area that is needed to meet demand for the different types of solar development is a function of solar energy capacity. For the contiguous U.S., NREL projects 456,000 MW of UPV and DUPV solar capacity in 2040 in the Mid-case Scenario. This can be translated to land area using a generalized national array-density estimate for UPV/DUPV developed by NREL: 39MW/km^2 or 6.3 acres/MW (Brown et al. 2020). Using the conversion equation, we determined that this amount of generation will require ~11,700 km^2 (~2.9 million acres) of land to meet capacity/demand for utility-scale PV in the ReEDS Mid-case Scenario, which is somewhere between the land area of New Jersey and Connecticut.

Technical Suitability Component (Where):
An area is considered suitable for solar development if it meets a set of criteria outlined in the Technical Suitability and Limits sub-models below.

Technical suitability is determined using the key technological and economic factors that govern realistic areas for siting solar power. These factors include: (1) elevation; (2) slope; (3) proximity to existing transmission infrastructure; and (4) proximity to urban and populated places. We did not include land cost as a suitability characteristic, as this has been shown to be a minor factor in the economics of solar energy development, whereas proximity to existing transmission infrastructure is critically important.

Spatial data for elevation/derived data (e.g. slope), existing transmission infrastructure, urban/populated places, and other variables were acquired from various sources. A full description of all data and sources to be used in the model is available in Table 2.

We account for the differences between UPV and DUPV development in three specific ways: (1) size ranges; (2) proximity to linking infrastructure; and (3) proximity to urban (UHD) areas. First, we limit the size of DUPV development by adjusting the patch builder function to allow new solar growth to range between 5-7 acres, or ~1MW of capacity. We link DUPV development to existing substation nodes within a 3-mile distance. We also allow DUPV development to occur nearer to UHD and LDR development since it directly feeds into distribution networks. For UPV, we apply similar parameterization, but alter the size parameter to allow UPV developments to grow between 550-650 acres, or ~100MW of relative capacity. New UPV development is linked to transmission lines within a 5-mile distance and is excluded within 10 miles of the FUT UHD and LDR development types.

Table 2: Model Input Data

Component	*Sub-Model*	*Dataset*	*Source*	*Characteristics*	*Scale*	*Collected*
Demand	D	ReEDS Mid-case Scenario Solar Generation	NREL	Non-Spatial	State	Yes
	D	Per-Capita Array Density	NREL	Non-Spatial	State	Yes
Suitability	TS	Elevation	USGS	Spatial	Continuous Raster (30m2 pixel)	Yes
	TS	Slope	Derived	Spatial	Continuous Raster (30m2 pixel)	Yes
	TS	Transmission Lines	EIA	Spatial	Line/Vector	Yes
	TS	Electricity Substations	EIA	Spatial	Point/Vector	Yes
Limits	Limits	Protected Areas Database (PAD-US)	USGS	Spatial	Polygon/Vector	Yes

	Limits	FUT 2016 – UHD & LDR Lands	AFT	Spatial	Raster (30m2 pixel)	Yes
	Limits	Predicted Land Value Raster	Nolte et al. 2020	Spatial	Raster (480m2)	Yes
Transition Rates	TR	FUT 2001 Land-Use Dataset	AFT	Spatial	Raster (30m2 pixel)	Yes
	TR	FUT 2016 Land-Use Dataset	AFT	Spatial	Raster (30m2 pixel)	Yes
	TR	Global Dataset of Wind and Solar Farms - Solar Footprints	Dunnett et al. 2019)	Spatial	Polygon/Vector	Yes

Limits to solar development are modeled in the same way as limits to UHD and LDR development in the *FUT2040* future development modeling (see Xie et al. 2022). Solar development is not placed on protected lands, federal lands, or existing UHD or LDR. While there are some land use types in LDR areas that may be subject to solar development in the real world, identifying them reliably is too challenging, which represents a limitation of this analysis. Likewise, it is expected that some solar development will occur on federal lands such as those managed by the Bureau of Land Management and the U.S. Forest Service, but determining which federal lands are suitable for solar development was beyond the scope of this analysis. Local opposition to solar development can also impose limits on development, especially in residential areas with politically powerful residents. To incorporate an aspect of "*NIMBYism"* into the model, we leverage a spatialized land value index dataset developed by Nolte et al. (2020) to restrict solar development on land in the upper 5% of national value.

Overall Suitability is determined by combining the technical suitability and limits maps. Areas that have limits to development (binary: 1 = not limited, 0 = limited) are removed from the technical suitability map using a spatial masking process. The simplified deployment equation to determine suitability is:

$$\boldsymbol{Suitability\ (S) = TS * L}$$

Where TS is the technical suitability map and L represents the Limits map. The overall suitability map is then used as an input to determine where solar development is likely to occur in the weights-of-evidence conditional transition probability process (see below).

Transition Probabilities Component (How Likely):
Transition probabilities are expressed as the likelihood/probability that a given land use type will be converted to solar development based on previously observed solar development land conversions. Transition probabilities are measured at the pixel level and are calculated by generating a matrix of observed pixel-to-pixel conversions between two input land-use maps at different time steps (Dunnett et al. 2020). Initial transition probabilities are calculated using a recently published dataset of solar plant footprints that have been incorporated into to the FUT 2001 and FUT 2016 land use datasets using spatial overlay processes (Table 2). Solar plants that have been developed since 2001 were identified and combined with the FUT 2001 and 2016 maps to calculate the transition rates for each FUT land-cover type based on observed increases in solar development. These transition rates are used to extrapolate potential future transition probabilities in 2040 based on the following equation:

$$S(t+1) = \boxed{P_{ij}} * S(t)$$

$$P_{ij} = \begin{pmatrix} P_{1.1} & \cdots & P_{1.n} \\ \vdots & \ddots & \vdots \\ P_{n.1} & \cdots & P_{n.n} \end{pmatrix}$$

S(t), S(T+1) = System Status at Time (t or t+1)
P_{ij} = Transition Probability Matrix
$P_{1.1 \ldots n.n}$ = Transition of individual land uses to solar (% converted)

Dinamica ego applies a Bayesian probability weights-of-evidence (WOE) method that combines land-use transition rates with suitability variables to produce conditional transition probability maps that highlight the most favorable areas for change. In the WOE approach, continuous variables like elevation and distances are categorized according to ranges and split into buffers that are used to train the model. Model weights for each variable are estimated for all breakpoints (buffer ranges). If multicollinearity among any of the variables is present within a given buffer range, one of the correlated variables is removed within that range to reduce bias.

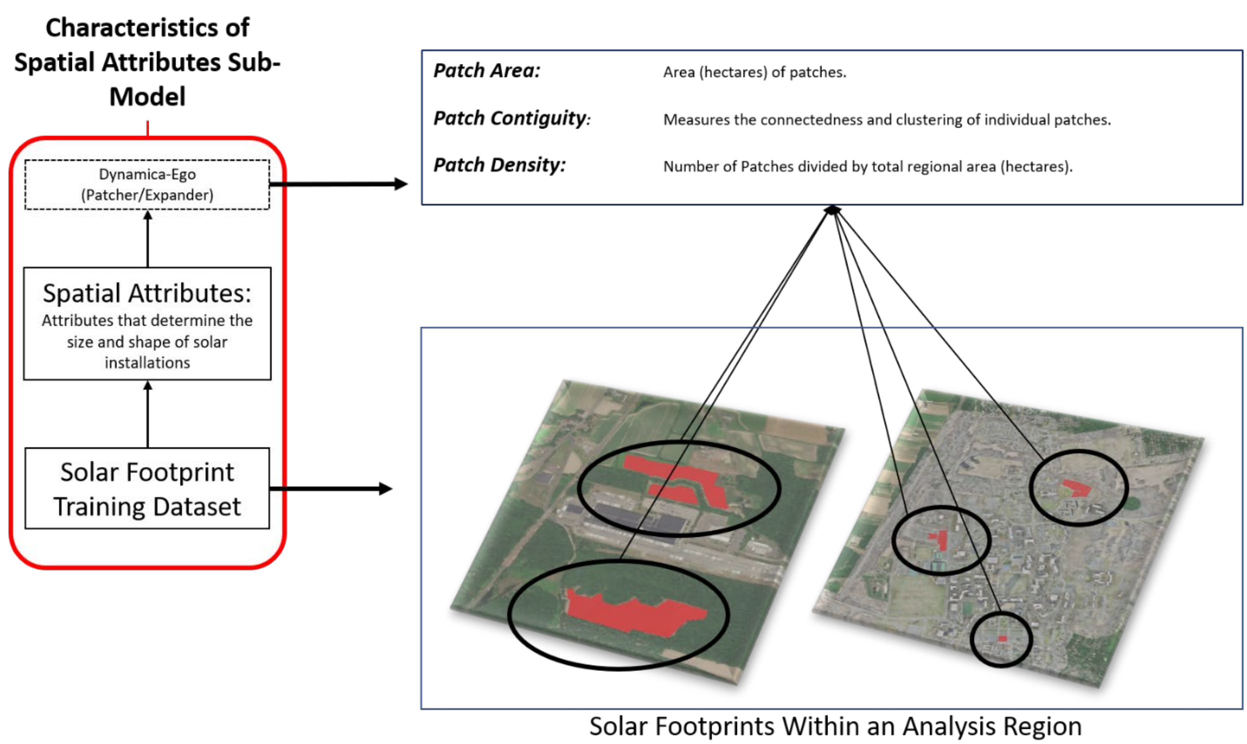

Figure 2: *Spatial attributes of solar footprints are computed using Fragstats software. Patch area, patch contiguity, and patch density are all defined and computed for solar footprints within each analysis region and used as inputs into the cellular automata spatial allocation model to "grow" realistic patches of new/future solar development.*

Spatial Attributes Component (Size and Shape):
To capture variation in the size and shape of future solar development, we computed patch characteristics of existing solar development for each analysis region. Specifically, we measured the mean patch area, contiguity, and patch density of solar patches using Fragstats patch dynamics statistical software. Mean patch area, contiguity, and density are comprehensive measurements of the size and shape of land use patches and can help determine how connected and/or diffuse solar development is within an analysis region. Figure 2 outlines an example of how patches of solar development might be characterized based on variations in their size and shape. The model allows for variation in array size around the means of ~6 and ~600 acres for DUPV and UPV, respectively, as well as array shape.

The spatial attributes/patch characteristics of solar farm footprints are used as inputs into the cellular automata portion of the spatial allocation model. The variations in the size, shape, and density of solar footprints among analysis regions produced more realistic patterns of "new" solar development based on the patch characteristic of individual regions. For example, solar development in west Texas is more likely to be large, dense, and contiguous, while solar development in Vermont is more likely to be smaller and more dispersed due to the background features of these two landscapes (e.g. slope, land use/cover). As the model 'seeds' the landscape to search for new development, the patch characteristics component determines how new solar development patches will 'grow' based on a set of neighborhood transition rules that incorporate the derived patch attributes (e.g. shape and density) and conditional transition probabilities for each land use type.

Final Spatial Allocation Model:
The final spatial allocation model combined the Demand, WOE Transition Probabilities, and Spatial Attributes components to disperse and grow new patches of solar development on the landscape within analysis regions in 2040. The model projected the amount of solar development we can expect to see over time according to the NREL Mid-case demand scenario and grew realistic patterns of new solar development based on observed conditions and suitable locations within analysis regions. Figure 3 outlines the model components that were included in the Markov-CA algorithm to predict and finalize maps for solar development in 2040.

We developed the model in the Dinamica EGO modeling software environment, a flexible and commonly used platform for land-change modeling (Argemiro et al. 2020). CA spatial allocation in Dinamica Ego uses the patcher functor, which relies on the observed spatial patterns within an analysis region to predict the location, size, and shape of new patches. The prune factor, which is how the model leverages stochasticity, specifies the size of the vector where cells are ranked for inclusion in a new patch once a seed cell has been identified. The patcher function then continues to seed the landscape and grow new patches of solar until demand has been met. We set a minimum developable land threshold to simplify the analysis and avoid allocating unrealistically small amounts of solar capacity (e.g., 0.07 MW).

Once the *FUT2040* projected urban development modeling maps for 2040 were finalized (Xie et al. 2022), we ran the solar model and quantified the amount and quality of farmland that might be impacted in states and counties throughout the country.

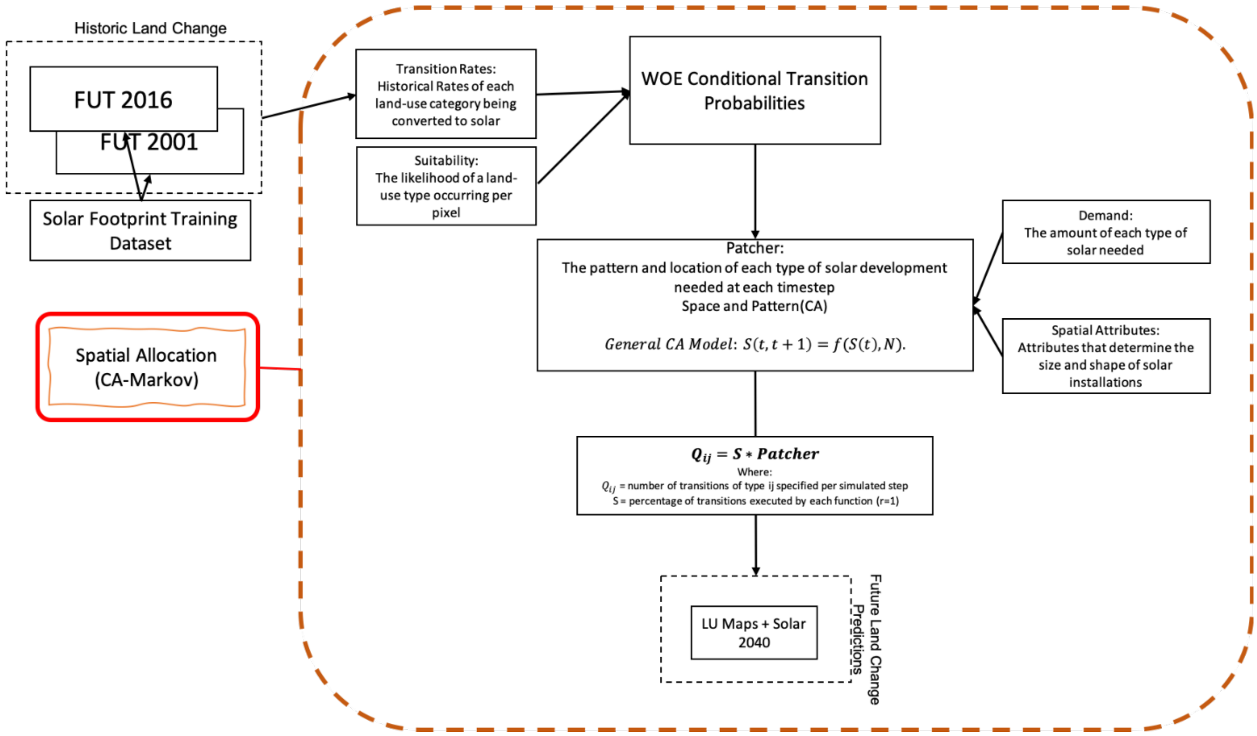

Figure 3: *Spatial Allocation Markov-CA Solar Growth Algorithm. Using Dinamica EGO urban growth modeling tools, we inputted the model components that determine demand, suitability, transition probabilities, and spatial attributes for solar development to predict future solar development in 2040. The Patcher tool accepts the spatial attributes component, demand cell transition numbers, and conditional transition probability surface to determine where and how to "grow" new patches of development at each time step. The Patcher tool outputs updated surfaces that are inclusive of new solar development at each timestep.*

Findings

Our model projected 2.5 million acres of new utility-scale solar installations (DUPV and UPV) from 2020-2040. This is slightly lower than the NREL ReEDS Mid-case Scenario total of ~2.9 million acres due to modeling challenges, potentially including the integration with the *FUT2040* projections of new UHD and LDR land use. Additionally, some of the transition rules that were implemented might have over-restricted solar development in some cases. For instance, the transition probabilities for both UPV and DUPV showed that a small proportion of UHD and LDR land was converted to solar between 2001 and 2016; however, these land use types were restricted from development in our model. This is primarily an issue of underlying data. Our model was built on maps of *land use,* which are inherently aggregations of multiple types of *land cover.* Realistically, UHD and LDR land uses that include open space, forest, or grass land-cover types can be—and have been—used for DUPV solar development. However, our underlying dataset does not allow us to determine which UHD and LDR lands are eligible for utility-scale solar development, so we excluded them entirely. This may have resulted in an under-projection of solar installations.

The projected deployment of solar energy installations, and their impact on agricultural land, is concentrated in specific areas of the country (Figure 4, Tables 3 & 4). Based on historical patterns of solar land conversion as documented in the Markov-CA model, 2.1 million acres (83%) of the total solar development from 2020-2040 is likely to occur on agricultural lands (Table 5).

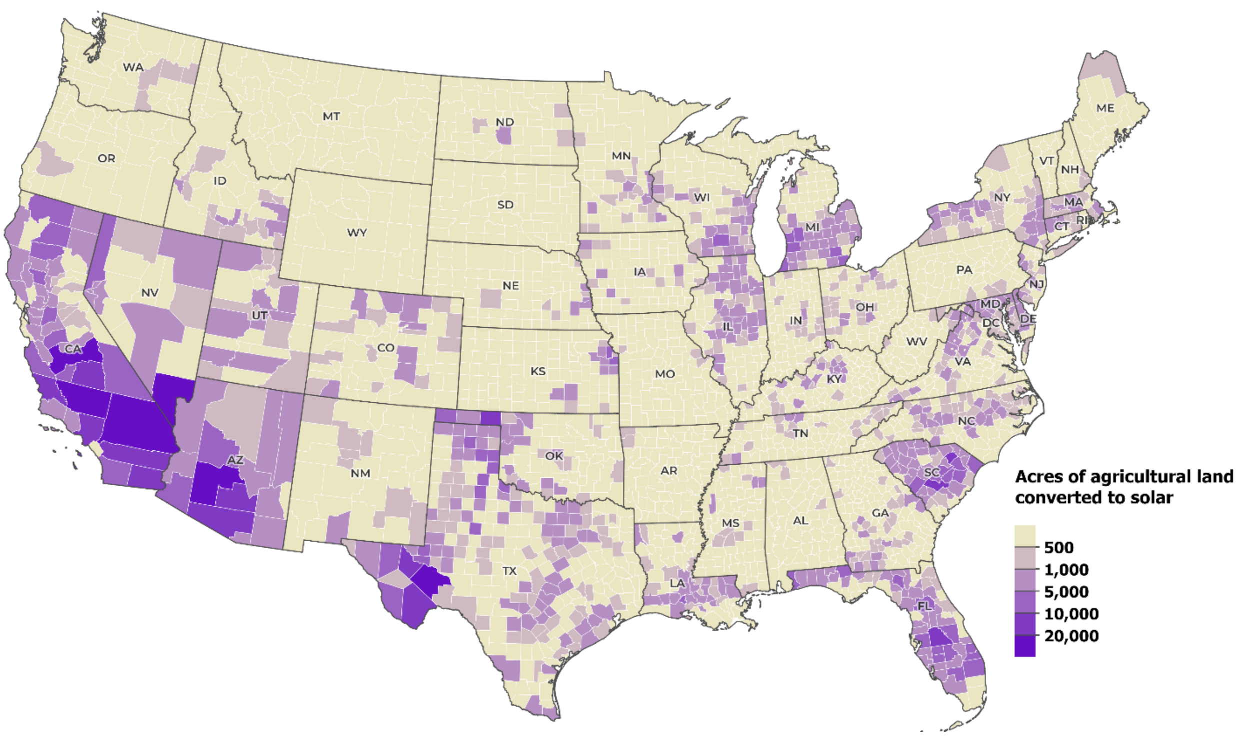

Figure 4. Projected acres of agricultural land converted to utility-scale solar photovoltaics energy generation facilities by state from 2020-2040.

Table 3: Projected acres of agricultural land converted to utility-scale solar photovoltaics energy generation facilities by state from 2020-2040.

State	*Acres*	*State*	*Acres*	*State*	*Acres*
Texas	345,200	Kansas	36,600	Massachusetts	10,400
California	311,200	Ohio	32,600	New Mexico	9,000
Florida	188,000	Minnesota	29,700	Alabama	6,700
South Carolina	138,500	Maryland	28,200	Connecticut	6,600
Michigan	93,900	Colorado	27,400	Oregon	6,300
Arizona	89,100	Indiana	23,300	Arkansas	6,000
Illinois	82,400	Tennessee	23,300	Washington	5,800
Oklahoma	60,200	Iowa	22,600	Delaware	5,400
Wisconsin	54,300	Mississippi	20,600	North Dakota	4,900
North Carolina	51,100	Utah	20,000	New Hampshire	2,400
Louisiana	48,000	Idaho	19,700	Maine	1,500
Virginia	45,900	Nebraska	16,000	Montana	1,500
New York	45,100	West Virginia	15,000	Vermont	1,200
Kentucky	42,700	Pennsylvania	11,800	Wyoming	1,000
Georgia	41,900	New Jersey	11,500	Rhode Island	1,000
Nevada	41,500	Missouri	10,800	South Dakota	800

Contiguous United States: 2,098,600 acres

Table 4. Counties with the most acres of agricultural land projected to be converted to utility-scale photovoltaics energy generation facilities from 2020-2040.

County	*State*	*Acres*	*County*	*State*	*Acres*
Kern	California	57,400	San Luis Obispo	California	12,000
Pecos	Texas	43,200	Tulare	California	11,800
Fresno	California	32,500	Riverside	California	10,600
Maricopa	Arizona	26,300	Orangeburg	South Carolina	10,200
San Bernardino	California	24,200	Culberson	Texas	9,900
Clark	Nevada	20,300	Siskiyou	California	9,600
Pinal	Arizona	19,100	Collingsworth	Texas	9,000
Polk	Florida	17,900	Yavapai	Arizona	8,700
Brewster	Texas	17,500	Colusa	California	8,600
Reeves	Texas	14,600	Tehama	California	8,500
Imperial	California	13,600	Hendry	Florida	8,400
Darlington	South Carolina	13,600	Presidio	Texas	8,300
Beaver	Oklahoma	13,100	Berrien	Michigan	8,200
Los Angeles	California	12,000	Kings	California	8,100
Pima	Arizona	12,000	Jackson	Florida	8,100

Table 5. Projected total acres of land converted to utility-scale solar photovoltaics energy generation facilities across the contiguous U.S. from 2020-2040, by land-use type.

Land Use	***Acres***
Cropland	1,017,500
Pastureland	358,500
Rangeland	652,000
Woodland	70,500
Forestland	340,900
Other	95,300
Total	2,534,800

Nearly half of the solar conversion on agricultural land is projected to occur on Nationally Significant land, the nation's best land for long-term production. Our model projected 1,018,100 acres of conversion on Nationally Significant land, which is 49% of the total agricultural land conversion (2,098,600). Solar developers favor the attributes of high-quality farmland since it is more likely to be flat, dry, cleared, and close to existing infrastructure (Grout and Ifft 2018).

We also project that nearly 341 thousand acres of forestland will be converted to utility-scale solar development. Forests often serve as important buffers to agricultural lands and other open spaces (FAO 2016). Their conversion can have cascading effects that remove agricultural runoff and flooding controls, reduce biodiversity and pollinator habitat, and increase pest abundances—all of which can detrimentally impact farmland.

Discussion

The NREL ReEDS Mid-case Scenario used to drive our model does not eliminate all fossil fuels from the electricity sector, the stated goal of the Biden administration. To achieve this goal, it is estimated that a significantly larger amount of utility-scale solar will be needed, ranging from 5.3 to 7.4 million acres in 2040 (Larson et al. 2021; U.S. DOE 2021). Even more solar would be needed to fully electrify transportation, heating, and other energy needs. As a result, modeling based on the NREL ReEDS Mid-case Scenario may greatly underestimate future solar energy demand and impacts. Without good planning and effective permitting processes, the impact of solar development on U.S. agricultural lands could be significant.

References

Argemiro T., A. Leite-Filho, B. Soares-Filho, J. Davis, and H. Rodrigues. 2020. *Modeling Environmental Dynamics with Dinamica EGO.* Guide Book 2.0. Copyright © 2019, 2020 by Centro de Sensoriamento Remoto.

Brown, M., W. Cole, K. Eurek, J. Becker, D. Bielen, I. Chernyakhovskiy, S. Cohen et al. 2020. *Regional Energy Deployment System (ReEDS) Model Documentation: Version 2019*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-74111. March 2020. 140 pp.

Cadenasso, M., S. Pickett and K. Schwartz. 2007. *Spatial heterogeneity in urban ecosystems: Reconceptualizing land cover and a framework for classification.* Frontiers in Ecology and the Environment Volume 5(2): 80-88.

Cole, W., S. Corcoran, N. Gates, T. Mai, and P. Das. 2020. *2020 Standard Scenarios Report: A U.S. Electricity Sector Outlook*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-77442.

Dunnett, S., A. Sorichetta, G. Taylor and F. Eigenbrod. 2020. *Harmonised global datasets of wind and solar farm locations and power.* Nature Scientific Data*,* 7(130). April 2020.

Freedgood, J., M. Hunter, J. Dempsey and A. Sorensen. 2020. *Farms Under Threat: The State of the States*. Washington, D.C: American Farmland Trust. 65 pp.

Food and Agriculture Organization (FAO). 2016. *State of the World's Forests 2016. Forests and agriculture: land use challenges and opportunities*. Rome. 126 pp.

Grout, T, and J. Ifft. *Approaches to balancing solar expansion and farmland preservation: A comparison across selected states*. Charles H. Dyson School of Applied Economics and Management. Cornell University. May 2018. EB 2018-04. 10 pp.

Keshtkar, H. and W. Voigt. 2016. *A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models*. Modeling Earth Systems and Environment Volume 2 Article 10.

Larson, E., C. Greig, J. Jenkins, E. Mayfield, A. Pascale, C. Zhang, J. Drossman, R. Williams, S. Pacala, et al. 2021. *Net-Zero America: Potential Pathways, Infrastructure, and Impacts, Final report*. Princeton University, Princeton, NJ. October 29, 2021. 348 pp.

Meentemeyer, R., W. Tang, M. Dorning, J. Vogler, N. Cunniffee and D. Shoemaker. 2013. *FUTURES: Multilevel simulations of emerging urban-rural landscape structure using a stochastic patch-growing algorithm*. Annals of the Association of American Geographers Volume 103(4):785-807.

Nolte, C. 2020. *High-Resolution Land Value Maps Reveal Underestimation of Conservation Costs in the United States*. PNAS, 117 (47): 29577-29583.

U.S. Department of Energy. 2021. *Solar Futures Study*. Office of Energy Efficiency & Renewable Energy. September 2021. 310 pp.

Xie, Y. and T. Lark. 2022. *Description of the approach, data and analytical methods used for the Farms Under Threat 2040 projections of future agricultural land conversion*. Nelson Institute Center for Sustainability and the Global Environment (SAGE). University of Wisconsin-Madison.