Spatially-explicit probabilistic projections of granular energy technology diffusion at subnational level

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Xin Wen, Evelina Trutnevyte

Renewable Energy Systems
Institute for Environmental Sciences
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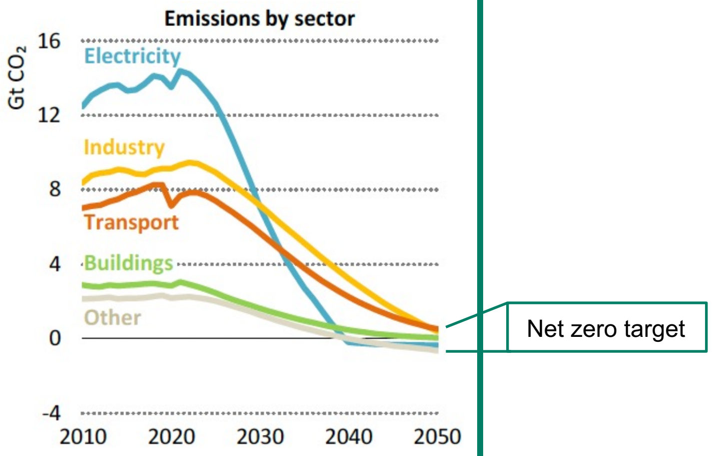
July 24-27, 2023

RES

sweet swiss energy research for the energy transition
SURE

Swiss National Science Foundation
Grant no. 186834 (**ACCURACY**)

Global energy-related CO_2 emissions by sector in the Net Zero Emissions Scenario, 2010-2050



International Energy Agency 2022

International Energy Agency (2022), *World Energy Outlook 2022*. Trutnevyte, E. (2016), *Energy*, 106, 182–193.

Models set energy transition targets for net zero

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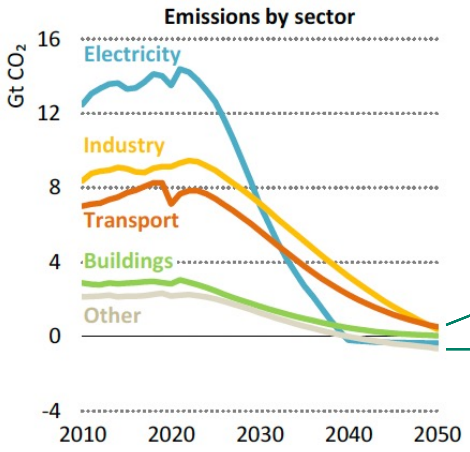
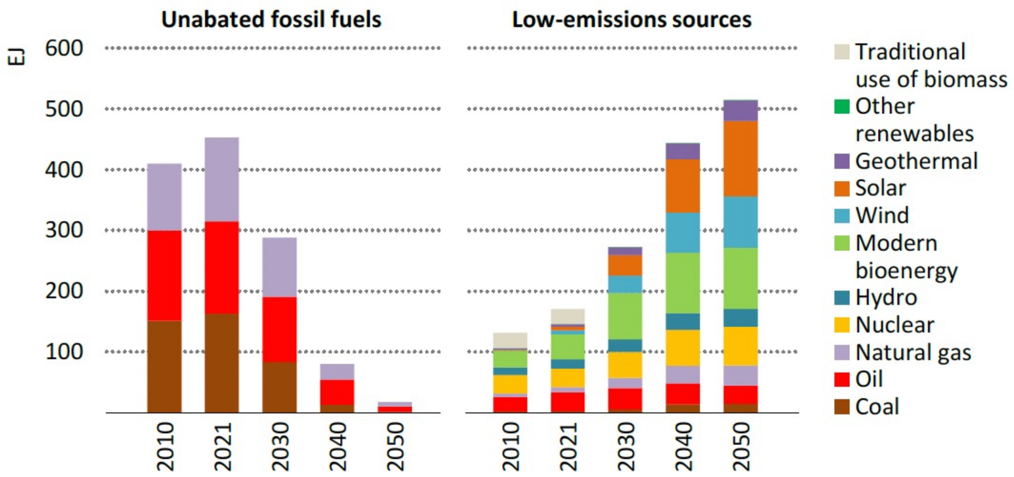


International Energy Agency 2022

Net zero target

Global total energy supply in the Net Zero Emissions Scenario, 2010-2050



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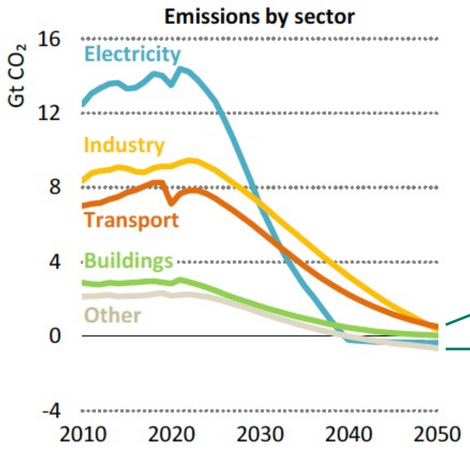

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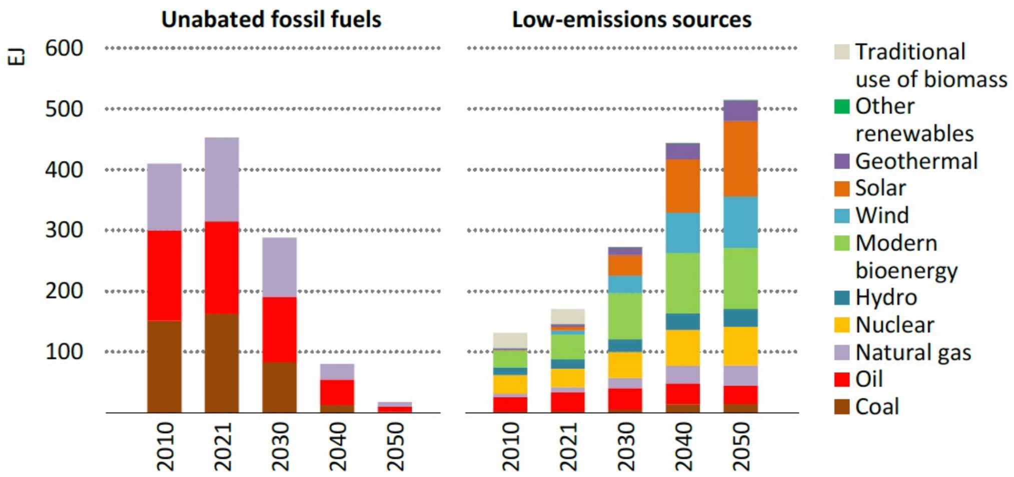


International Energy Agency 2022

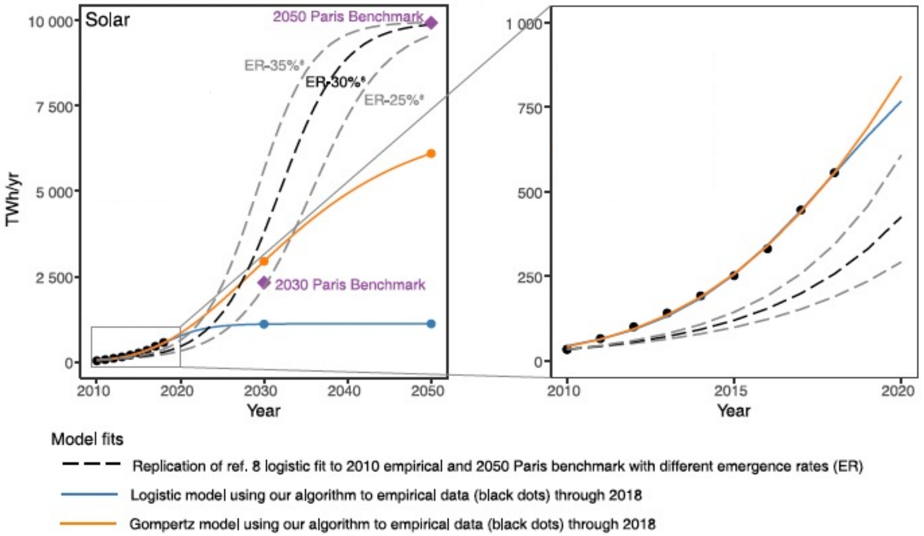
… but miss to inform about realistic pathways (Trutnevyte 2016)

Need	Realistic projections

International Energy Agency (2022), *World Energy Outlook 2022*. Trutnevyte, E. (2016), *Energy*, 106, 182–193.

Projections of energy technology diffusion

Projections of global solar power to 2050



adapted from Cherp et al. 2021

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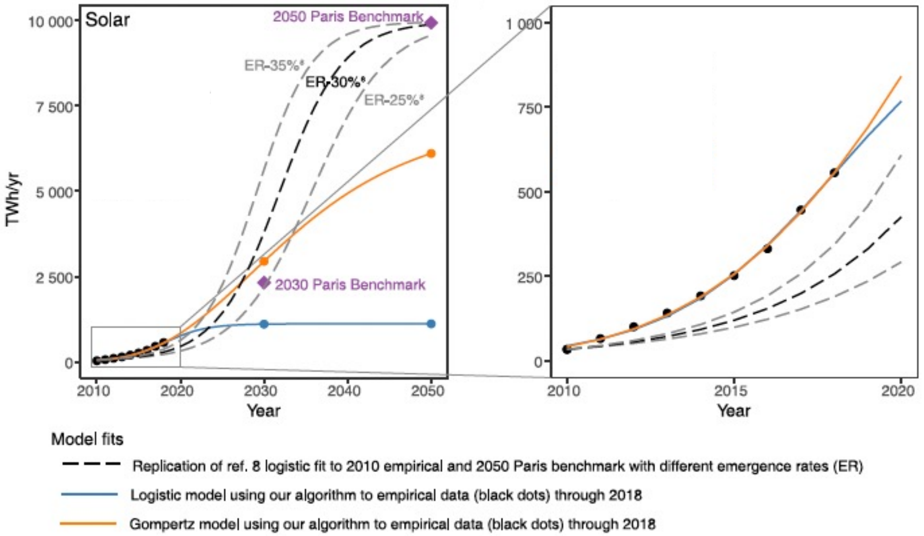

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Common projections

- Deterministic and
  do not account for uncertainties
  (Yue et al. 2018, Trutnevyte et al. 2022)

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Projections of energy technology diffusion

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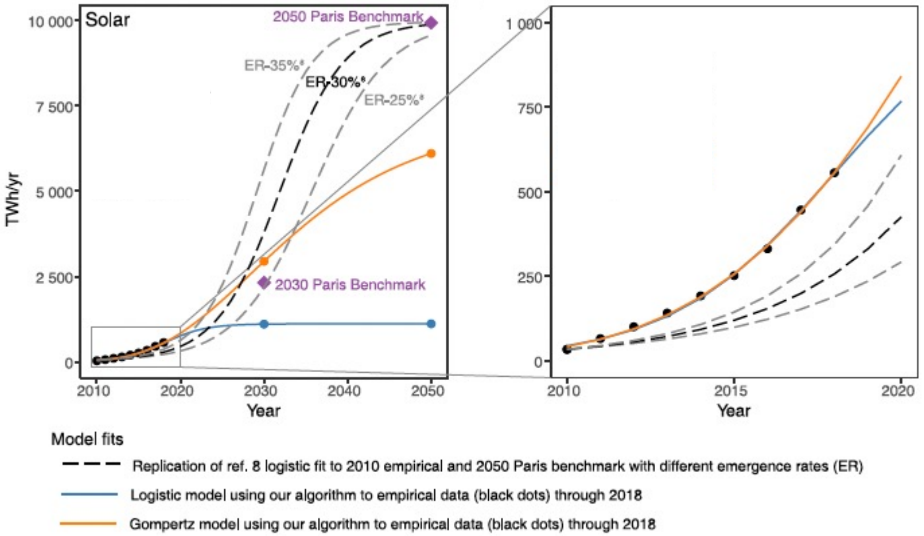

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- Deterministic and
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- Overconfidence (Morgan et al. 2008)

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Projections of energy technology diffusion

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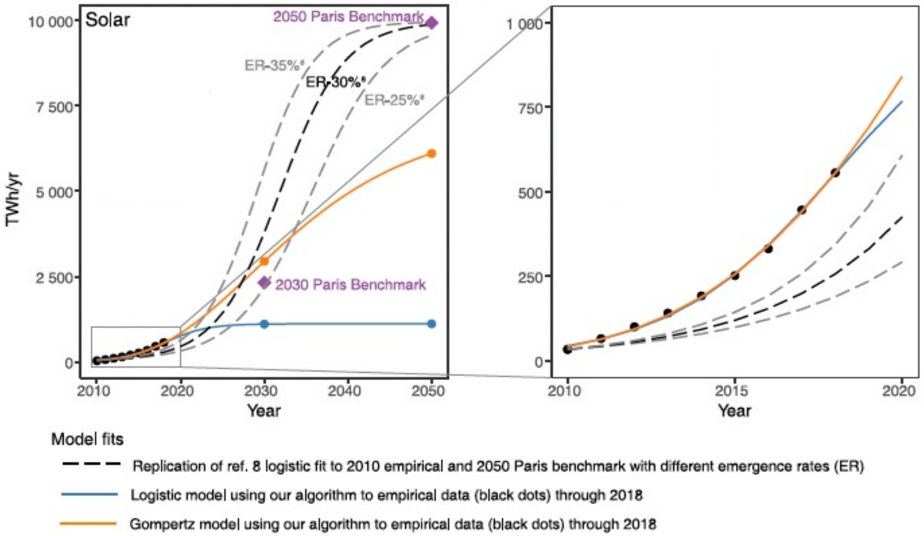

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Common projections

- Deterministic and do not account for uncertainties (Yue et al. 2018, Trutnevyte et al. 2022)
- Overconfidence (Morgan et al. 2008)
- Projections of different models
  → can vary significantly and are sensitive to parameter choice (Höök et al. 2011, Young et al. 1993, Lekvall et al. 1973, Geroski et al. 2000)

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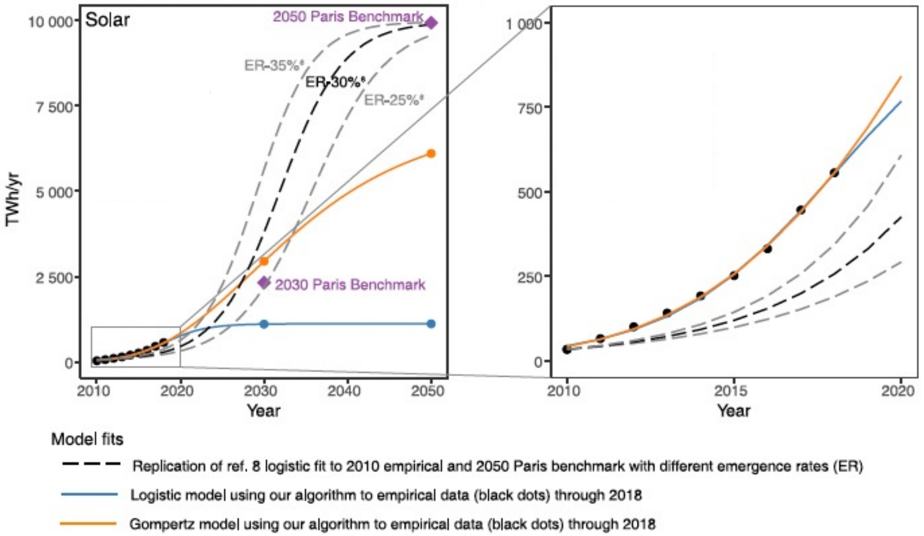

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Need	Probabilistic projections	Evaluation framework

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Research goals and set-up

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Research goals

New method for projections of granular energy technology diffusion that accounts for

- **probabilities**
- a **diversity of models** with different characteristics
- model **evaluation** and weighting
- **spatial features** and resolutions

Research goals and set-up

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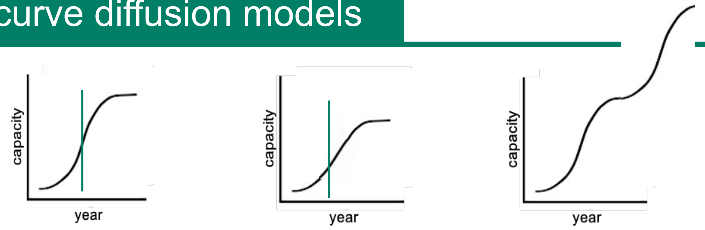
S-curve diffusion models



symmetric **asymmetric** **bi**

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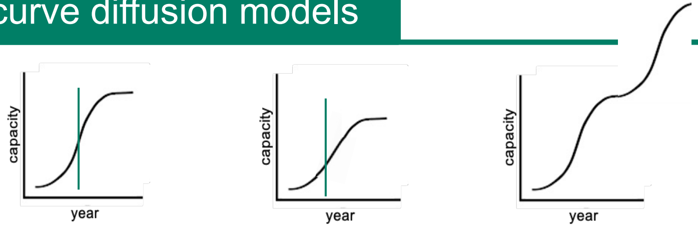
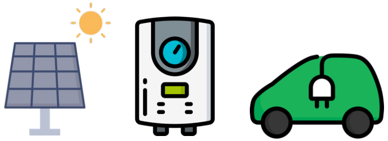
S-curve diffusion models

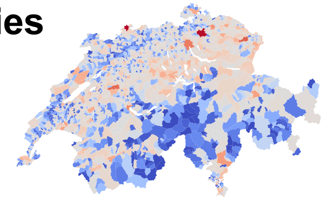


symmetric **asymmetric** **bi**

Case study

Solar photovoltaics (PV), heat pumps, and Battery Electric Vehicles (BEV)
in 2’148 Swiss **municipalities**





4-step method to create probabilistic projections

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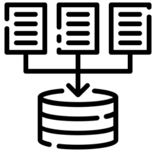
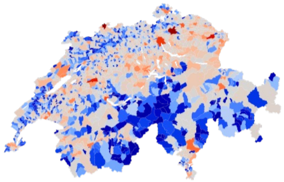
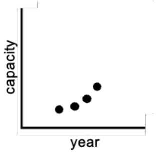
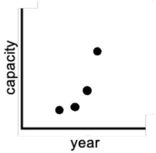
0) Data preparation
for each municipality
and technology diffusion





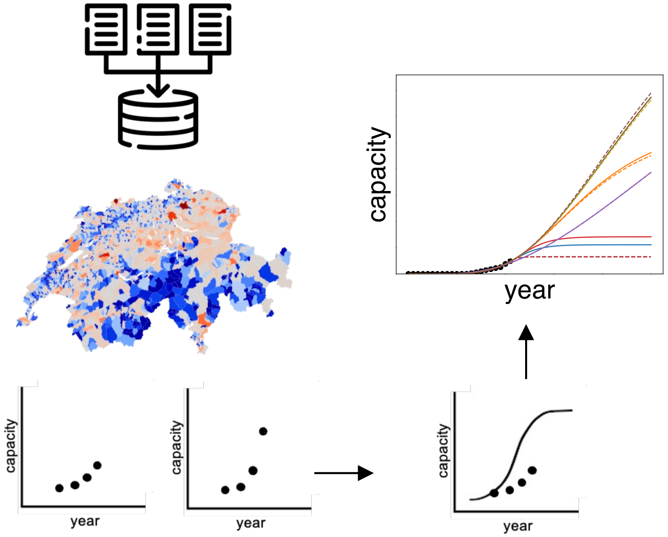




4-step method to create probabilistic projections

0) Data preparation
for each municipality
and technology diffusion

1) Deterministic projections
for each municipality
and 12 S-curve models

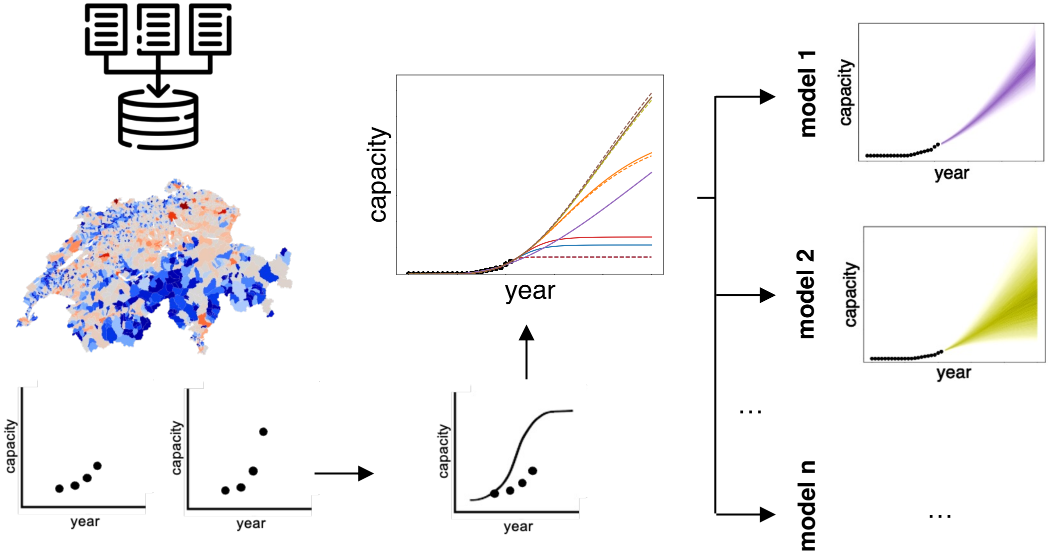


4-step method to create probabilistic projections

0) Data preparation for each municipality and technology diffusion

1) Deterministic projections for each municipality and 12 S-curve models

2) Probabilistic projections for each municipality and each S-curve model



4-step method to create probabilistic projections

0) Data preparation
for each municipality
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1) Deterministic projections
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2) Probabilistic projections
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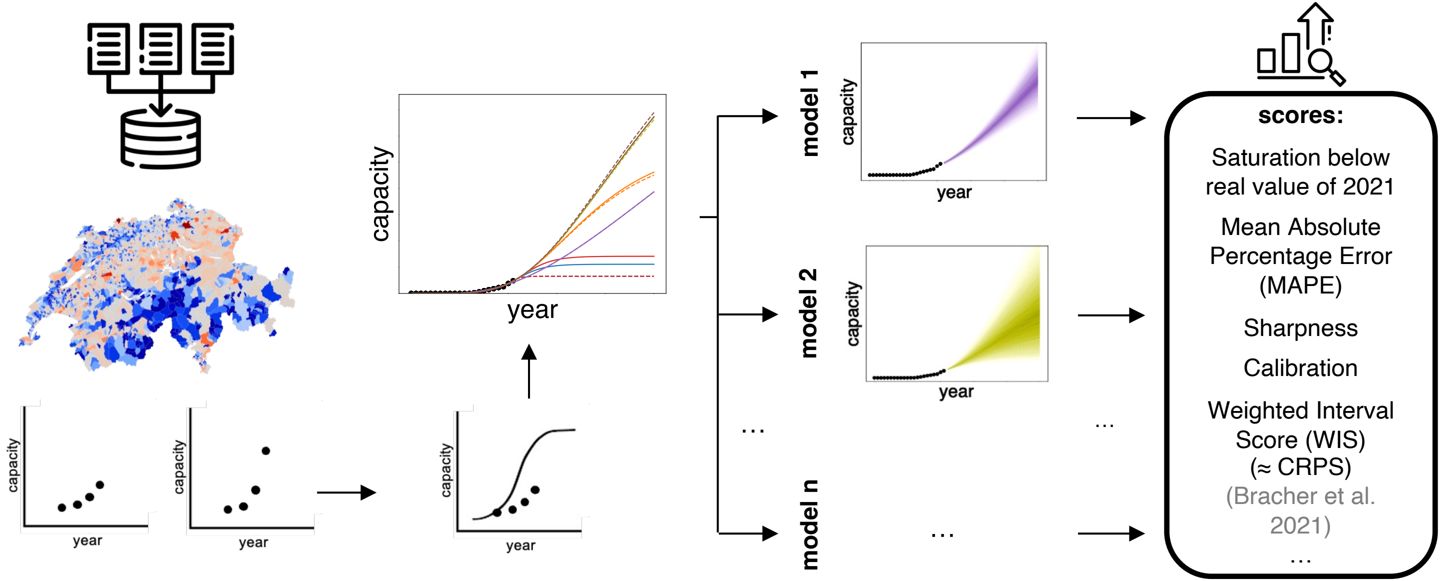
and each S-curve model

3) Performance evaluation
of each S-curve model
using *hindcasting*



Bracher, J. *et al.* (2021), *PLOS Computational Biology*, 17(2). Sun, X. *et al.* (2017), *Journal of Meteorological Research*, 31(3), 502–513.

CRPS: Continuous Ranked Probability Score

4-step method to create probabilistic projections

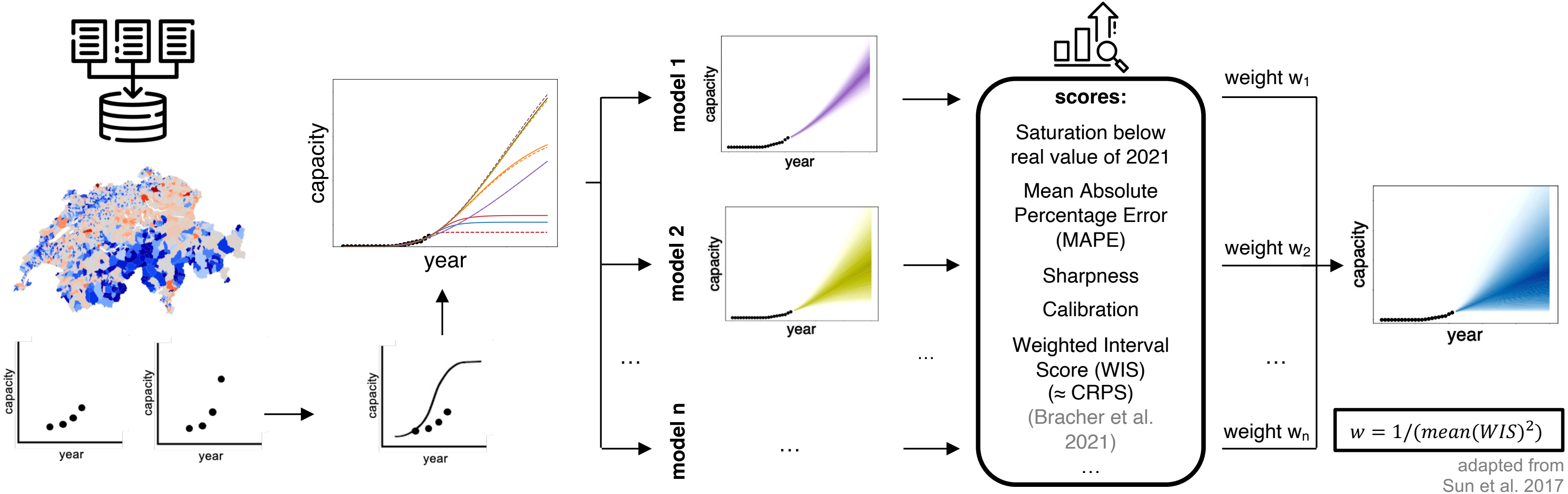
0) Data preparation for each municipality and technology diffusion

1) Deterministic projections for each municipality and 12 S-curve models

2) Probabilistic projections for each municipality and each S-curve model

3) Performance evaluation of each S-curve model using *hindcasting*

4) Probabilistic projections for each municipality using weighted models



adapted from Sun et al. 2017

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CRPS: Continuous Ranked Probability Score

Hindcasting

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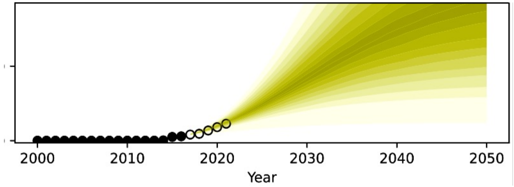
Retrospective model testing

- Evaluate the performance of models by comparing the calculated projections with real historical observations

- In each iteration:
  Split historical time series data in training set and out-of-sample test set



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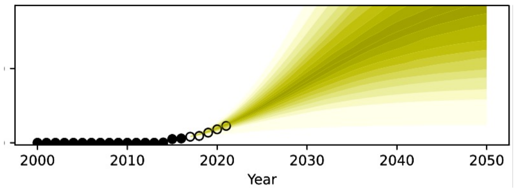
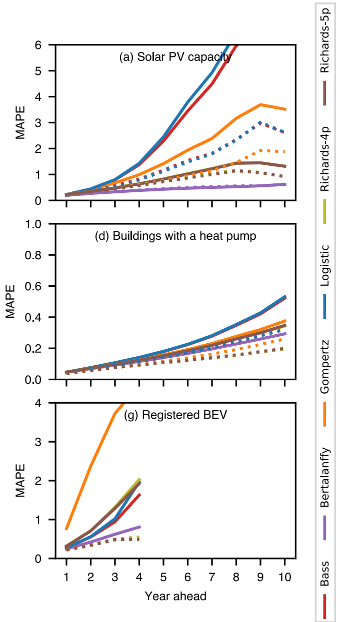


Solar PV
Train: 2000 – (2011 … 2021)
Test: (2012 … 2021) – 2021
→ 1- to 10-year-ahead

Heat pumps
Train: 2001 – (2011 … 2021)
Test: (2012 … 2021) – 2021
→ 1- to 10-year-ahead

BEV
Train: 2015 – (2017 … 2021)
Test: (2018 … 2021) – 2021
→ 1- to 4-year-ahead



MAPE: Mean Absolute Percentage Error

Probabilistic vs. deterministic projection

Probabilistic vs. deterministic projection

RES

model	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73	0.27	0.18	0.10	0.35	0.65	0.31	14.10	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52	0.54	0.29	0.13	0.42	0.58	0.37	7.40	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26	0.23	0.18	0.10	1.00	0.00	> 10	1.32	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29	0.28	0.59	0.10	0.61	0.39	0.39	7.72	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56	0.39	0.74	0.11	1.00	0.00	> 10	3.70	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69
	Solar PV capacity							Buildings with a heat pump							Registered BEV						

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Probabilistic vs. deterministic projection

RES

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Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
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Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69
	Solar PV capacity							Buildings with a heat pump							Registered BEV						

Findings

→ Higher accuracy with probabilistic projections

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

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Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52

model	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Buildings with a heat pump							
Bass	0.50	0.23	0.12	0.28	0.72	0.36	8.85
Bertalanffy	0.25	0.16	0.10	0.33	0.67	0.31	14.58
Gompertz	0.39	0.19	0.11	0.34	0.66	0.33	11.31
Logistic	0.52	0.24	0.13	0.28	0.72	0.36	8.87
Richards-4p	0.27	0.18	0.10	0.35	0.65	0.31	14.21
Richards-5p	0.27	0.18	0.10	0.35	0.65	0.31	14.10
Bi-Bass	0.54	0.29	0.13	0.42	0.58	0.37	7.40
Bi-Bertalanffy	0.23	0.18	0.10	1.00	0.00	> 10	1.32
Bi-Gompertz	0.28	0.59	0.10	0.61	0.39	0.39	7.72
Bi-Logistic	0.39	0.74	0.11	1.00	0.00	> 10	3.70
Bi-Richards-4p	0.28	0.23	0.10	1.00	0.00	> 10	6.90
Bi-Richards-5p	0.30	0.23	0.10	1.00	0.00	> 10	1.05

model	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Registered BEV							
Bass	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.11	1.03	0.31	1.00	0.00	> 10	6.69

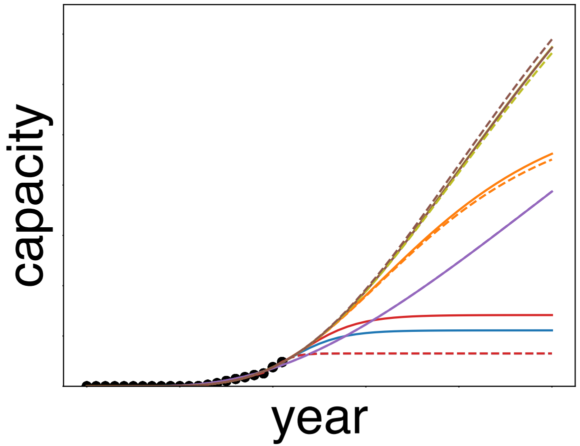
Findings

- → Higher accuracy with probabilistic projections
- → Underestimation of deterministic projections

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Probabilistic vs. deterministic projection

model	share of curves saturating below real value of 2021	MAPE (deterministic projection)
Bass	0.62	3.24
Bertalanffy	0.04	0.43
Gompertz	0.54	1.84
Logistic	0.63	3.47
Richards-4p	0.09	0.90
Richards-5p	0.11	0.89
Bi-Bass	0.48	2.99
Bi-Bertalanffy	0.04	0.43
Bi-Gompertz	0.35	4.46
Bi-Logistic	0.42	6.47
Bi-Richards-4p	0.11	1.04
Bi-Richards-5p	0.05	1.06



Findings

- → Higher accuracy with probabilistic projections
- → Underestimation of deterministic projections

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Comparison of S-curve models

Comparison of S-curve models

model	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73	0.27	0.18	0.10	0.35	0.65	0.31	14.10	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52	0.54	0.29	0.13	0.42	0.58	0.37	7.40	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26	0.23	0.18	0.10	1.00	0.00	> 10	1.32	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29	0.28	0.59	0.10	0.61	0.39	0.39	7.72	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56	0.39	0.74	0.11	1.00	0.00	> 10	3.70	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69
	Solar PV capacity							Buildings with a heat pump							Registered BEV						

Sun, X. *et al.* (2017), *Journal of Meteorological Research*, 31(3), 502–513.

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Comparison of S-curve models

model	Solar PV capacity							Buildings with a heat pump							Registered BEV						
	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73	0.27	0.18	0.10	0.35	0.65	0.31	14.10	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52	0.54	0.29	0.13	0.42	0.58	0.37	7.40	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26	0.23	0.18	0.10	1.00	0.00	> 10	1.32	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29	0.28	0.59	0.10	0.61	0.39	0.39	7.72	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56	0.39	0.74	0.11	1.00	0.00	> 10	3.70	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69

Findings

→ Higher accuracy and precision for Bertalanffy and Richards

Sun, X. *et al.* (2017), *Journal of Meteorological Research*, 31(3), 502–513.

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Comparison of S-curve models

model	Solar PV capacity: share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	Buildings with a heat pump: share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	Registered BEV: share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73	0.27	0.18	0.10	0.35	0.65	0.31	14.10	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52	0.54	0.29	0.13	0.42	0.58	0.37	7.40	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26	0.23	0.18	0.10	1.00	0.00	> 10	1.32	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29	0.28	0.59	0.10	0.61	0.39	0.39	7.72	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56	0.39	0.74	0.11	1.00	0.00	> 10	3.70	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69

Findings

- → Higher accuracy and precision for Bertalanffy and Richards
- → Higher weights for Bertalanffy and Richards

Weight:

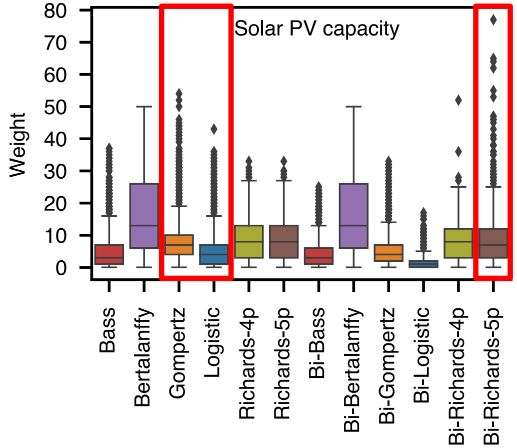
$$w = 1/(mean(WIS)^2)$$

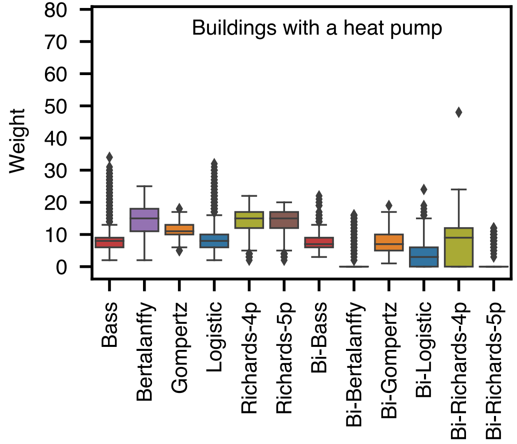
adapted from Sun et al. 2017

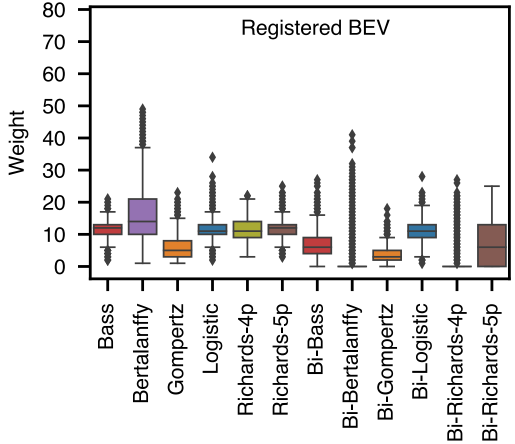
Sun, X. *et al.* (2017), *Journal of Meteorological Research*, 31(3), 502–513.

MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Comparison of S-curve models







Comparison of S-curve models

model	Solar PV capacity						
	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52

model	Buildings with a heat pump						
	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.50	0.23	0.12	0.28	0.72	0.36	8.85
Bertalanffy	0.25	0.16	0.10	0.33	0.67	0.31	14.58
Gompertz	0.39	0.19	0.11	0.34	0.66	0.33	11.31
Logistic	0.52	0.24	0.13	0.28	0.72	0.36	8.87
Richards-4p	0.27	0.18	0.10	0.35	0.65	0.31	14.21
Richards-5p	0.27	0.18	0.10	0.35	0.65	0.31	14.10
Bi-Bass	0.54	0.29	0.13	0.42	0.58	0.37	7.40
Bi-Bertalanffy	0.23	0.18	0.10	1.00	0.00	> 10	1.32
Bi-Gompertz	0.28	0.59	0.10	0.61	0.39	0.39	7.72
Bi-Logistic	0.39	0.74	0.11	1.00	0.00	> 10	3.70
Bi-Richards-4p	0.28	0.23	0.10	1.00	0.00	> 10	6.90
Bi-Richards-5p	0.30	0.23	0.10	1.00	0.00	> 10	1.05

model	Registered BEV						
	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.11	1.03	0.31	1.00	0.00	> 10	6.69

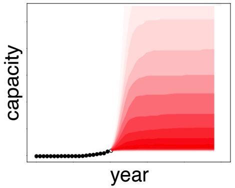
MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Comparison of S-curve models

model	Solar PV capacity							Buildings with a heat pump							Registered BEV						
	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
Richards-5p	0.11	0.89	0.55	0.14	0.86	1.98	8.73	0.27	0.18	0.10	0.35	0.65	0.31	14.10	0.21	1.06	0.33	0.33	0.67	1.13	11.45
Bi-Bass	0.48	2.99	0.90	0.36	0.64	3.08	4.52	0.54	0.29	0.13	0.42	0.58	0.37	7.40	0.23	1.89	0.34	0.70	0.30	1.45	6.94
Bi-Bertalanffy	0.04	0.43	0.37	0.06	0.94	1.49	17.26	0.23	0.18	0.10	1.00	0.00	> 10	1.32	0.13	0.56	0.30	1.00	0.00	> 10	1.61
Bi-Gompertz	0.35	4.46	0.64	0.69	0.31	3.03	5.29	0.28	0.59	0.10	0.61	0.39	0.39	7.72	0.17	5.05	0.32	1.00	0.00	2.36	3.42
Bi-Logistic	0.42	6.47	0.95	0.67	0.33	6.30	1.56	0.39	0.74	0.11	1.00	0.00	> 10	3.70	0.24	0.95	0.33	0.44	0.56	1.08	11.09
Bi-Richards-4p	0.11	1.04	0.57	0.17	0.83	1.98	8.22	0.28	0.23	0.10	1.00	0.00	> 10	6.90	0.09	0.97	0.30	1.00	0.00	> 10	2.35
Bi-Richards-5p	0.05	1.06	0.58	0.16	0.84	2.03	8.52	0.30	0.23	0.10	1.00	0.00	> 10	1.05	0.11	1.03	0.31	1.00	0.00	> 10	6.69

Findings

→ High sharpness penalty: broad intervals



MAPE: Mean Absolute Percentage Error, WIS: Weighted Interval Score

Comparison of S-curve models

model	Solar PV capacity							Buildings with a heat pump							Registered BEV						
	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight	share of curves saturating below real value of 2021	MAPE (deterministic projection)	MAPE (probabilistic projection)	sharpness / WIS	calibration / WIS	WIS	weight
Bass	0.62	3.24	0.91	0.28	0.72	3.12	5.47	0.50	0.23	0.12	0.28	0.72	0.36	8.85	0.25	0.85	0.34	0.39	0.61	1.09	11.54
Bertalanffy	0.04	0.43	0.37	0.07	0.93	1.49	17.37	0.25	0.16	0.10	0.33	0.67	0.31	14.58	0.23	0.52	0.33	0.22	0.78	1.07	16.20
Gompertz	0.54	1.84	0.65	0.32	0.68	2.08	8.72	0.39	0.19	0.11	0.34	0.66	0.33	11.31	0.27	2.83	0.33	0.59	0.41	1.78	5.68
Logistic	0.63	3.47	0.89	0.27	0.73	3.10	5.64	0.52	0.24	0.13	0.28	0.72	0.36	8.87	0.28	0.96	0.33	0.35	0.65	1.08	11.47
Richards-4p	0.09	0.90	0.57	0.13	0.87	2.04	8.56	0.27	0.18	0.10	0.35	0.65	0.31	14.21	0.24	1.09	0.33	0.30	0.70	1.13	11.56
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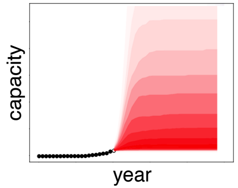
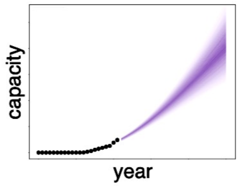
→ High sharpness penalty: broad intervals

→ High calibration penalty: overconfidence





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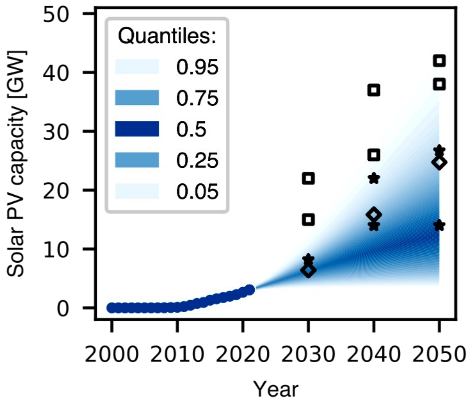
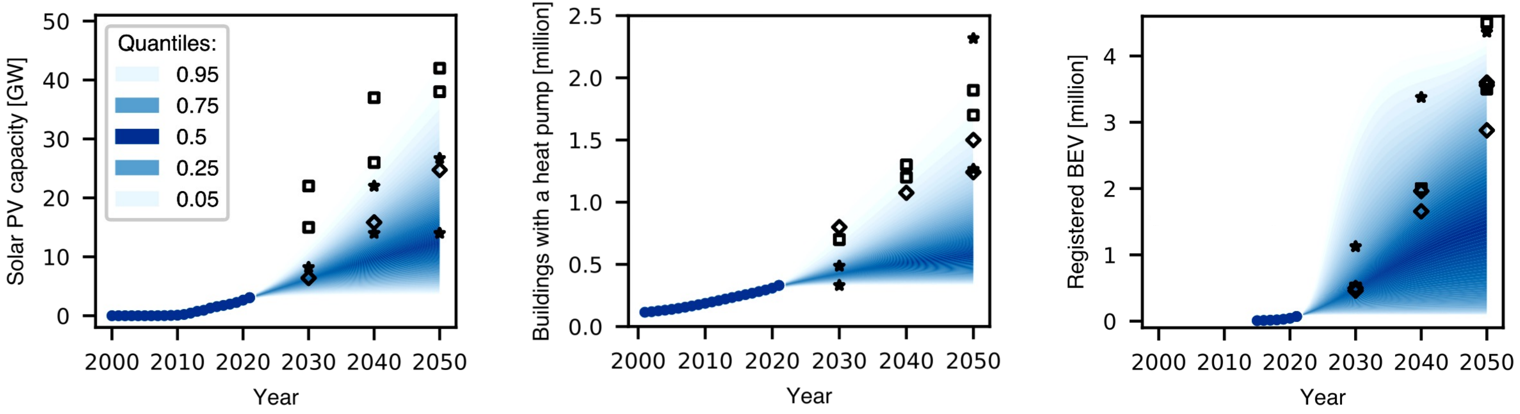
Technology diffusion in Switzerland

Technology diffusion in Switzerland



(◊) Prognos et al. 2020
(□) Consentec et al. 2022
(*) Verband Schweizerischer Elektrizitätsunternehmen (VSE) 2022

Technology diffusion in Switzerland



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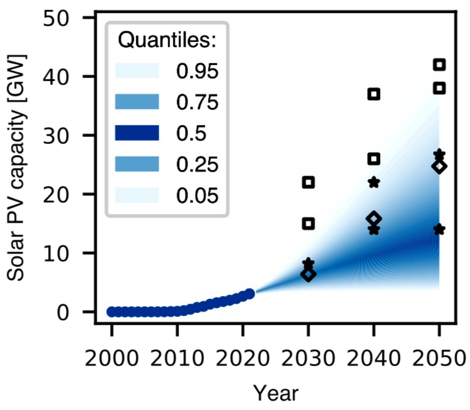

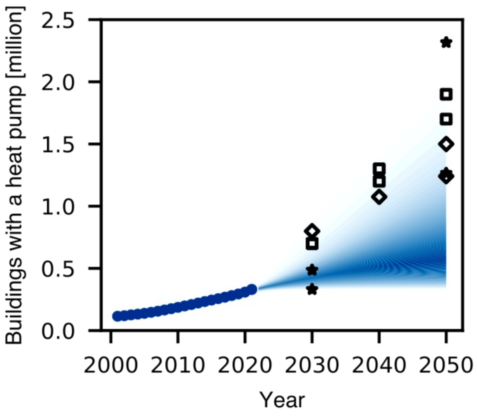

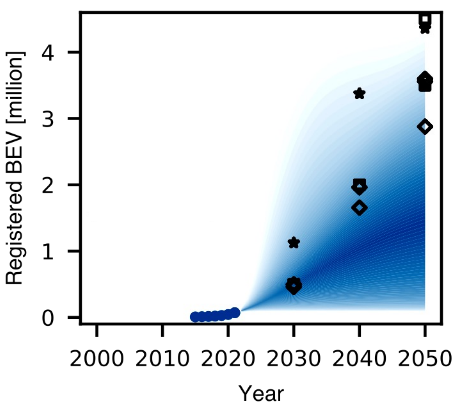

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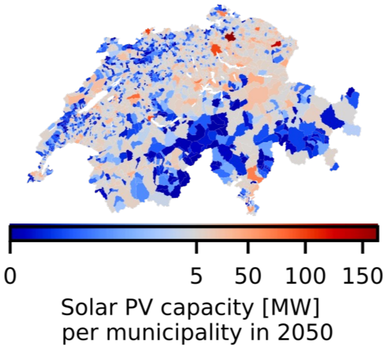

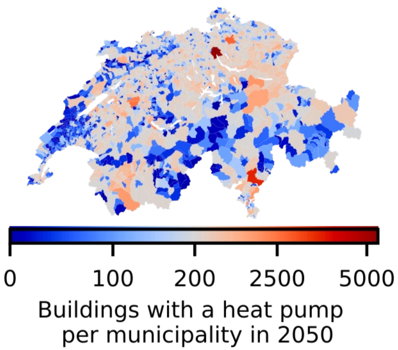

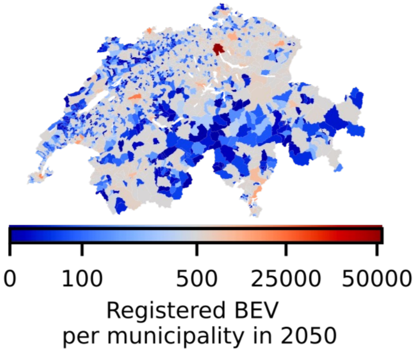

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RES

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  - → Anticipation of future technology diffusion with higher accuracy
  - → Compensation for underestimation and low saturation

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- **Highest capacities** of solar PV, heat pumps, and BEV are most likely **near population centers**

Key implications on methods

For decision-makers

For modelers

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- **Choice of models, criteria, and weighting**

Thank you!

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