Neil Weisenfeld

Senior Energy Resilience Expert

ICF

U.S. Department of ENERGY | Office of Electricity

An increasing number of utilities are conducting climate vulnerability and adaptation studies

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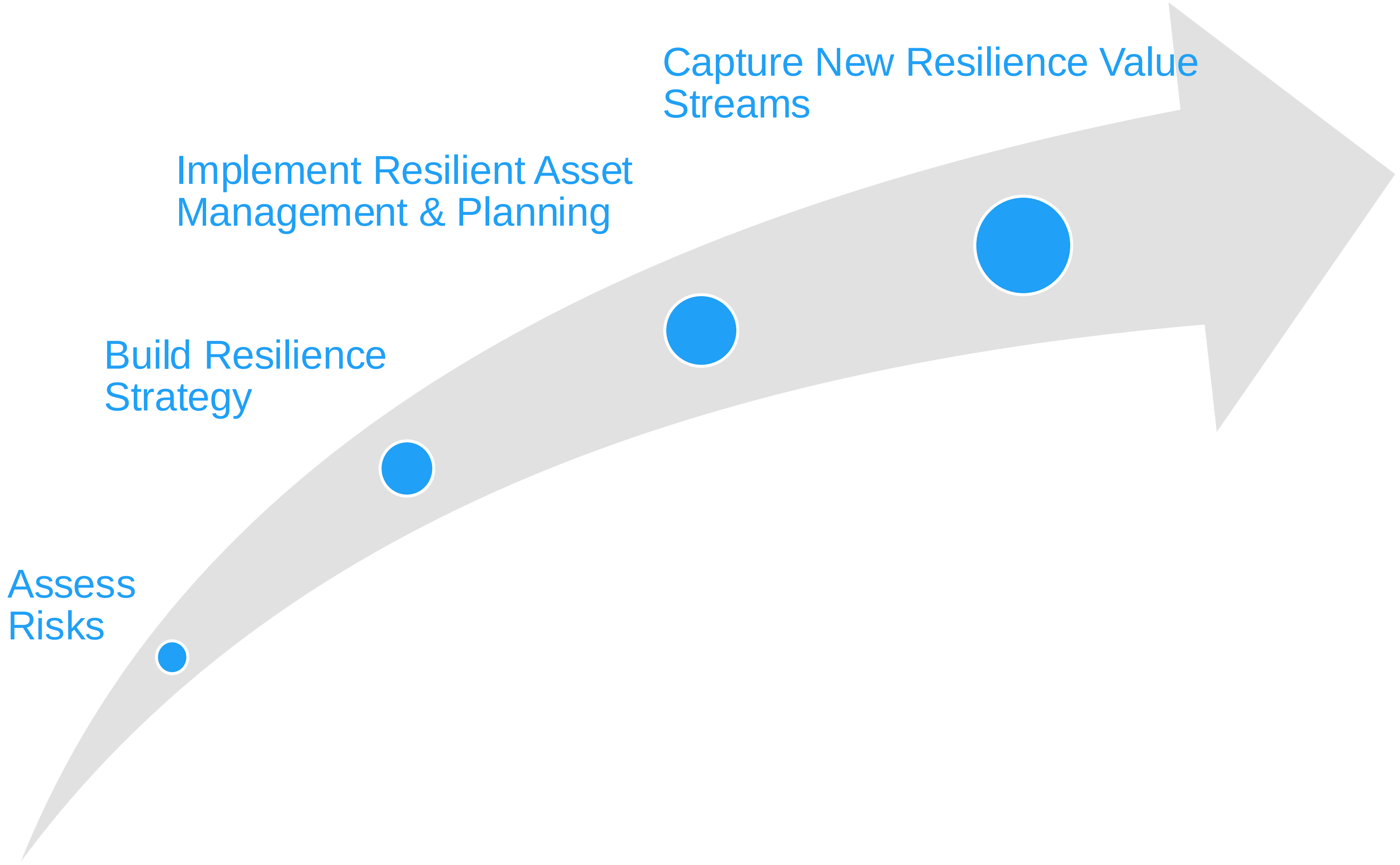
Building energy resilience includes risk assessment, strategy development and execution



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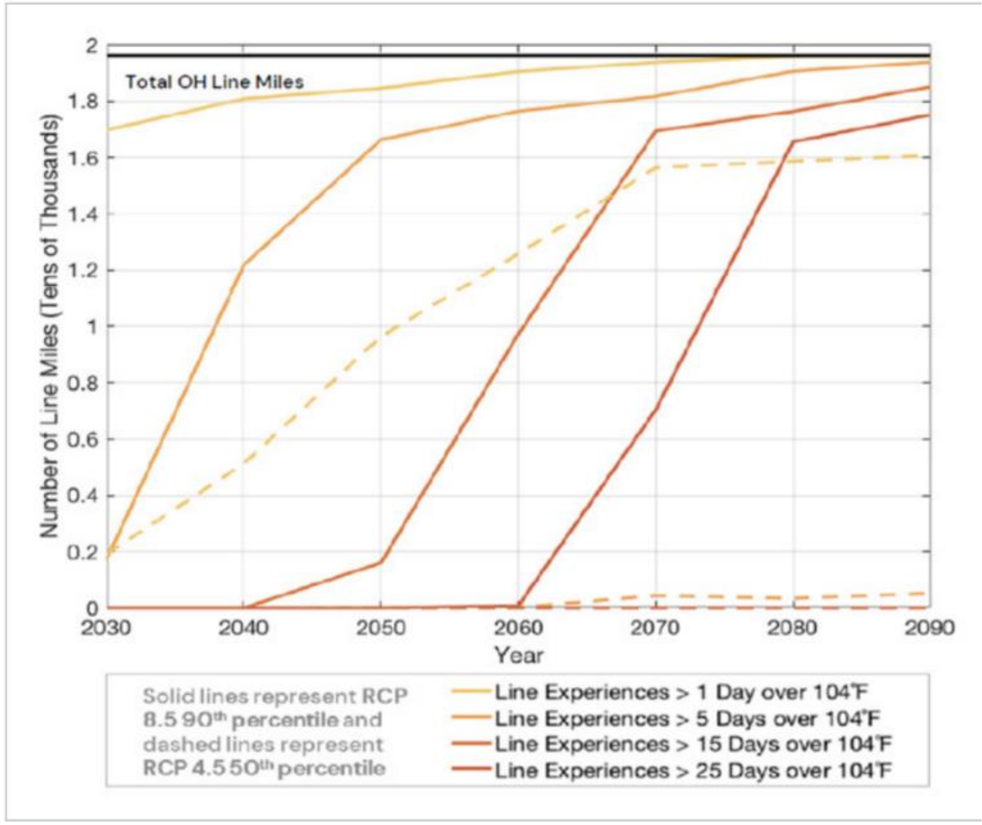
Project Example:

Duke Energy Climate Study



Goal

- Evaluate present-day infrastructure, design specifications, and procedures against expected climate change
- Identify adaptation options to build resilience

ICF's role

Climate Vulnerability Analysis | Climate Adaptation Planning | Stakeholder Engagement

- Developed downscaled climate projections out to mid-century for Duke's service territory
- Screened operations, planning and asset types for climate sensitivity
- Identified adaptation options to build resilience to climate risks
- Developed a prioritization framework which incorporates flexible adaptation and signposts to guide execution over the planning horizon

Outcomes

A publicly filed Climate Resilience and Adaptation Report that outlines a set of recommendations for potential system upgrades based on an understanding of the range of potential impacts due to climate change.

Some critical gaps regarding operational reliability and resilience

- Poor understanding of asset health and failure rates, often due to lack of data
- Deterministic design standards (IEEE, NESC), while climate risk is probabilistic
- Lack of a standard definition and way to measure resilience
- Gaps in understanding of extreme event risks.
  - For example, the 2021 Spokane, WA heat wave, which was a 1-in-1000 year event, resulted in significant overloads to Avista grid infrastructure which caused over 20,000 customer outages.

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Thank you

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Risk-Informed Analytics for Power Grid Resilience

at the asset, regional, and system level

Hiba Baroud, Ph.D.

Director (interim), Vanderbilt Center for Sustainability, Energy, and Climate (VSEC)

Civil and Environmental Engineering

Earth and Environmental Sciences

Computer Science

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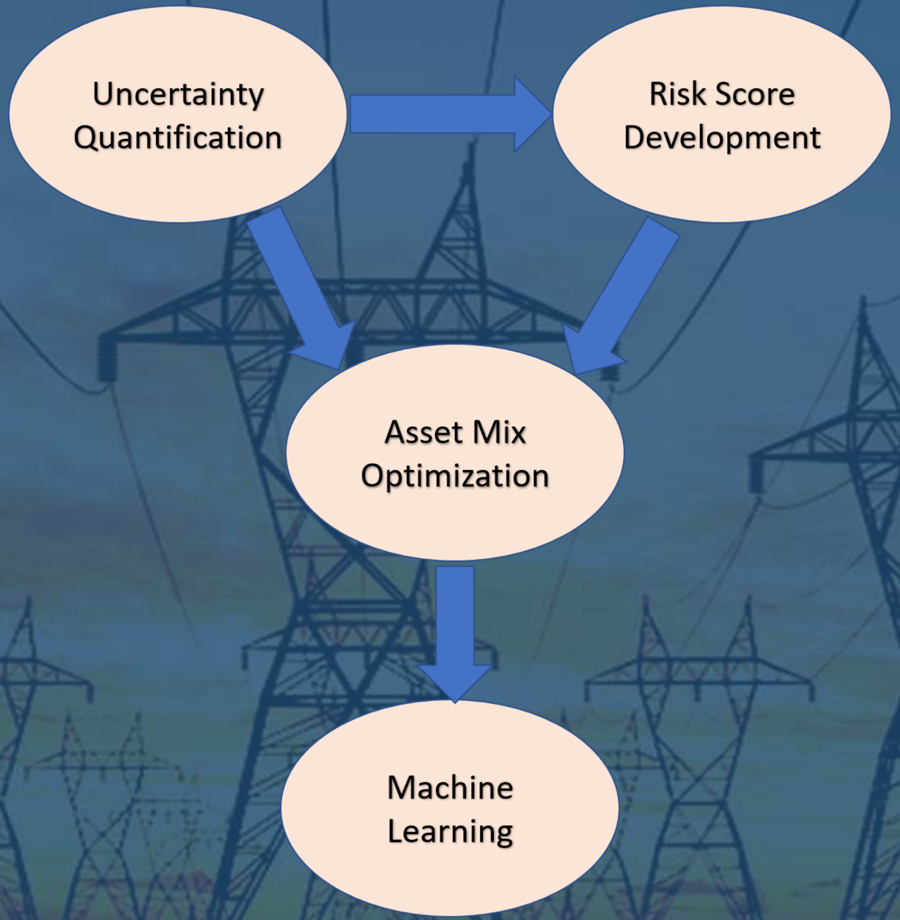
Predicting risk to inform decisions at the *asset level*

Risk-Aware Market Clearing for Power Systems

Objective: Power grid risk management

- Address varying demand, supply and price
  - Hourly, daily, seasonal
  - Mix of conventional and renewable sources
  - Different decision horizons: One day to 15 min
- Quantify uncertainty and risk
- Develop risk-informed optimization
- Use machine learning to enable fast decisions
- Collaborate with industry (MISO)

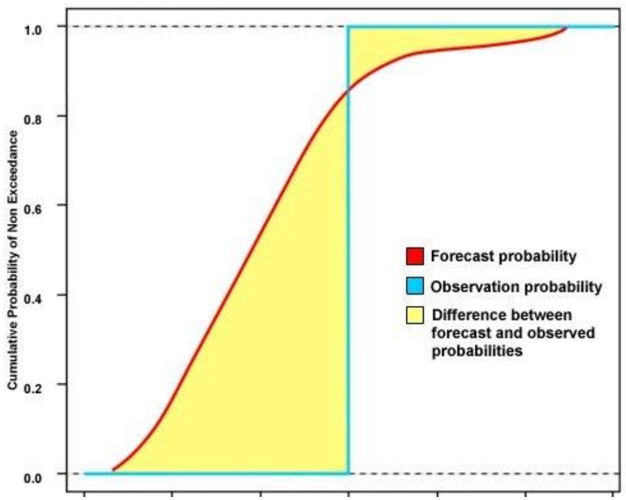


Georgia Tech ISyE H. Milton Stewart School of Industrial and Systems Engineering

Vanderbilt University

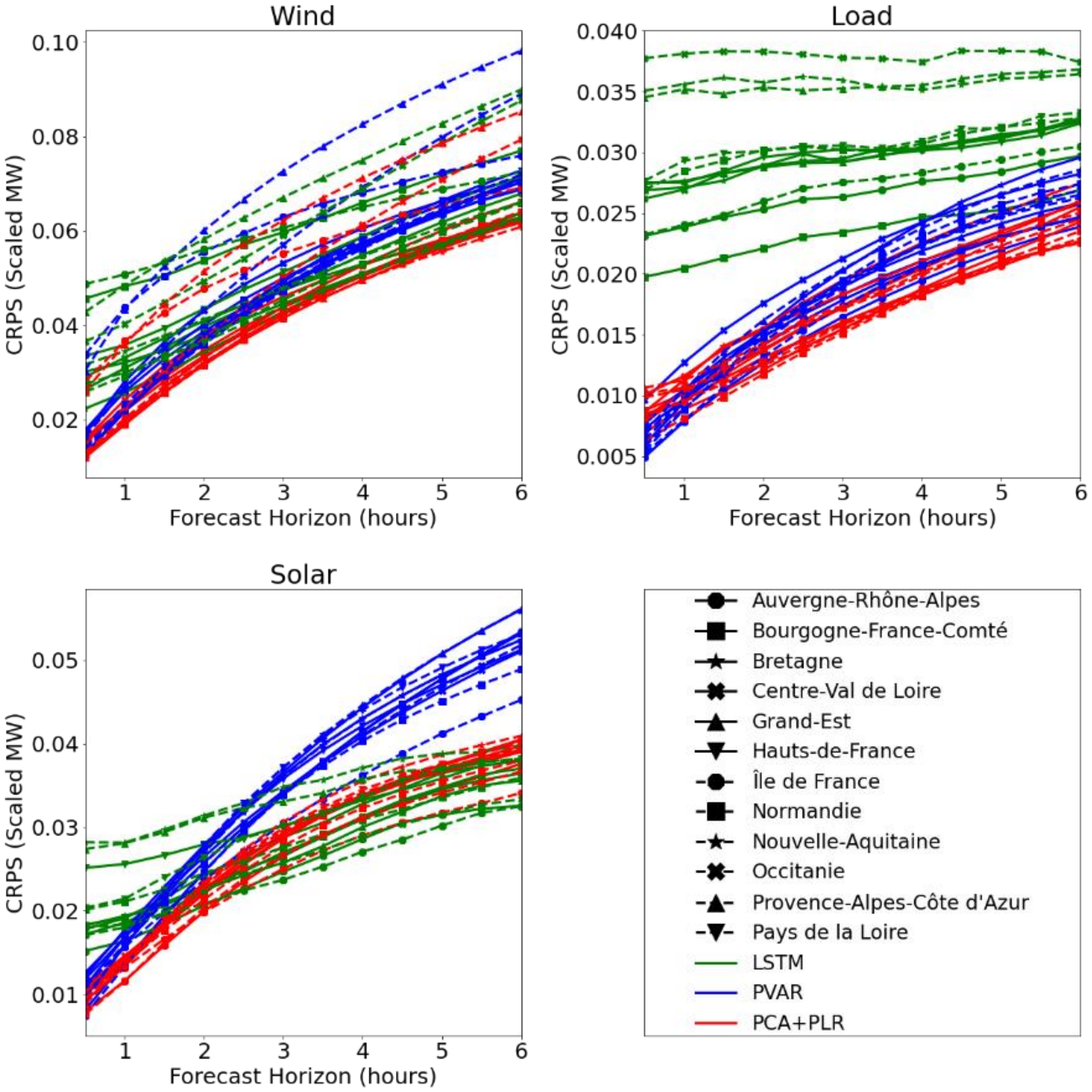
arpa·e U.S. Department of Energy

- Jointly forecast wind/solar generation and load demand time series for multiple time steps into the future
    - $p(\boldsymbol{X}_{Future}) = p_F(\boldsymbol{X}_{Future}|\boldsymbol{X}_{Past})$
- Forecasting is used to support stochastic unit commitment and dispatch for day-to-day operations



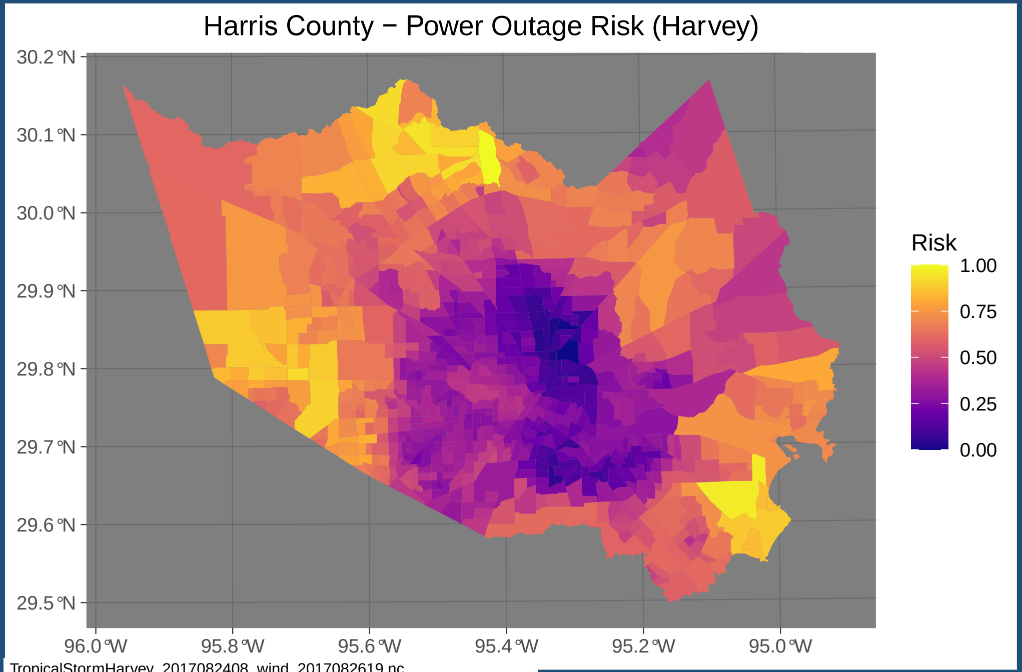
Probabilistic validation metrics

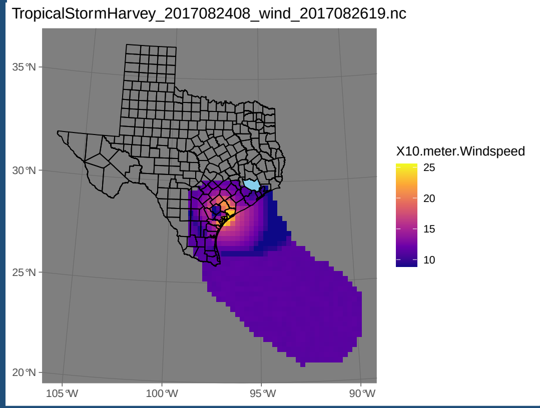
- Continuous Ranked Probability Score (CRPS)



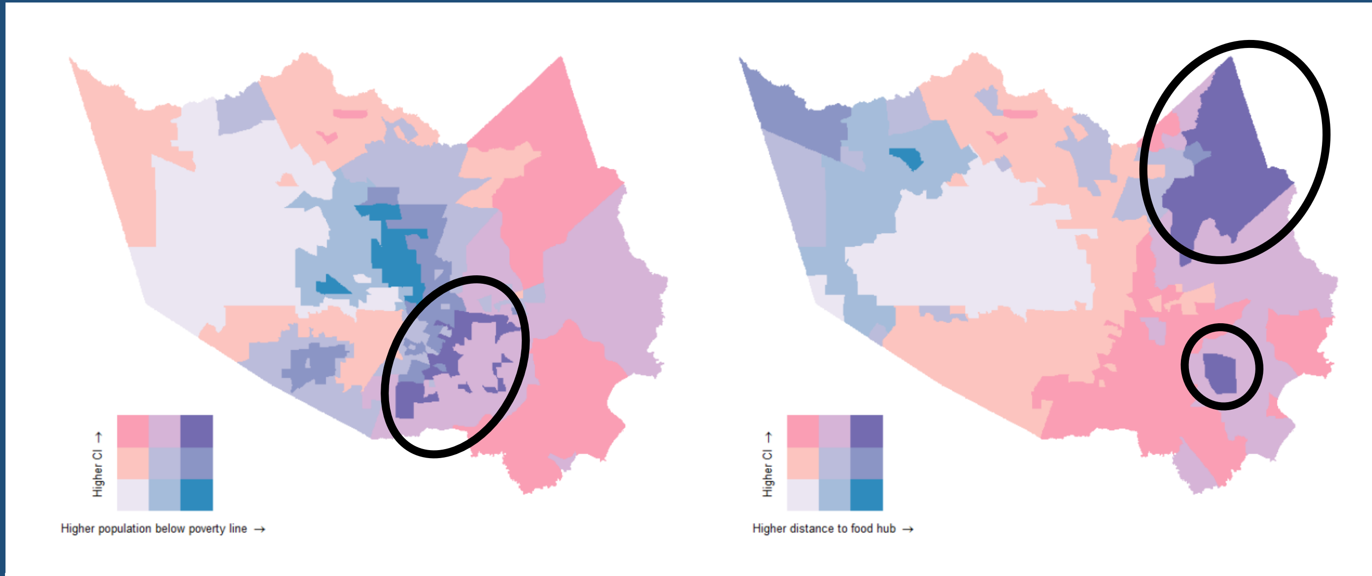
Stover, O., Nath, P., Karve, P., Mahadevan, S. and Baroud, H., 2024. Dependence structure learning and joint probabilistic forecasting of stochastic power grid variables. Applied Energy, 357, p.122438.

Analyzing risk at the *regional* level



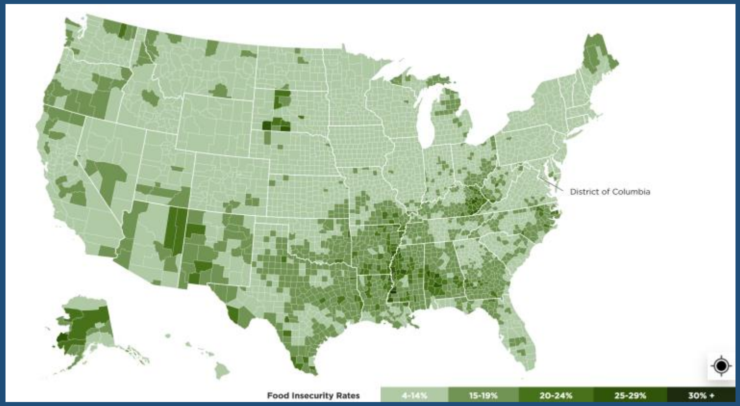


Probabilistic prediction of power outage risk



(a) Power vulnerability and percentage of people below poverty level

(b) Power vulnerability and distance to closest food hub



Houston, Texas

- Highest food insecurity rate in the country
- Vulnerable to hurricanes, storms, and flooding

Wehbe, C. and Baroud, H., 2024. Limitations and considerations of using composite indicators to measure vulnerability to natural hazards. Scientific Reports, 14(1), p.19333.

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UTHealth The University of Texas Health Science Center at Houston

houston foodbank

NSF

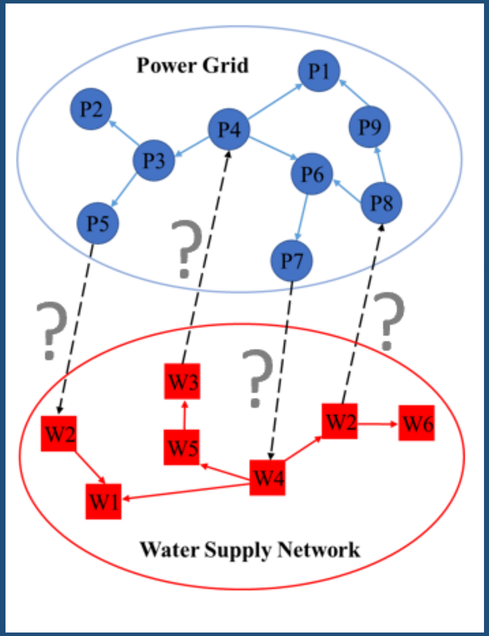
Managing risk
at the *system* (of interdependent networks) level

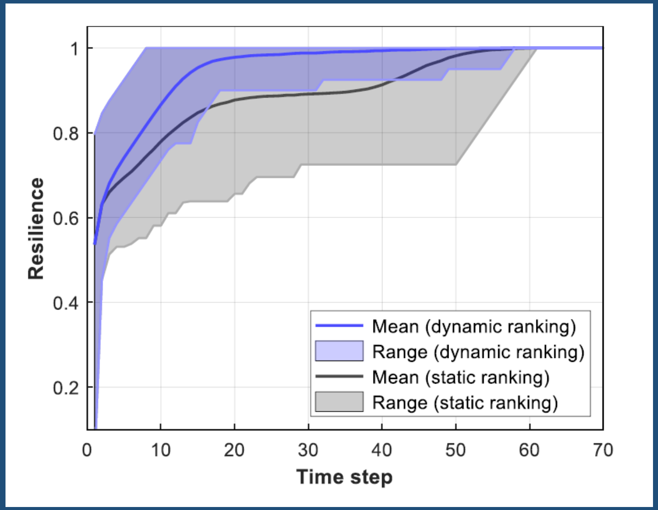
The Challenge

We know more about individual systems and less about their connections

Proposed solutions

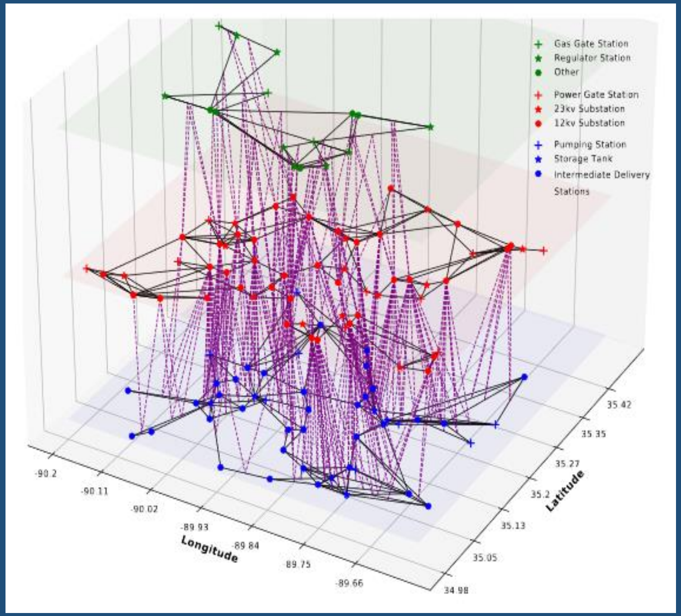
- Learn interdependencies
  - Data-driven methods to learn infrastructure interdependencies





Resilience of infrastructure systems is improved by 60%

- Simulate synthetic interdependencies
  - Generate synthetic interdependent critical infrastructure networks (SICIN) that complete real-world data on infrastructure systems



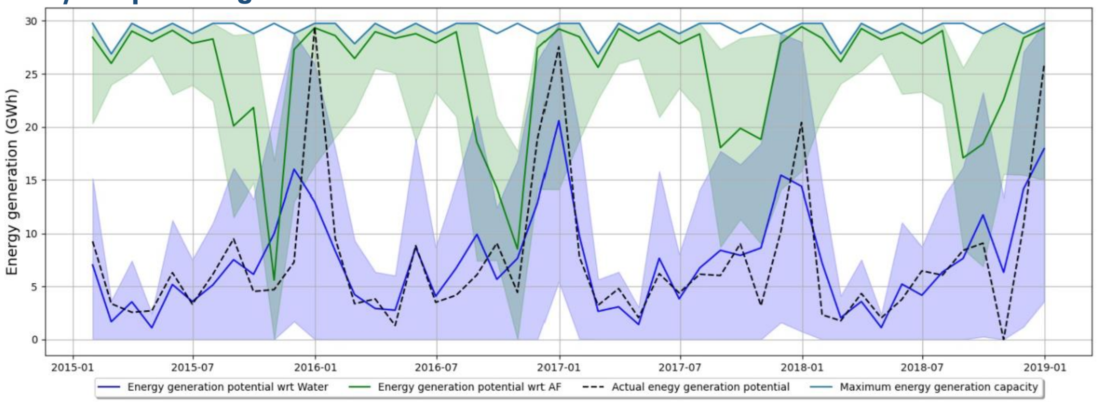
Yu, J. and H. Baroud. 2019. Modeling Uncertain and Dynamic Interdependencies of Infrastructure Systems Using Stochastic Block Models. ASCE-ASME Journal of Risk and Uncertainty in Eng.

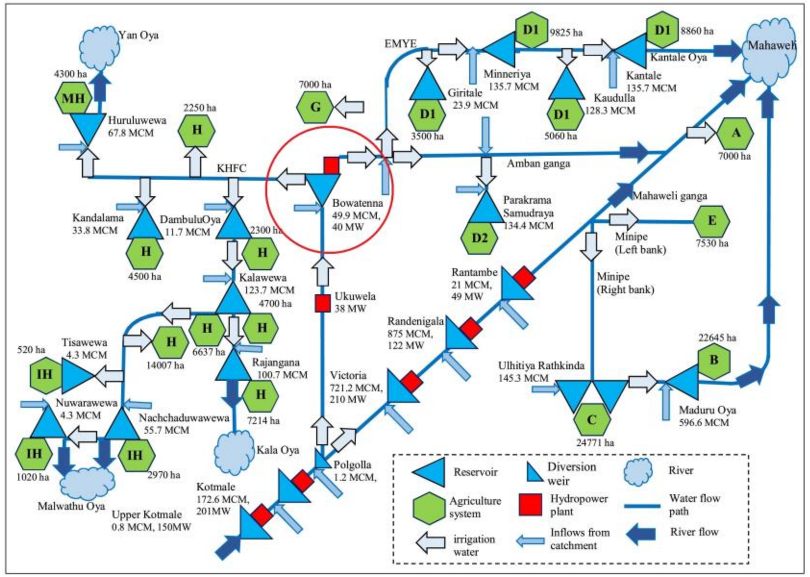
Wang, Y., Yu, J.Z. and Baroud, H., 2021. Generating synthetic systems of interdependent critical infrastructure networks. IEEE Systems Journal, 16(2), pp.3191-3202.

Long-term risk

Water Energy

Impact of water and infrastructure availability on hydropower generation in Sri Lanka

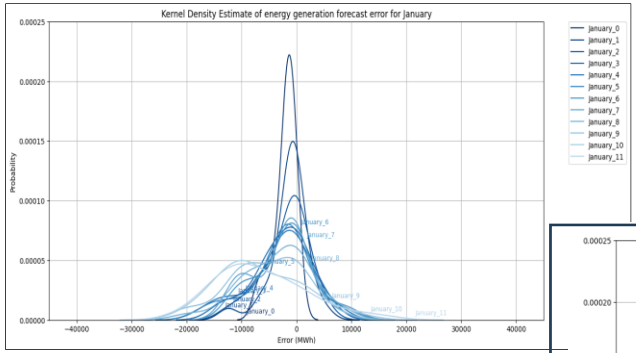




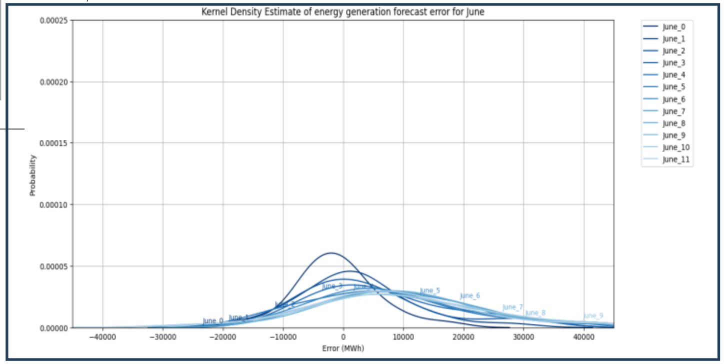
Error in water inflow forecast in Blue Mesa reservoir in the Colorado River Basin

Month / Months in advance

Month	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
December	1.41	2.26	4.26	1.44	0.04	-0.29	-0.75	-4.28	-4.44	-7.75	-8.84	-9.18	-8.38	-8.38	-7.91	-7.57	-9.87	-9.34	-10.17	-10.34	-10.34	-10.76	-10.95	-9.82
November	0.52	0.27	-0.72	-2.07	-4.05	-6.20	-10.15	-11.14	-15.60	-16.54	-17.30	-16.65	-16.90	-17.11	-18.67	-19.40	-18.94	-19.26	-18.97	-18.97	-19.40	-19.44	-18.48	-19.19
October	2.11	-3.33	-4.34	-5.84	-6.40	-14.51	-16.95	-23.65	-23.95	-25.24	-23.94	-24.71	-26.81	-29.83	-31.14	-31.44	-31.62	-32.50	-32.50	-32.64	-29.94	-29.08	-26.82	-26.32
September	-11.15	-14.58	-13.23	-14.91	-20.58	-23.96	-30.35	-29.40	-30.76	-32.10	-32.49	-38.05	-40.02	-39.80	-38.28	-37.82	-38.47	-38.26	-37.34	-35.75	-36.81	-36.26	-36.26	-36.48
August	-0.57	-2.11	-1.87	-3.88	-9.04	-19.65	-21.26	-22.00	-24.20	-25.57	-27.62	-29.69	-29.64	-33.00	-33.06	-41.06	-41.94	-41.25	-40.40	-41.00	-43.10	-43.23	-43.45	-43.31
July	-1.35	-2.40	-8.04	-17.69	-38.78	-40.80	-45.89	-51.20	-56.31	-58.73	-61.76	-62.58	-68.99	-69.01	-78.27	-78.57	-78.82	-77.91	-79.01	-79.44	-79.45	-79.72	-80.82	-81.16
June	-5.14	-15.20	-31.86	-44.84	-47.49	-50.82	-57.65	-62.74	-67.53	-77.23	-77.58	-74.99	-75.05	-76.78	-76.82	-76.61	-77.73	-78.28	-78.76	-78.70	-78.55	-78.57	-79.78	-80.14
May	-4.52	-11.89	-18.73	-21.22	-19.20	-22.41	-27.13	-28.89	-34.85	-36.53	-35.61	-35.79	-42.19	-42.53	-42.99	-44.63	-44.77	-45.95	-45.93	-45.90	-46.03	-46.87	-47.39	-48.03
April	-2.31	-0.51	-3.37	0.92	1.69	-0.93	-0.57	-3.39	-4.07	-3.38	-4.54	-12.53	-13.72	-14.10	-14.62	-15.22	-13.16	-13.16	-13.44	-13.23	-14.18	-14.47	-15.07	-14.66
March	4.36	2.16	4.38	7.33	7.42	6.98	6.33	5.28	3.37	2.66	-4.44	-5.10	-6.61	-7.67	-7.76	-7.60	-7.60	-7.81	-7.76	-8.76	-8.67	-9.04	-9.33	-9.33
February	0.80	3.49	2.79	3.60	3.15	2.42	1.40	0.20	-0.86	-7.39	-7.79	-10.07	-11.24	-11.65	-11.16	-11.16	-10.76	-10.53	-12.40	-12.64	-13.28	-13.30	-13.30	-13.85
January	0.70	0.73	1.45	1.20	-0.68	-2.71	-2.81	-3.26	-7.95	-8.10	-11.09	-12.05	-12.29	-11.36	-11.36	-10.97	-10.80	-13.33	-12.96	-13.65	-13.81	-13.81	-14.27	-13.66



Error in energy generation forecast



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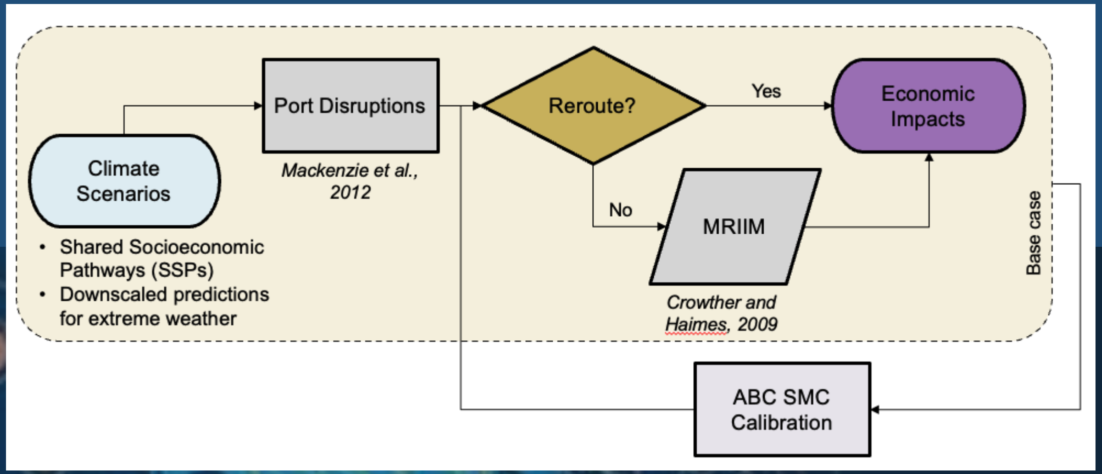
De Silva, T. et al. (2025) A Data-Driven for Forecasting Hydropower Generation Under the Uncertainty of Water and Infrastructure Reliability [In prep]

De Silva, T. et al. (2025) Analyzing Hydropower Generation Estimates in the Upper Colorado River Basin [In prep]

Gaps and future directions

- Return on investment in climate mitigation and adaptation
  - Why do it? And how much does it cost?
- Decarbonization and grid resilience
  - A win-win situation
- Coordination across sectors and stakeholder engagement
  - Co-producing useful and usable research



Johnson, P. M., et al. (2024). How flood-resilient port infrastructure can reduce economic impacts of climate change: A case study of the U.S. inland waterways? [Under review]