DOCKETED

Docket Number:	16-IEPR-05
Project Title:	Electricity Demand Forecast
TN #:	211950
Document Title:	Presentation - Predicting Adoption is Hard: Methods for Forecasting DGPV Adoption
Description:	Ben Sigrin, National Renewable Energy Laboratory
Filer:	Raquel Kravitz
Organization:	National Renewable Energy Laboratory
Submitter Role:	Public Agency
Submission Date:	6/23/2016 7:53:59 AM
Docketed Date:	6/23/2016

NREL
NATIONAL RENEWABLE ENERGY LABORATORY





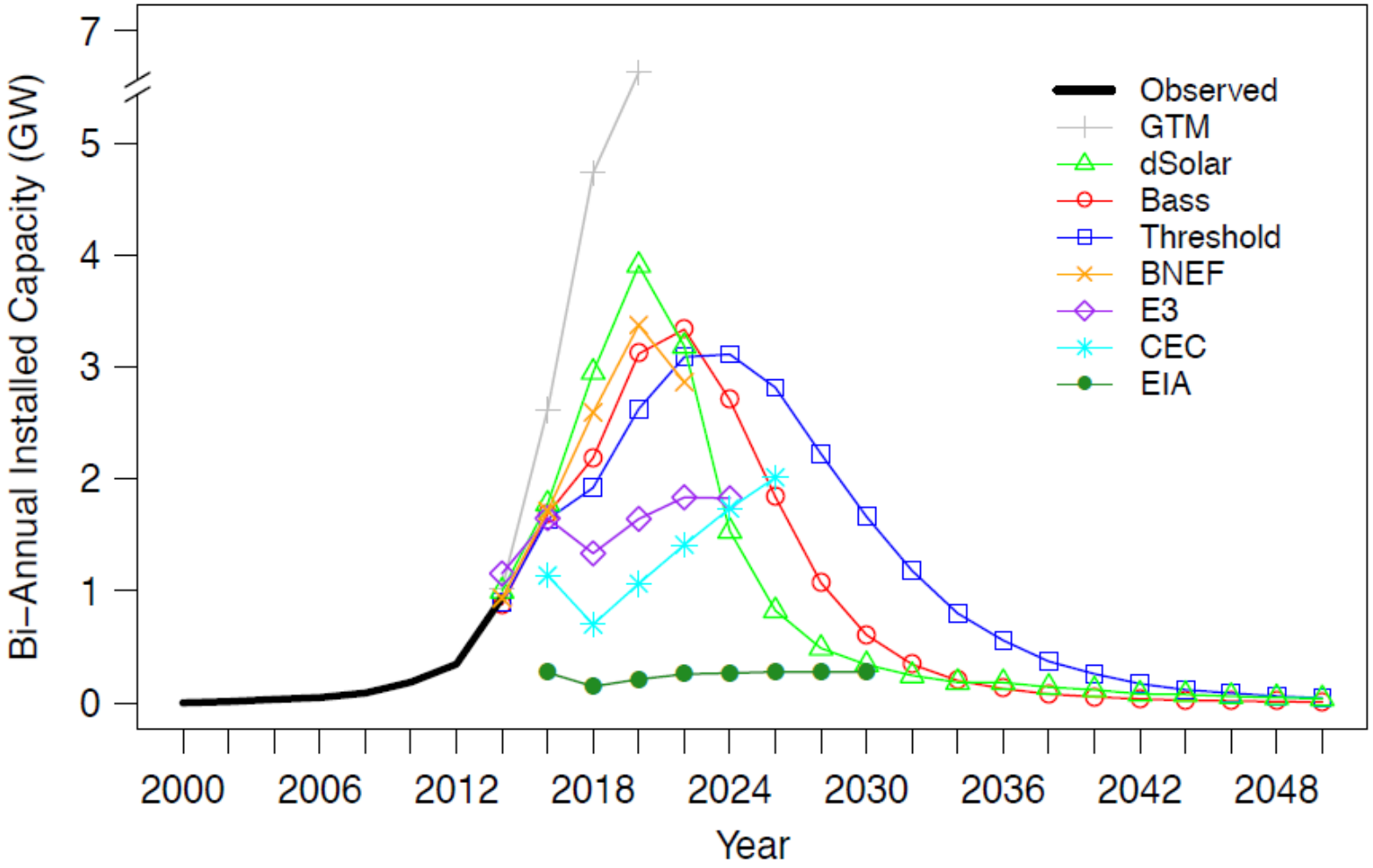
Predicting Adoption is Hard:

Methods for Forecasting DGPV Adoption

Ben Sigrin – NREL

June 23rd, 2016

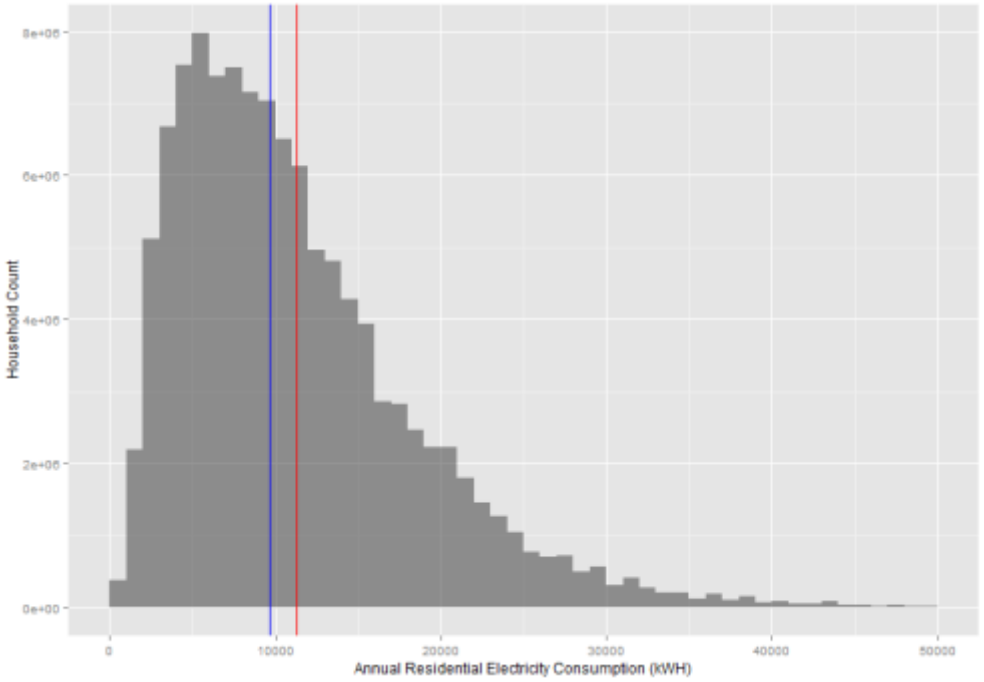
Distributed PV: How much and where!?



Dong & Sigrin (2016). "Forecasting Residential Solar Photovoltaic Deployment in California." Working Paper. The figure compares published and authors' forecasts for first-time adoption in the California residential sector.

Issues in Forecasting Distributed Energy Resources

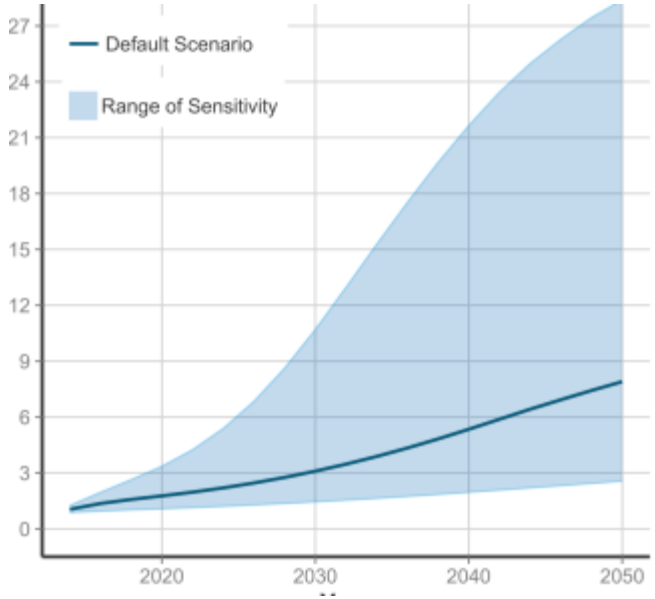
1) Heterogeneity in consumer preferences – differ not only in the attributes that define their adoption propensity, but also their response



2) Some specifications can suffer from "knife's edge" – improper specification can yield 'all or no one' response, especially for zero-down financing

Issues in Forecasting Distributed Energy Resources

3) Large data requirements – Depending on the model format, consistency and format of data can be overwhelming. Additionally, many of the data need to be continuously updated



4) Many sources of uncertainty– Uncertainties are in both the techno-economic assumptions (e.g. technology costs) and underlying model specification.

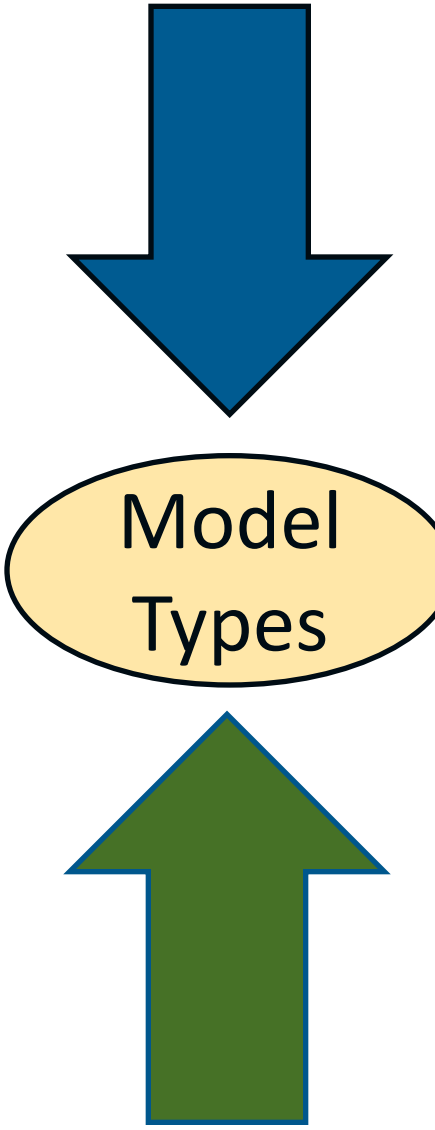
Methods for Forecasting DER Adoption

Top Down Modeling:

- Generally are econometric models of population-wide demand
- Advantage is tractability, ease of collecting data
- Disadvantages are inflexibility to consider new technologies, or evolving economic drivers; over-fitting and uncertainty

Bottoms-Up Modeling:

- Generally are engineering models of individual-level demand
- Advantages: Flexibility of the specification, limitless detail of important features
- Disadvantages: Data and computationally expensive



Top-down examples

"This study combines … several types of geospatial information—population demographics, solar irradiance … to identify which subsets of geospatial information are the best predictors of historical PV adoption."

	Subset Size								
Variable name	1	2	3	4	5	6	7	8	Full Model
mortgage2orHE	0.46				0.24				0.19
rooms		0.42	0.33	0.35	0.28	0.29	0.33	0.32	0.27
hev		0.38	0.41	0.40	0.40	0.38	0.38	0.31	0.25
masters			0.24			0.35	0.32	0.38	0.32
famsize				-0.28					-0.15
wood				-0.22		-0.24	-0.28	-0.28	NA
mortgage.over40pctincome					-0.18				-0.11
percentTPO					-0.17		-0.16	-0.18	-0.24
value.over1mil						-0.27	-0.30	-0.31	NA
white						0.27	0.24	0.27	NA
foreclosure								0.17	0.26
Adj. R-squared	0.21	0.34	0.38	0.41	0.43	0.45	0.47	0.49	0.55

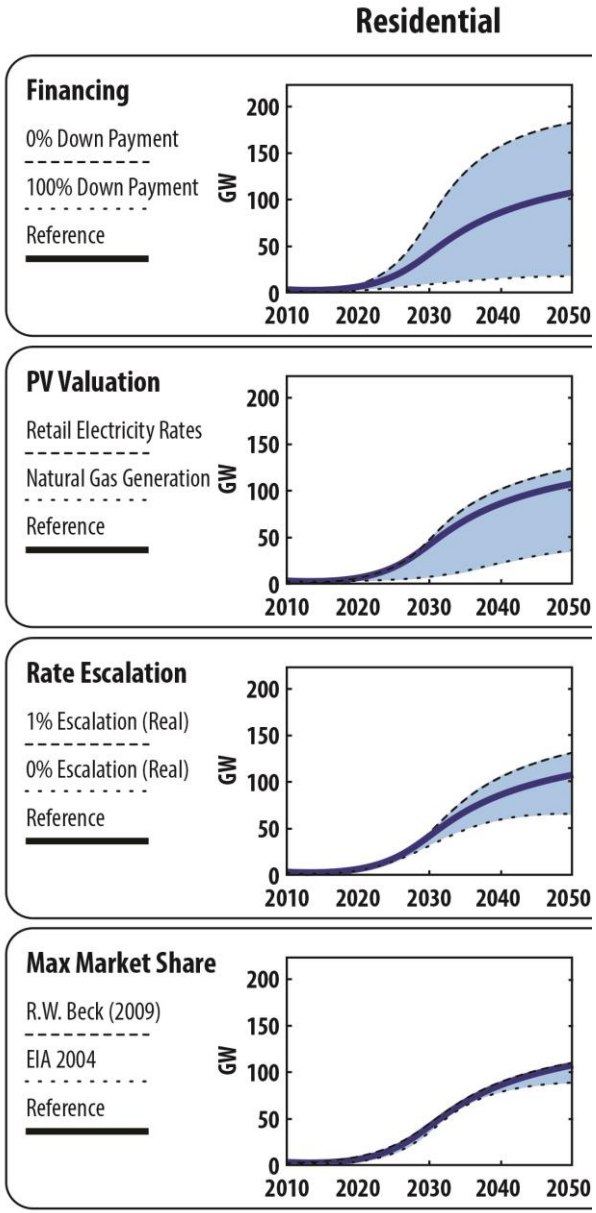
Legend: DPI, ACS, Canopy, Polk, Foreclosure, Insolation, CSI

Davidson et al (2014). "Modeling Photovoltaic Diffusion: An Analysis of Geospatial Datasets." *Environmental Research Letters* 9 (7): 074009. doi:10.1088/1748-9326/9/7/074009.

Bottoms-up Examples

NREL's SolarDS Model

- Bottom's up market penetration model
- Simulates household & business decisions through binned approach
  - Engineering sub-models of PV performance and financial performance
  - Draws on Bass theory to simulate customer adoption

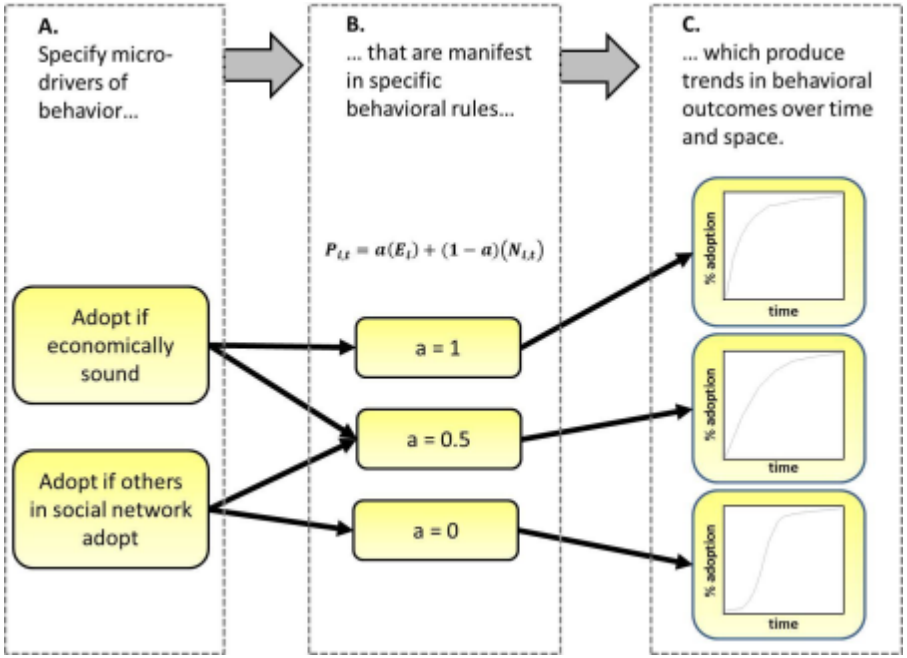


New Frontiers: Agent-Based Models

An emerging specification are Agent-Based Models (ABMs). ABMs are bottoms-up models of individual consumer behavior

ABMs are a useful method for simulating DER adoptions since agents represent underlying population heterogeneity. Agents can respond to economic drivers, as well as stimulated events (e.g. increasing electricity bills) as well as peer effects (e.g. influence of neighbors adopting).

Ultimately the methods offer a rich opportunity for model calibration and cross-validation

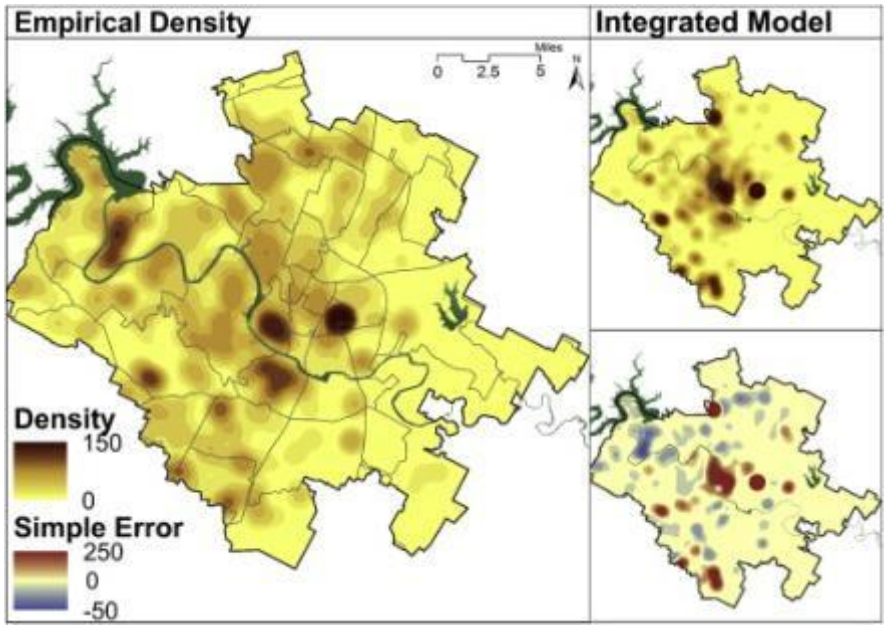


Essential building blocks for ABMs include:

- Theory-driven specification
- Calibration with empirical data
- Combination of economic and non-economic factors

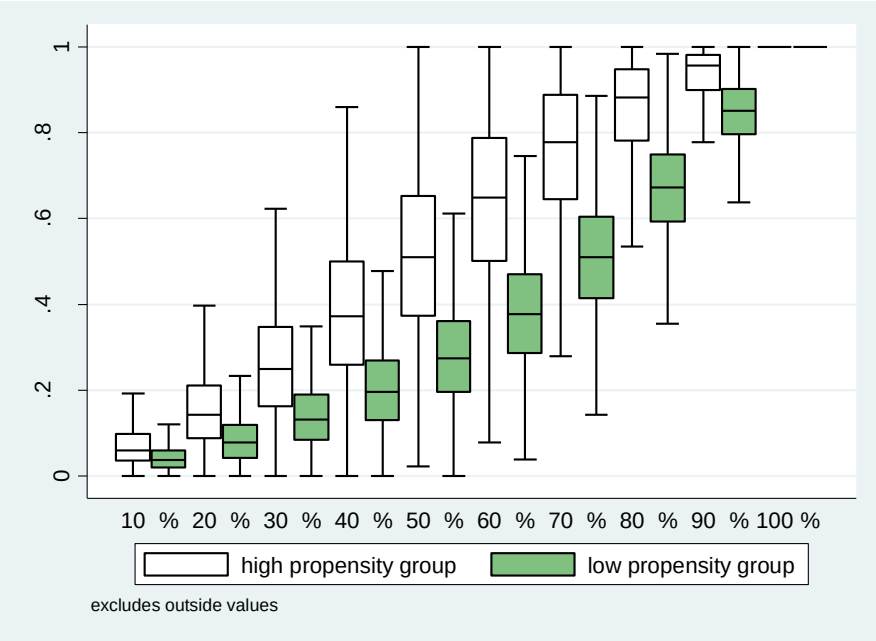
Rai & Henry 2016

ABMs continued



Empirical ABM for Austin, TX metro area based on household-level characteristics and adoption patterns. Factors influencing adoption included attitudes, perceived uncertainty, peer effects, and economic benefits

Rai & Robinson 2015; Robinson & Rai 2014

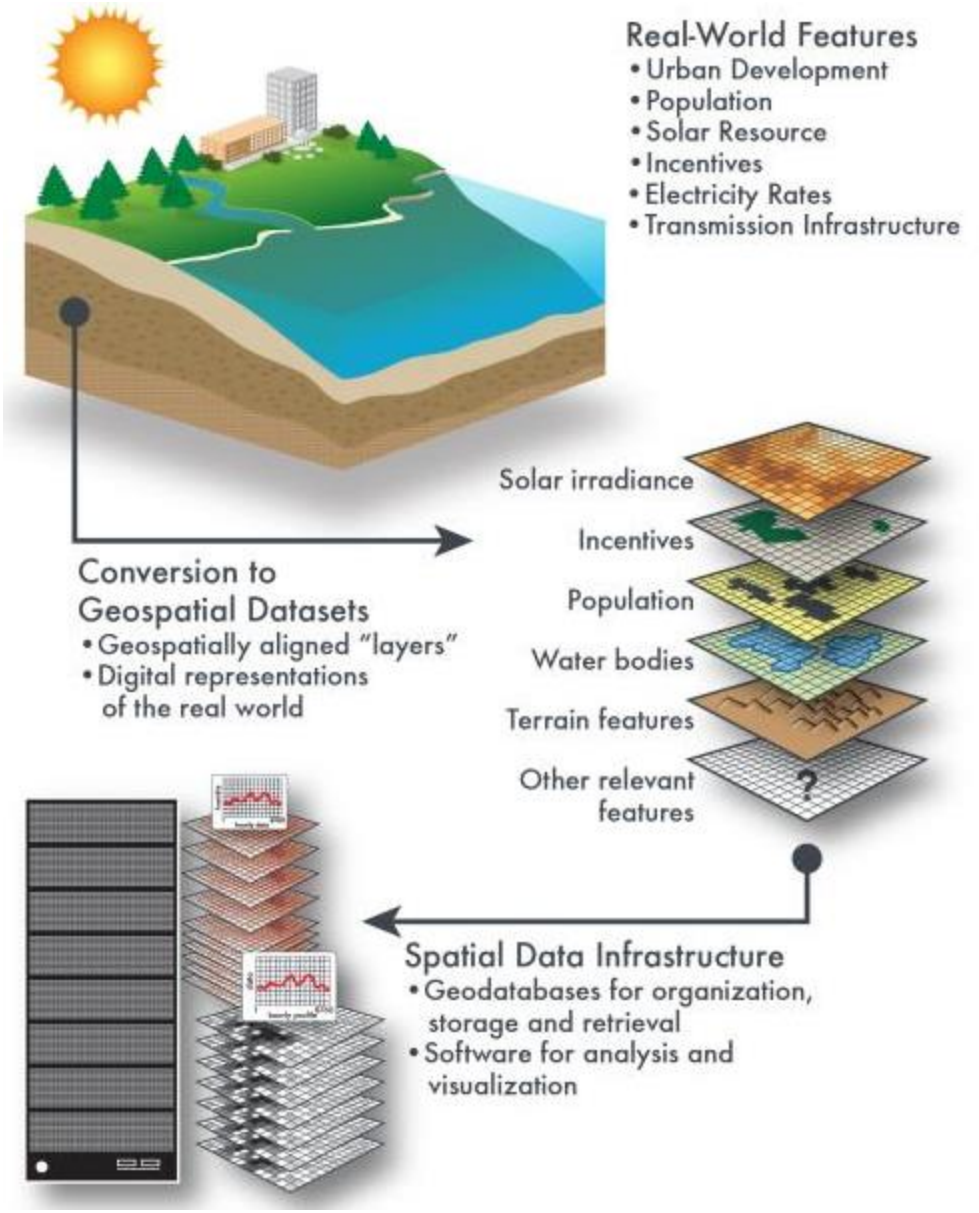


Theoretical ABM for Sacramento region exploring optimal allocation of rebates. If we assume segregation in social systems (i.e. differing propensity based on socio-demographics), then inequitable distribution of rebates is an inevitable consequence.

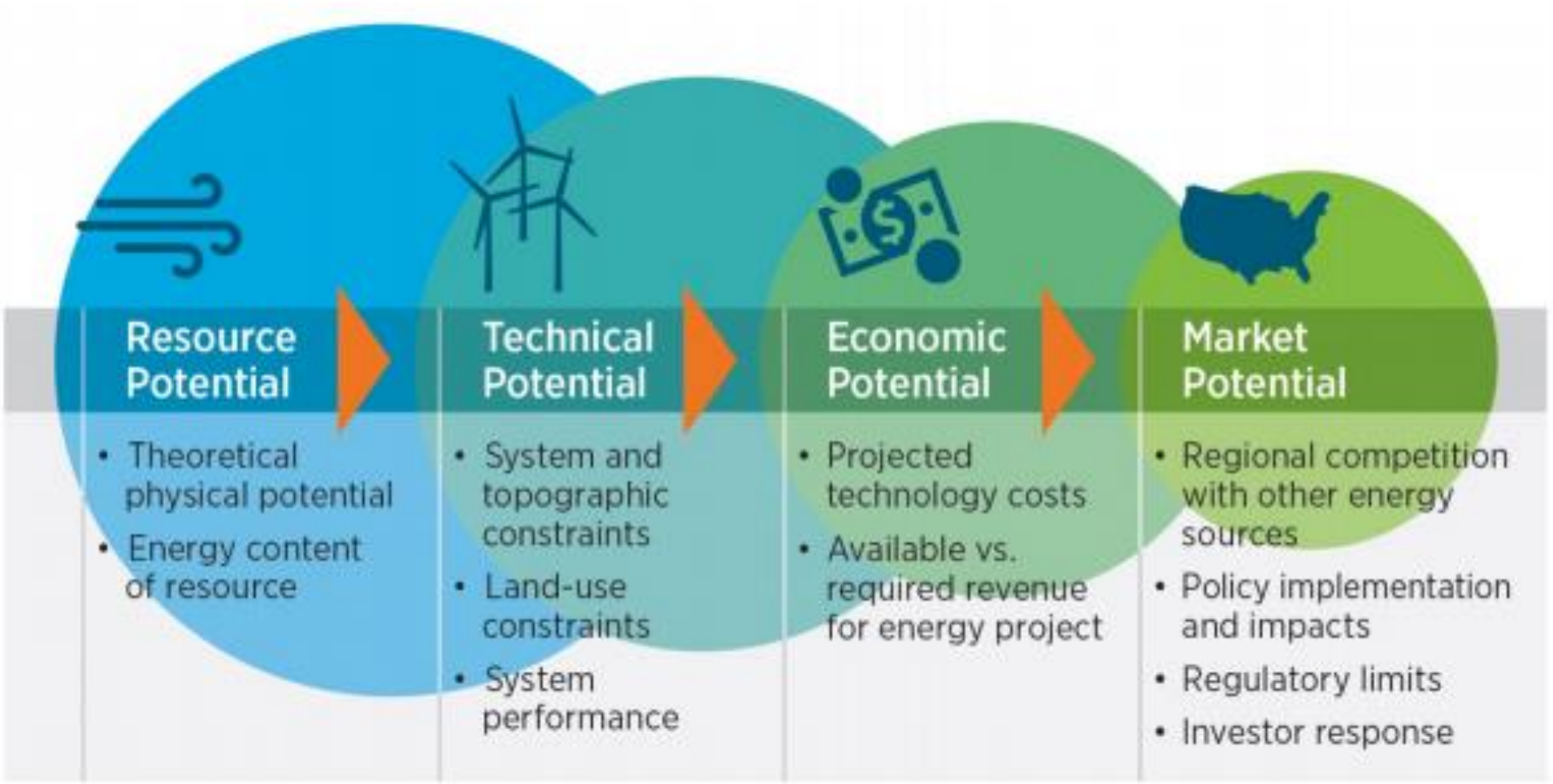
Henry, Pfeiffer, and Sigrin 2016

NREL's Current Approach: dSolar

- Fusing top-down (1/3) and bottoms-up (2/3) principles
- National Agent-Based Model, drawing on many of the principles from SolarDS
- Novel features are the foundation in spatial data and statistically-representative agents



Technical, Economic, and Market Potential

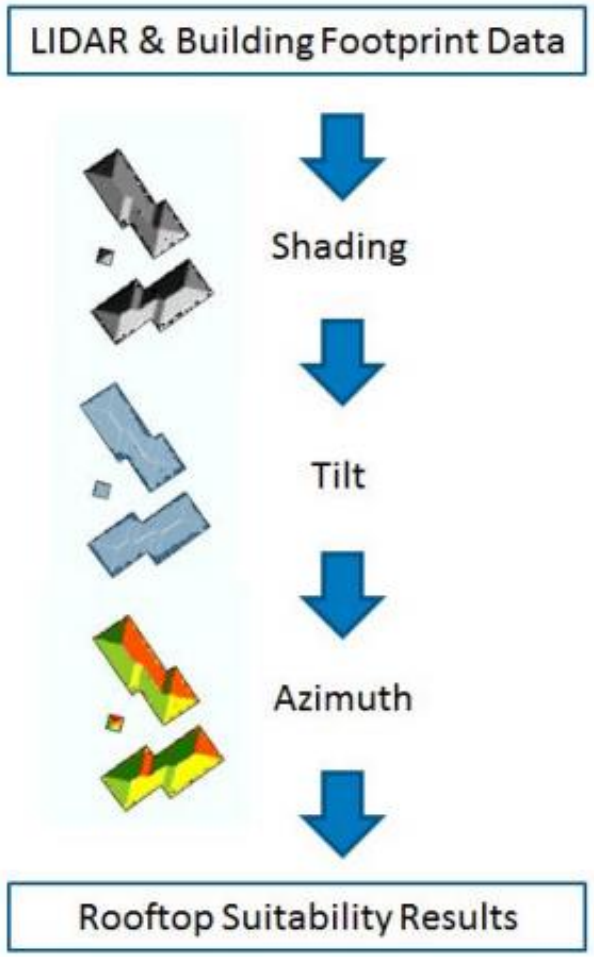


Source: Brown et al 2015

Getting the big things right: Technical potential

Estimating reference macro factors such as building counts, available roof space, and addressable load should be considered the first priority.

Increasingly, these estimates are based on information of actual buildings, or a sample of building in the region.



LiDAR-based assessment of national rooftop potential

Gagnon et al 2016

Getting the big things right: Economic potential

After estimating technical potential, economic potential should be evaluated. Relevant factors include:

- Retail rate structures
- Projected technology costs
- Applicable incentives
- Available financing terms

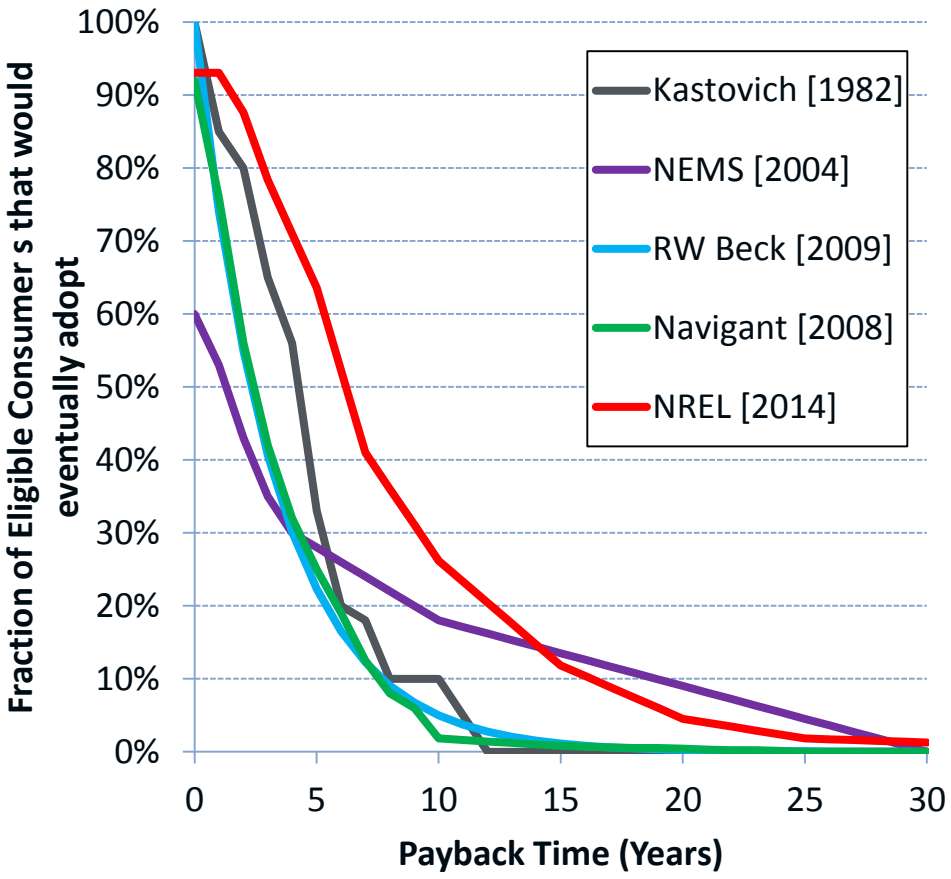
Particularly in California with tiered rate structures, PV economics are dependent on energy consumption levels. Thus, project economics depend on assumptions of customer load. Optimal system design is complex, and gets more complex with TOU rates and/or storage

Market Potential

Simulating customer decisions remains the most essential, yet uncertain aspect of diffusion modeling

Multiple adoption decision models could be used here

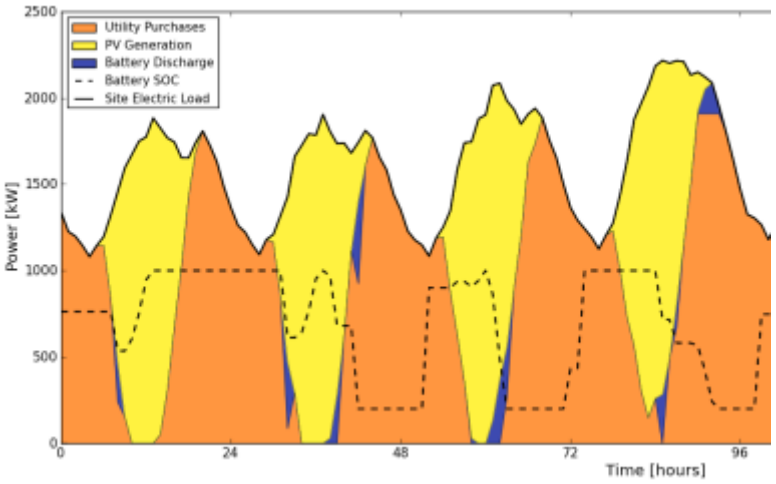
- Generalized Bass models
- Discrete Choice
- Machine Learning



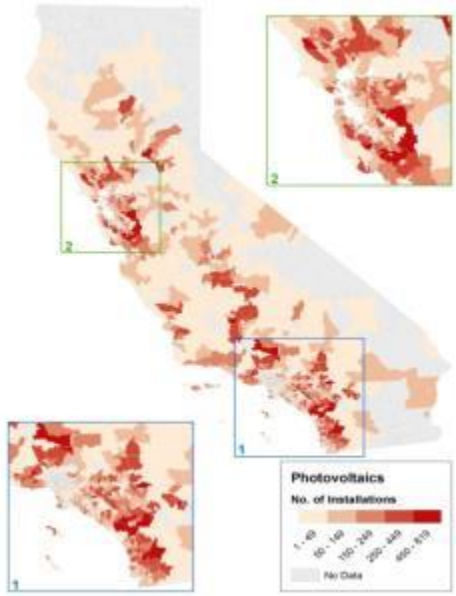
Max market share curves (above) are a common method for estimating demand

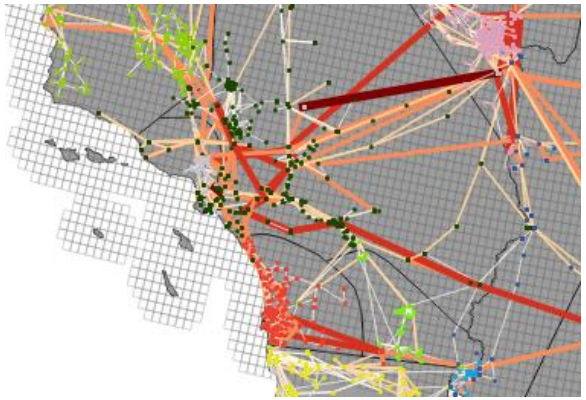
Where do we go from here?

- Spatial forecasting to understand DRP issues
- Interactions of EVs, HEMS, Storage and other DERs
- Breakout from early adopters to mass market



Storage, EVs, and HEMS will influence consumer load patterns





Spatial forecasting for distribution resource planning will become more important

Conclusion

- Forecasting DG adoption is hard, but the literature is growing quickly
- The most successful methods tend to use available data to calibrate models and use scenario analysis to understand tipping points
- The next generation of DER forecasting will need to incorporate spatial forecasts, especially for distribution resource planning.
- Influence of complimentary technologies (Energy Storage, Electric Vehicles, HEMS) will grow in relevance, particularly as consumer switch to TOU rates.

www.nrel.gov

NREL
NATIONAL RENEWABLE ENERGY LABORATORY

NREL is a national laboratory of the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, operated by the Alliance for Sustainable Energy, LLC.