Synthesis of multi-year PV production data using generative adversarial networks

Gregory M. Kimball, **Camille M. Pauchet, Rasoul Ghadami, Alberto Fonts Zaragoza**

SunPower Corporation, Richmond, CA 94804, USA

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Synthesis of multi-year PV production data using generative adversarial networks

- Insolation variability in the United States
- Synthesis of PV production data
  - Rule-based methods
  - Generative adversarial networks
- Evaluating generated data
  - Insolation statistics
  - Demand charge management

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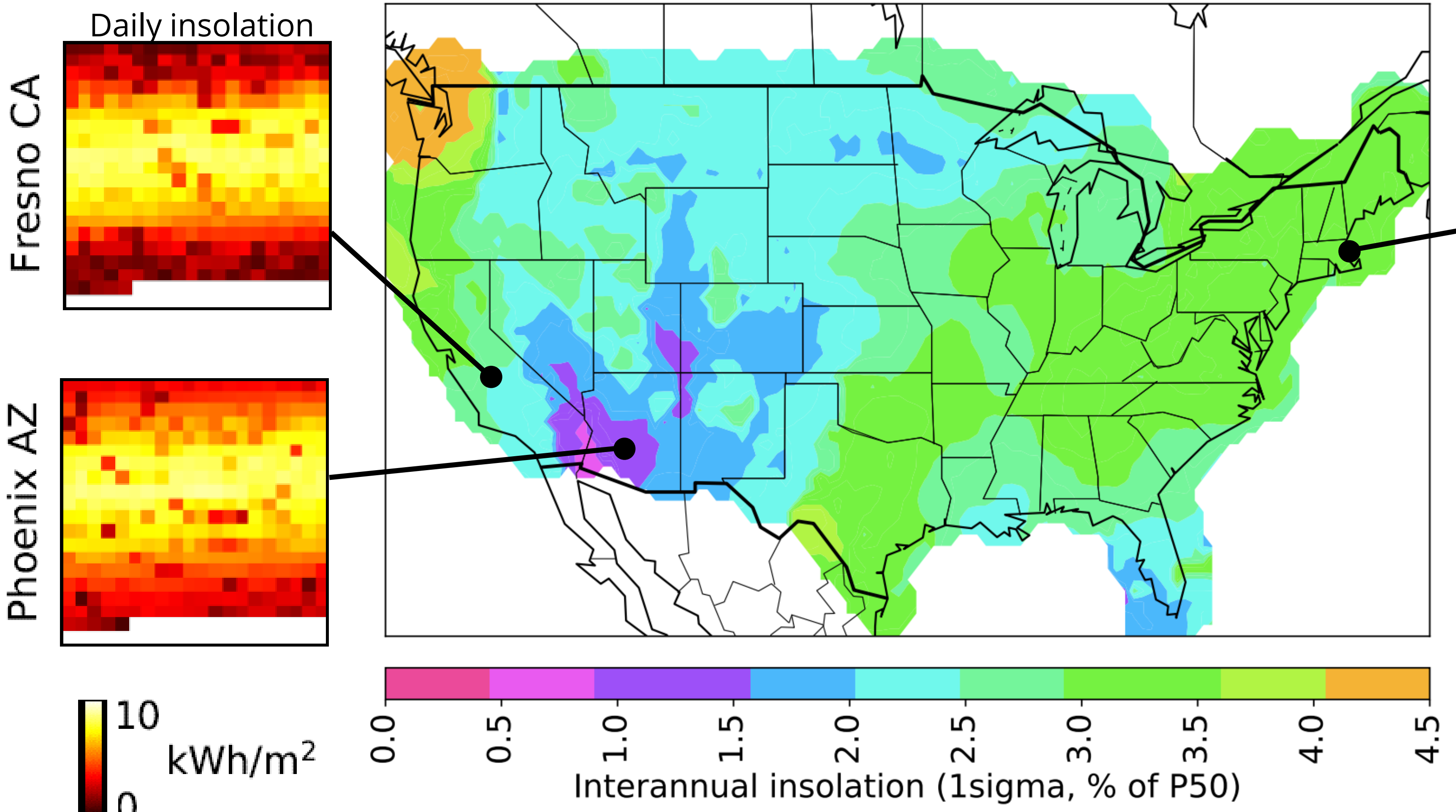
Insolation variability in the United States



Annual insolation varies 1-4% per year across the United States.

Insolation data source: National Solar Radiation Database https://nsrdb.nrel.gov/

G. Kimball, C. Chaudhari, P. Keelin, J. Dise, M. Grammatico, and B. Bourne, “Improved model of solar resource variability based on aggregation by region and climate zone,” in IEEE Photovoltaics Specialists Conference, pp. 2571–2574, June 2018.

Rule-based data synthesis

Rule-based method “V2”

Inputs

15-min, one year (n=35040)

Lat, Lon

Shuffle days*

Annual target (±X%)

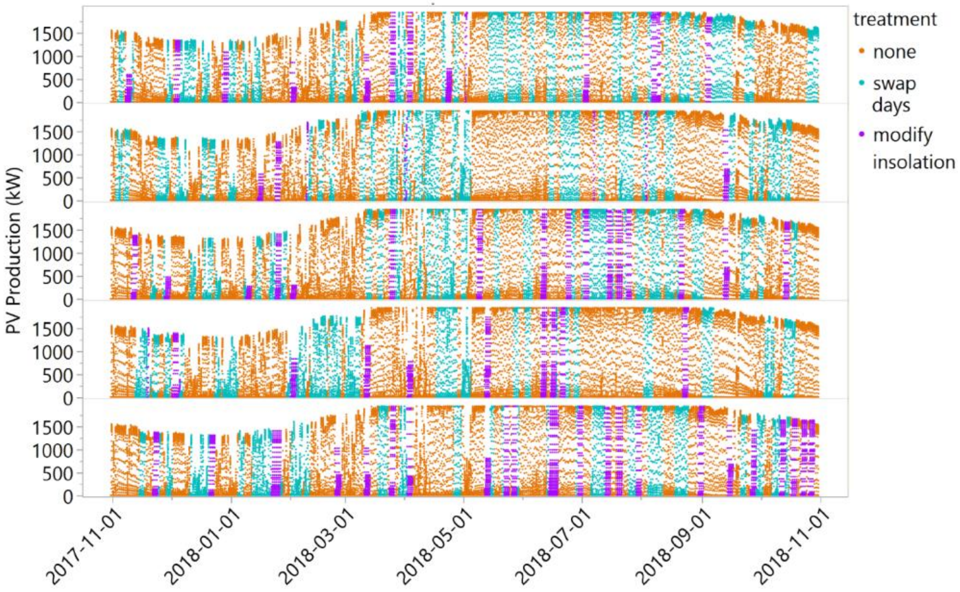
Copy days to meet annual target

Outputs

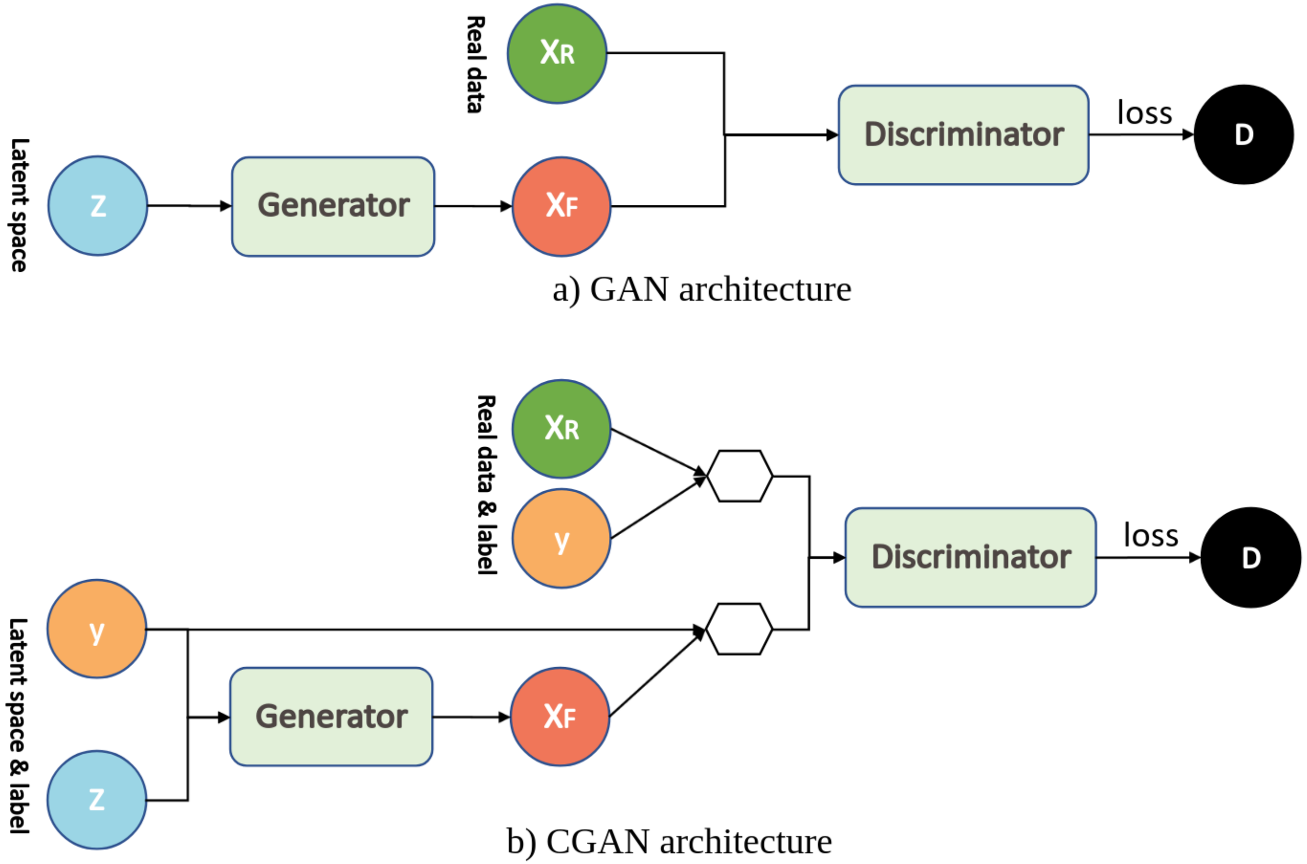
15-min, one year (n=35040)

* “V1” method skips the step “Shuffle days”

Methods based on shuffling and copying days yield reasonable synthetic data.



Generative adversarial network, pt1



a) GAN architecture

b) CGAN architecture

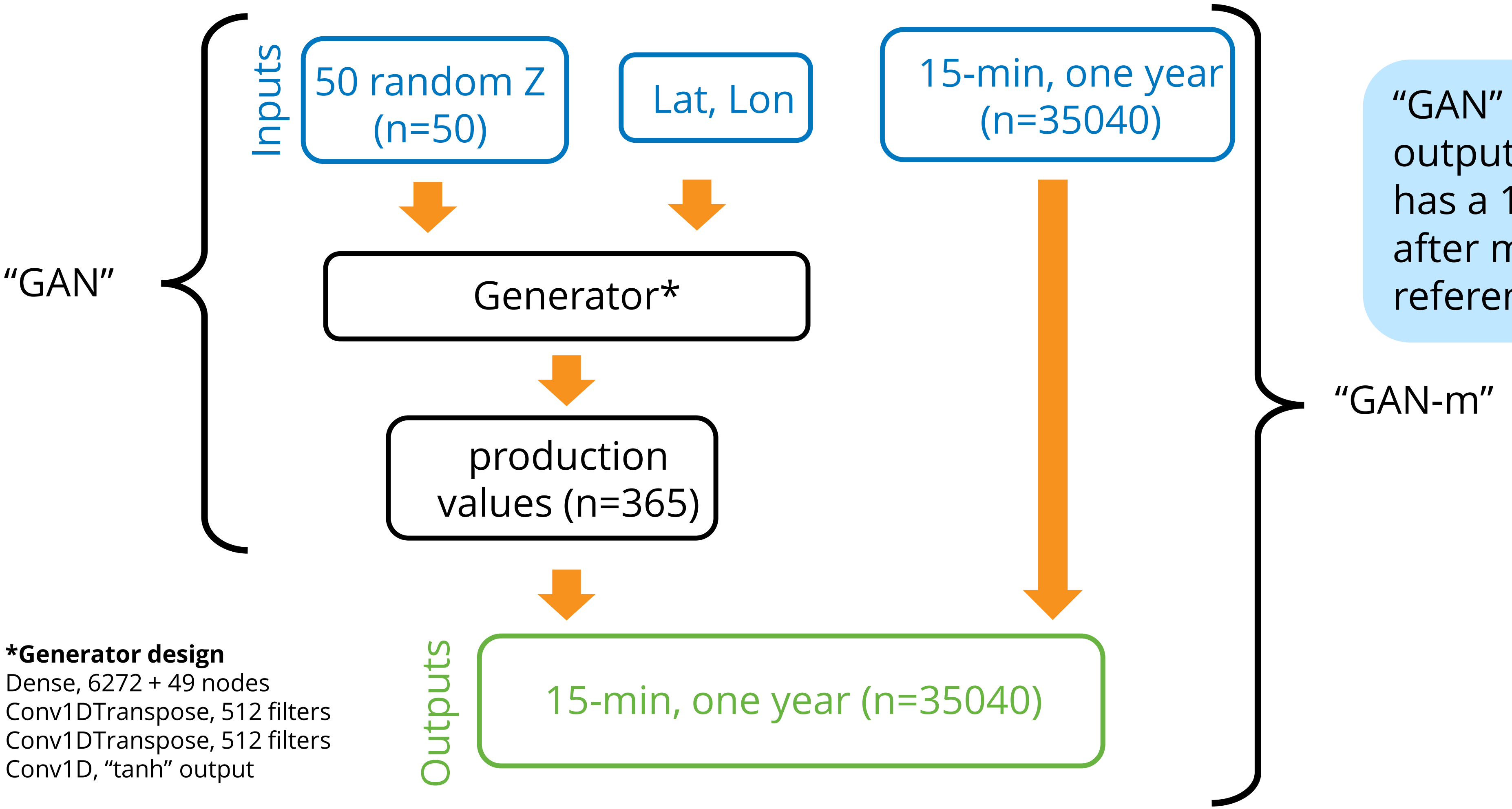
GANs are a flexible design pattern for generating diverse sets of one-year PV production data.

Reference labels

X_R: Real production data
X_F: Fake production data
Z: random values
y: site location

I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley,S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks,"2014.
Z. Lin, A. Jain, C. Wang, G. Fanti, and V. Sekar, "Using GANs for Sharing Networked Time Series Data: Challenges, Initial Promise, and Open Questions," Proceedings of the ACM Internet Measurement Conference, pp. 464–483, Oct. 2020. arXiv: 1909.13403.
Image credit: https://medium.com/@ma.bagheri/a-tutorial-on-conditional-generative-adversarial-nets-keras-implementation-694dcafa6282

Generative adversarial network, pt 2



"GAN" model has a daily output (n=365) and "GAN-m" has a 15-min output (n=35040) after matching days in the reference data set.

***Generator design**
Dense, 6272 + 49 nodes
Conv1DTranspose, 512 filters
Conv1DTranspose, 512 filters
Conv1D, "tanh" output

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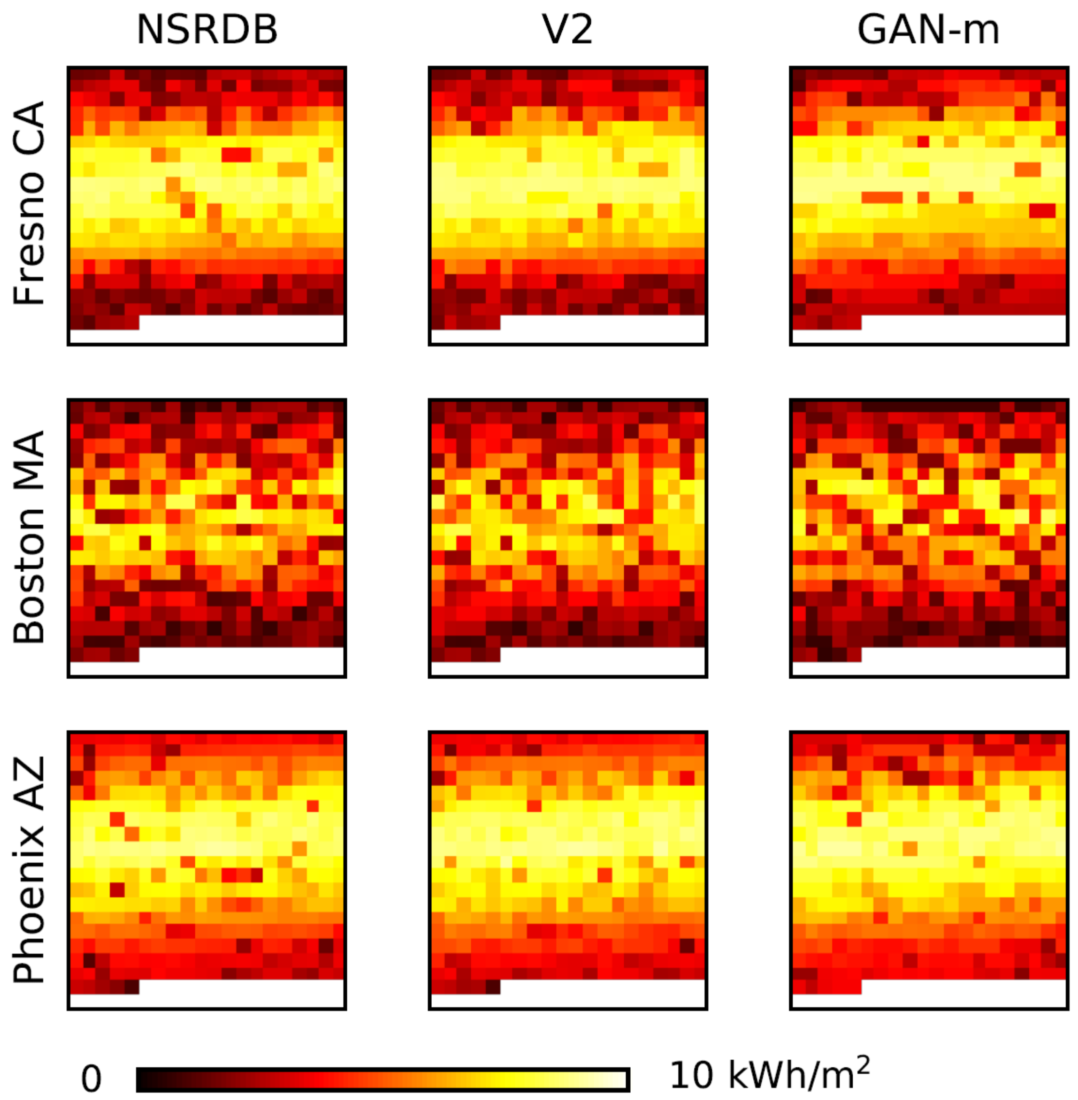
Synthetic insolation data



One year of daily insolation data (n=365) shown as 20x20 image

By inspection, rule-based and machine learning models generate reasonable insolation data

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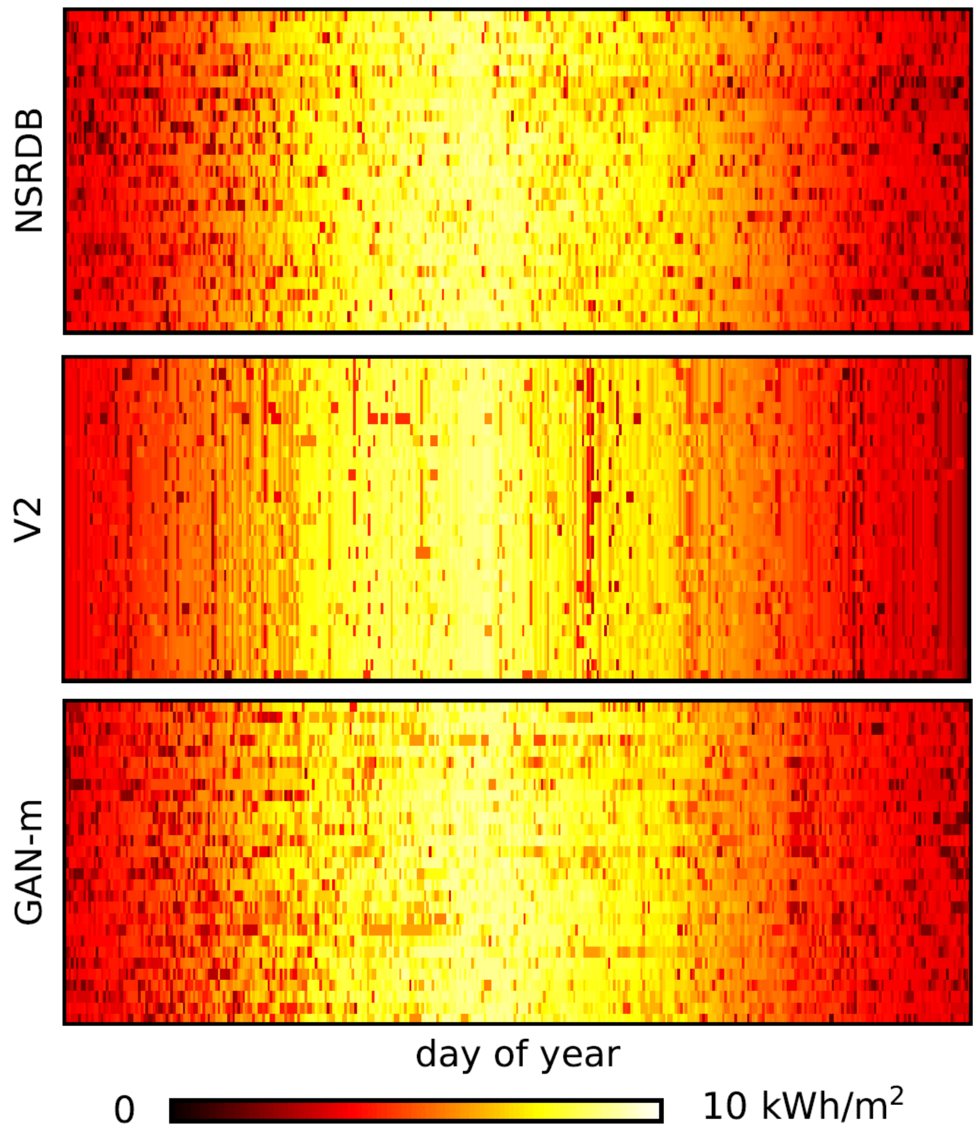
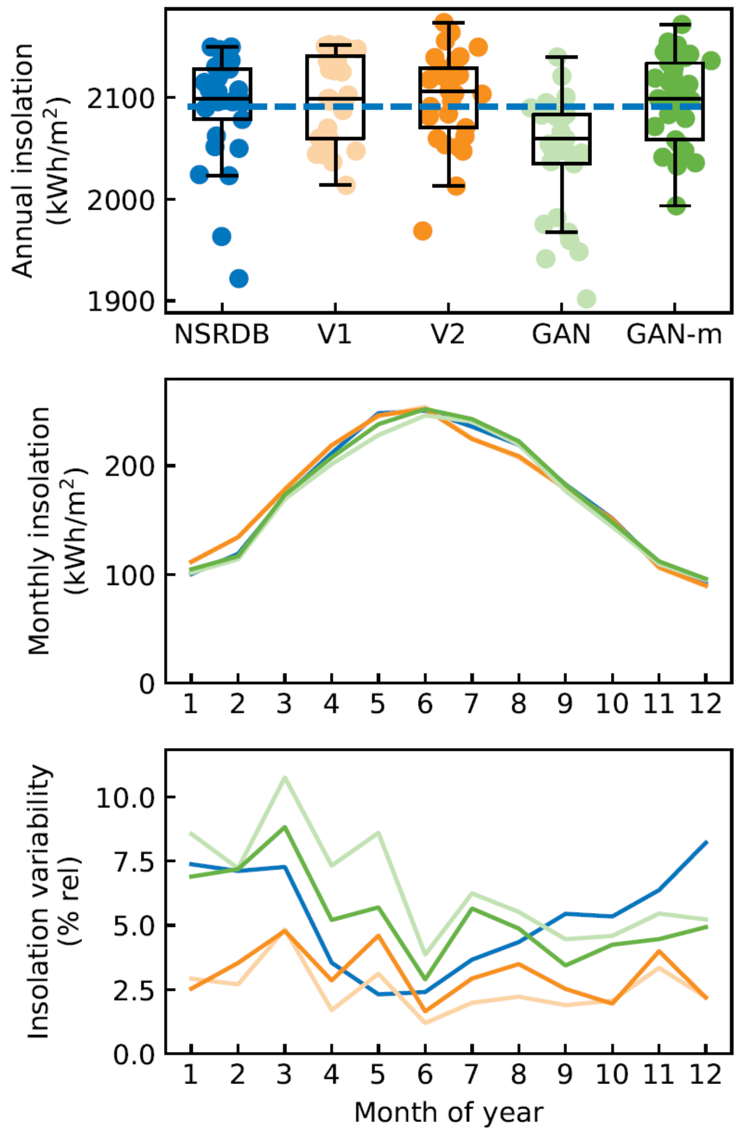
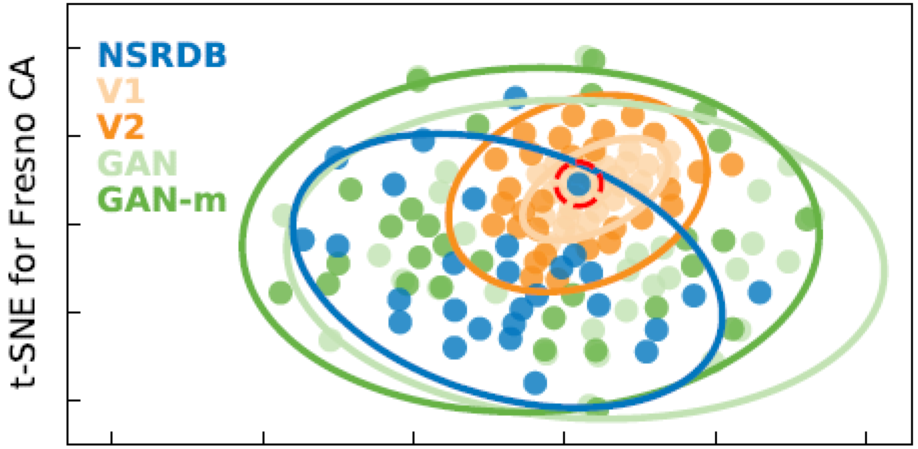
Validation example: Phoenix AZ

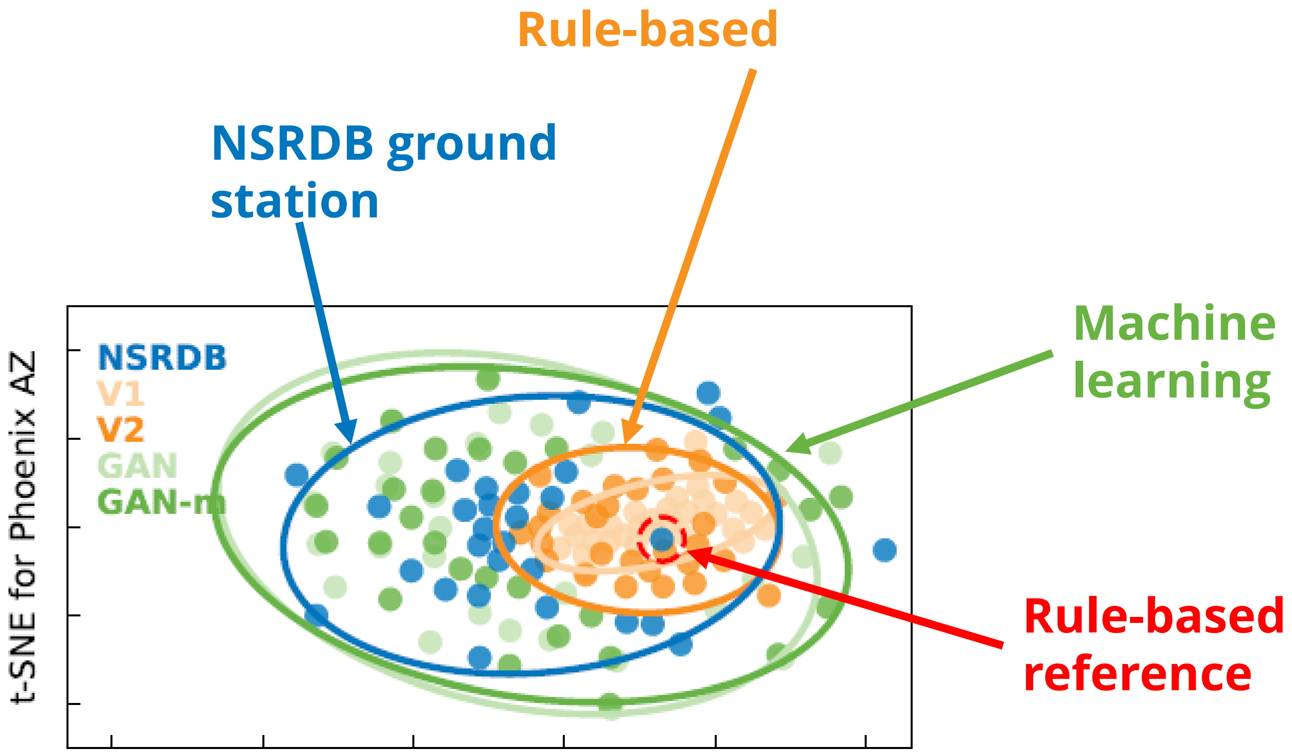


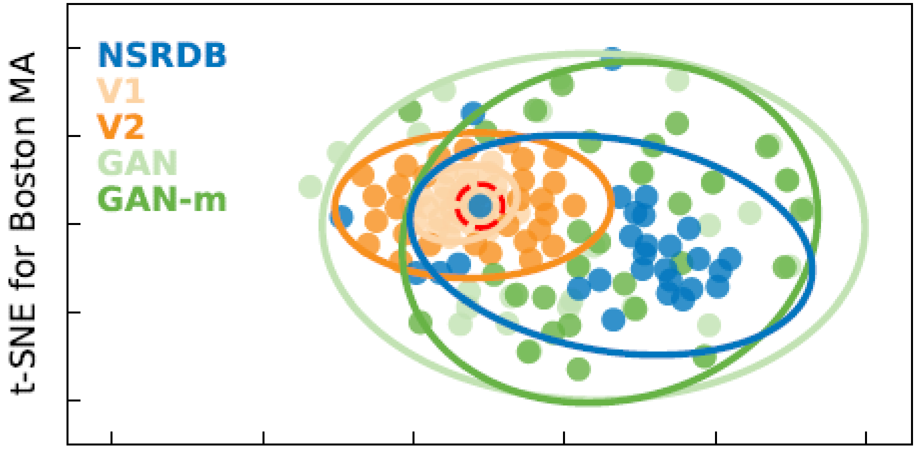


Annual and monthly insolation statistics show good correspondence over the 29-year analysis period.

Clustering analysis



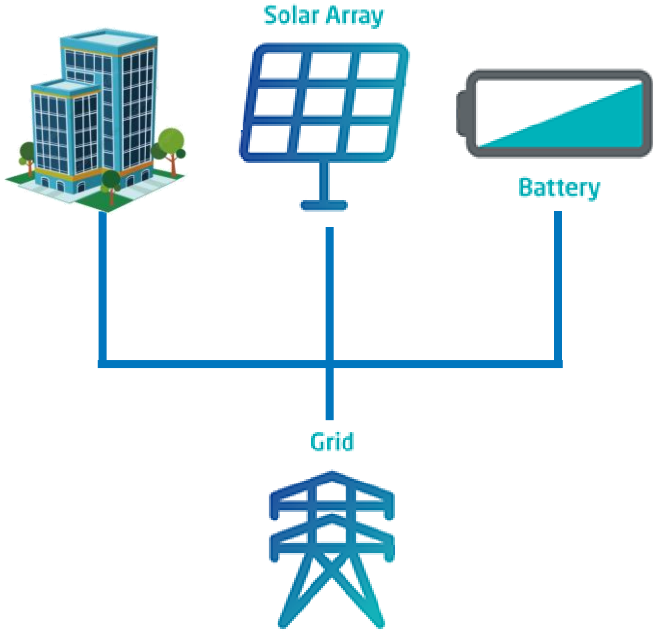


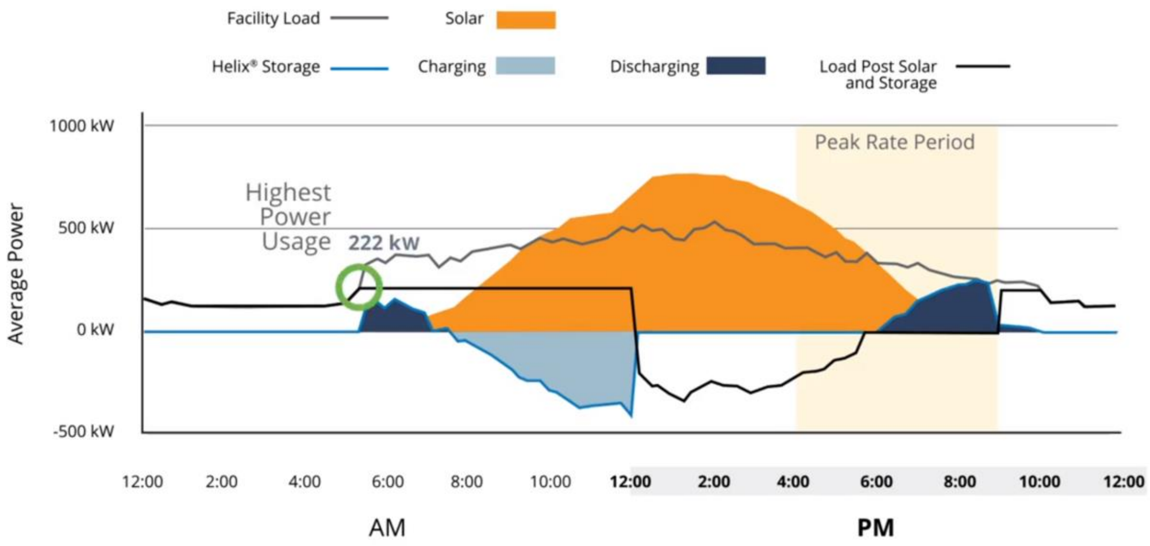


t-Distributed Neighbor Embedding (t-SNE) shows lower diversity for rule-based methods, and higher diversity for machine learning methods.

L. v. d. Maaten and G. Hinton, “Visualizing Data using t-SNE,”Journal of Machine Learning Research, vol. 9, no. 86, pp. 2579–2605, 2008.

Demand charge management analysis



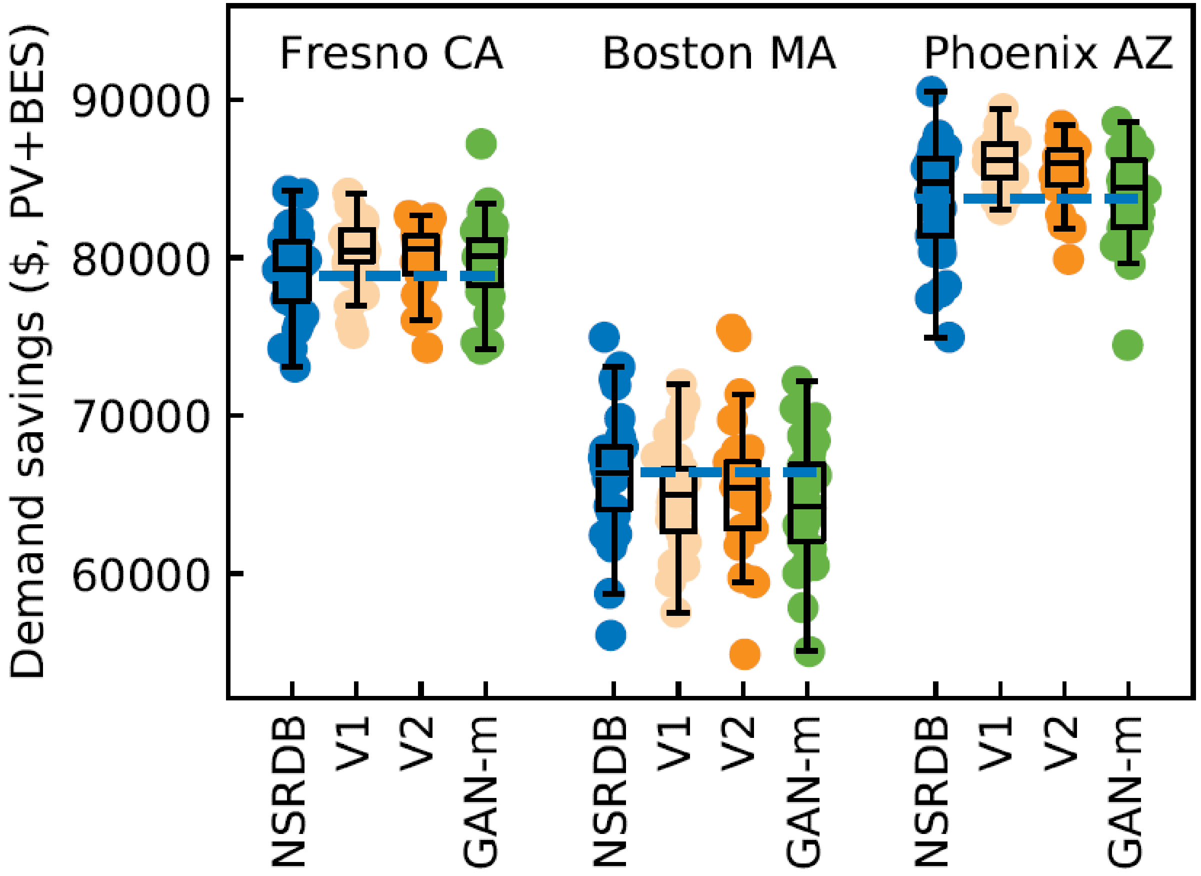


Solar + Storage systems reduce retail demand charges by predicting PV production and optimizing Battery dispatch.

https://www.youtube.com/watch?v=sy6Vvt9pfAI&feature=youtu.be
B. P. Bhattarai, K. S. Myers, and J. W. Bush, "Reducing demand charges and onsite generation variability using behind-the-meter energy storage," in 2016 IEEE Conference on Technologies for Sustainability (SusTech),pp. 140–146, Oct. 2016.
N. R. Darghouth, G. Barbose, J. Zuboy, P. J. Gagnon, A. D. Mills, and L. Bird, "Demand charge savings from solar PV and energy storage," Energy Policy, vol. 146, p. 111766, Nov. 2020.

Demand charge savings by data source

Impact of PV production variability
on demand savings



Both rule-based and machine learning models of PV production generate demand charge savings results consistent with ground-station data.

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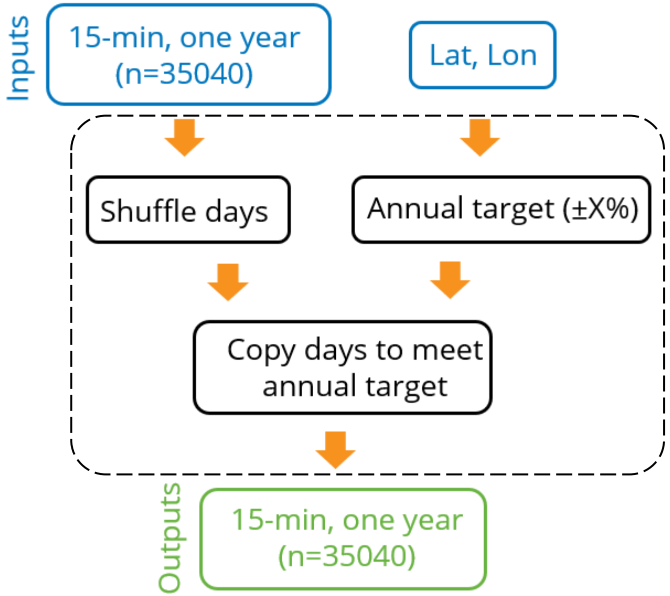
Summary

Data synthesis example

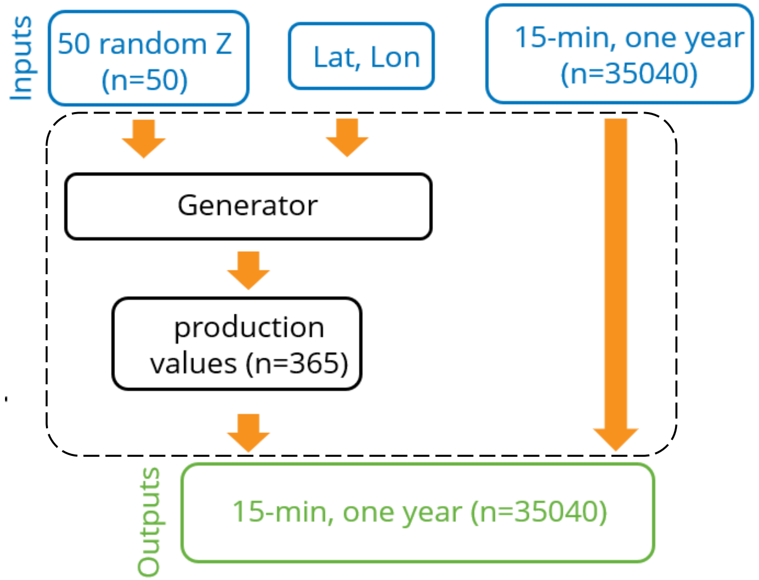
Inputs:
15-min irradiance data for 1974
Boston MA (42.32, -71.17)

Outputs:
X variants of 15-min irradiance data

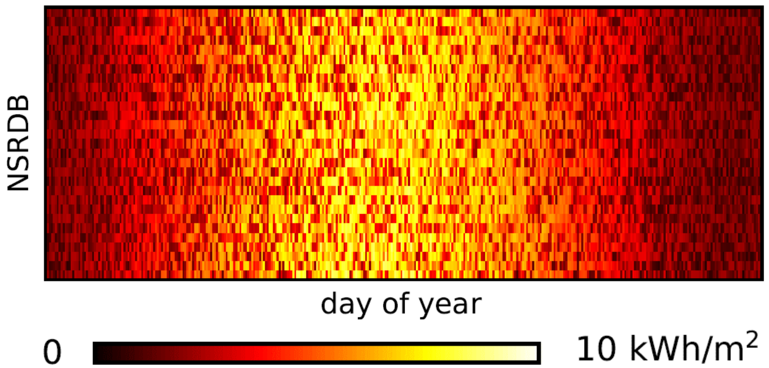
Rule-based method (V2)

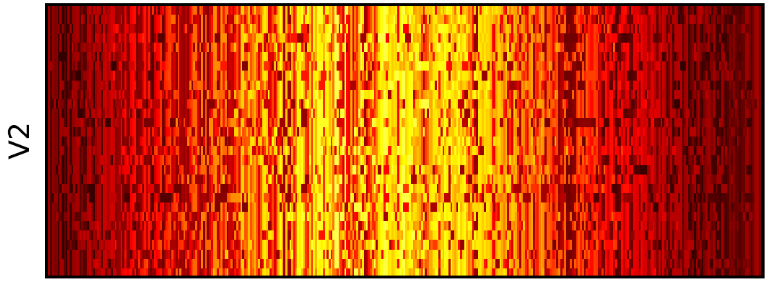


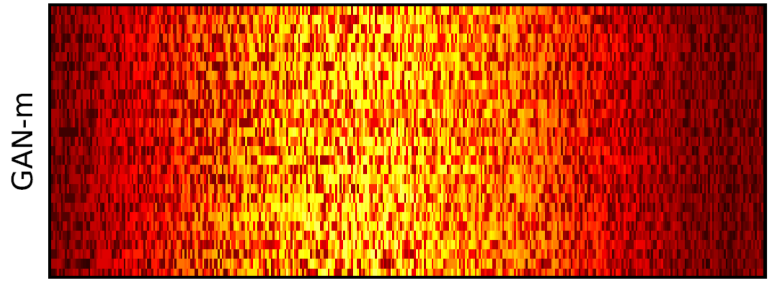
Machine learning method (GAN-m)



Reference (NSRDB, 1961-1990)







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