The Social Value of Demand-Side Management

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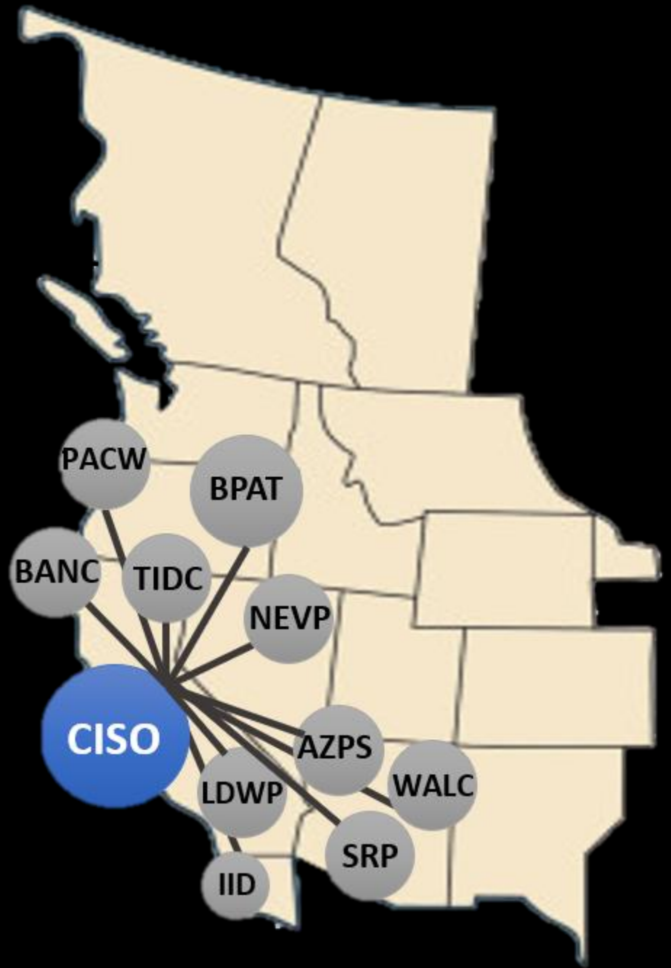
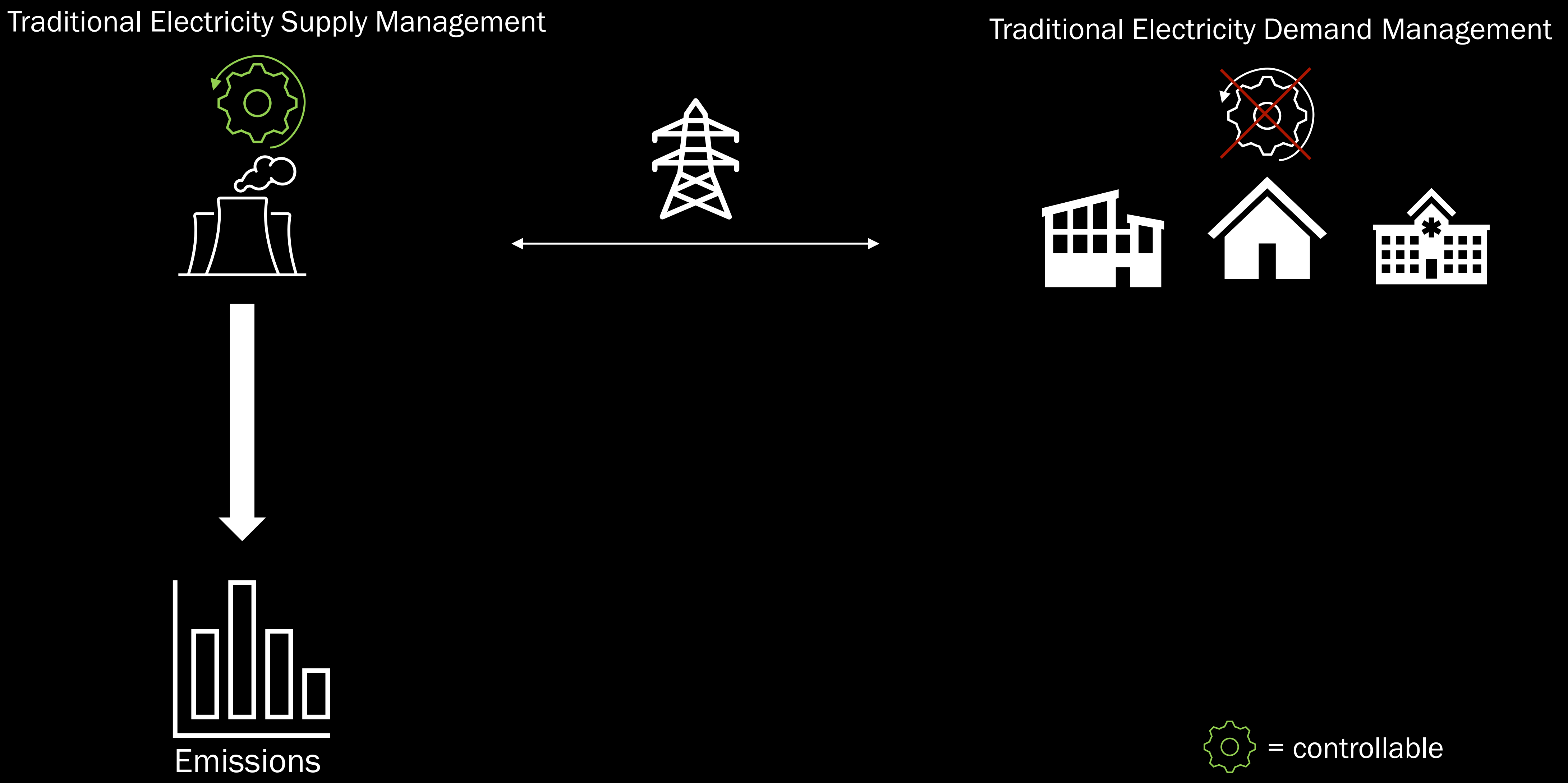
The California Independent System Operator (CAISO) oversees a high-renewable grid

- High penetrations of variable renewable energy (VRE), namely solar PV
- High penetrations of daytime solar PV are creating challenges like curtailment and grid stress via rapid evening ramping
- Because of this, CAISO also trades a lot of electricity, primarily by meeting ~25% of demand with imports

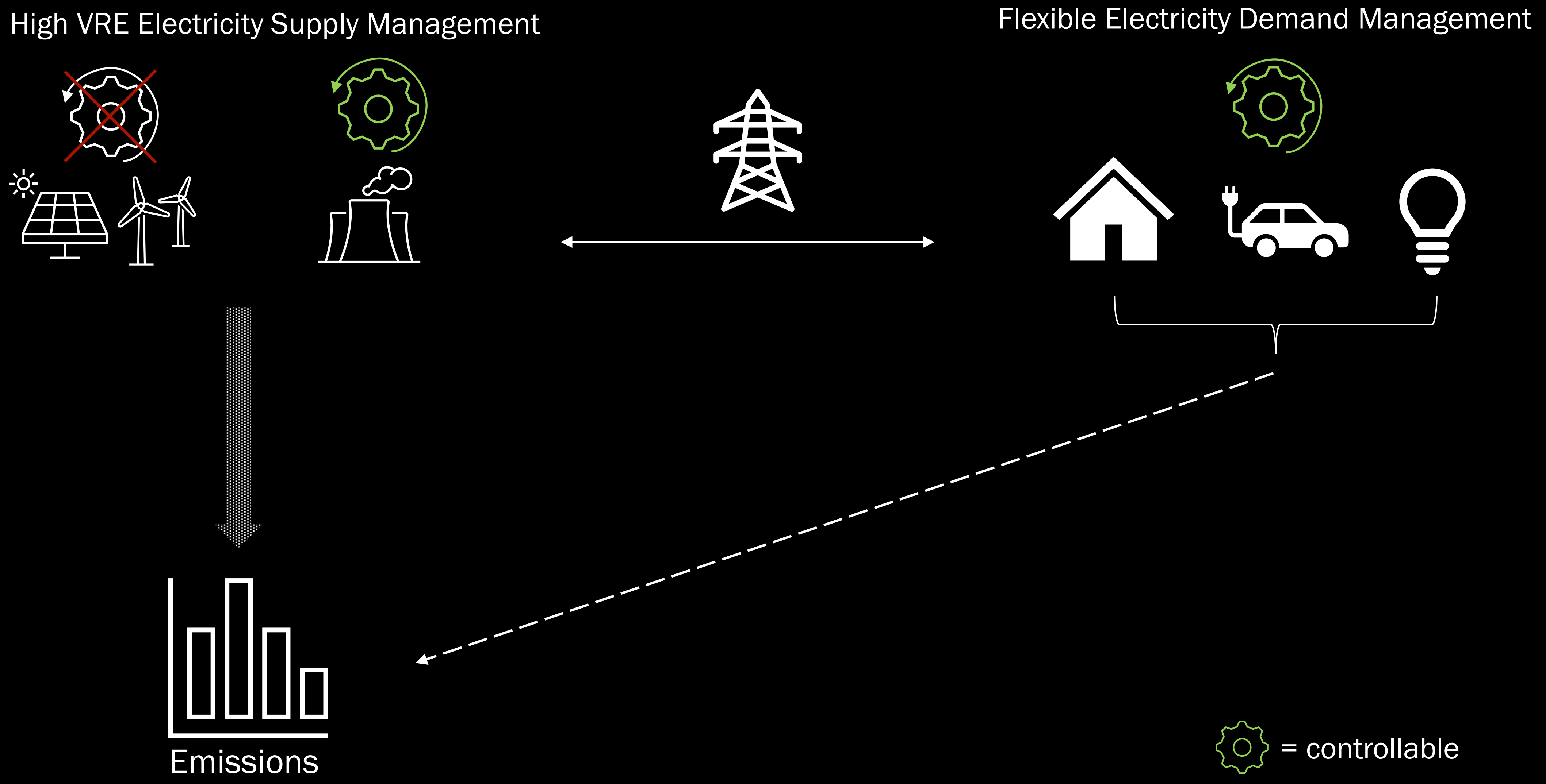


Zohrabian, Mayes, Sanders (2023)

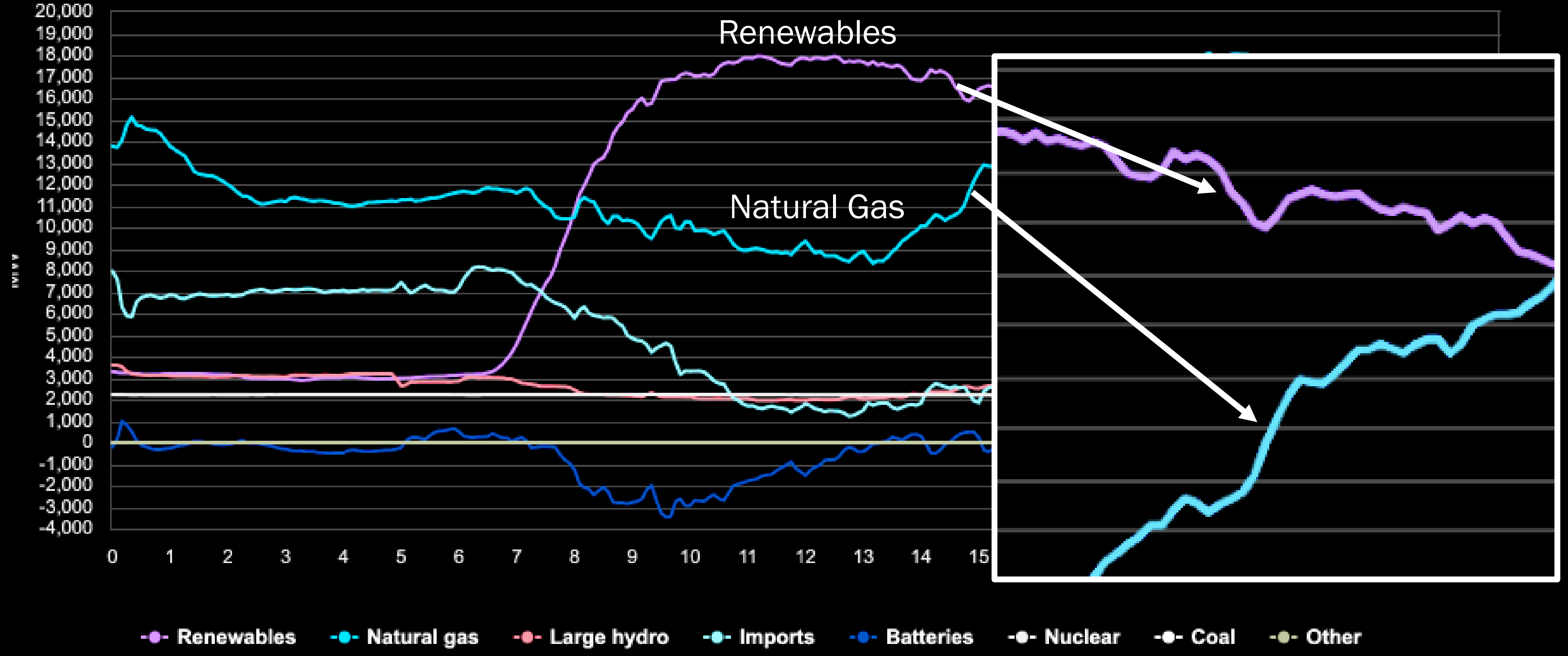
On traditional grids, flexibility comes from control of generation



As VRE penetrations increase, we look to the demand side for control



Marginal emissions factors quantify the changes in emissions per unit change in energy



Research Question: Can we quantify the emissions impact of DSM?

Zohrabian, Angineh, Stepp Mayes, and Kelly T. Sanders. “A data-driven framework for quantifying consumption-based monthly and hourly marginal emissions factors.” Journal of Cleaner Production 396 (2023): 136296.

Mayes, Stepp, Nicholas Klein, and Kelly T. Sanders. “Using Neural Networks to Forecast Marginal Emissions Factors: A CAISO Case Study.” Journal of Cleaner Production (in review)

Traditional Statistical MEF Models have limitations

$$\Delta E_t = MEF_t \times \Delta G_t + C_t$$

Regression of changes in emissions on changes in generation

- Do not account for grids with high fraction of VRE
- Ignore electricity imports and exports
- Regression reduces granularity and accuracy
- Generation, instead of demand, focused
- Retrospective

Before estimating MEFs, we calculate demand-based emissions by including imports and exports

$$E_t = \underbrace{E_t^C}_{\text{CAISO Emissions}} - \underbrace{E_t^X}_{\text{Exported Emissions}} + \underbrace{E_t^I}_{\text{Imported Emissions}}$$

$$E_t^X = \left(\sum_M \frac{E_t^C}{G_t^C} \times X_t^{C \to M}\right)_t$$

Emissions exported from CAISO depend on the amount of electricity exported and CAISO's grid mix

$$E_t^I = \left(\sum_M \frac{E_t^M}{G_t^M} \times I_t^{M \to C}\right)_t$$

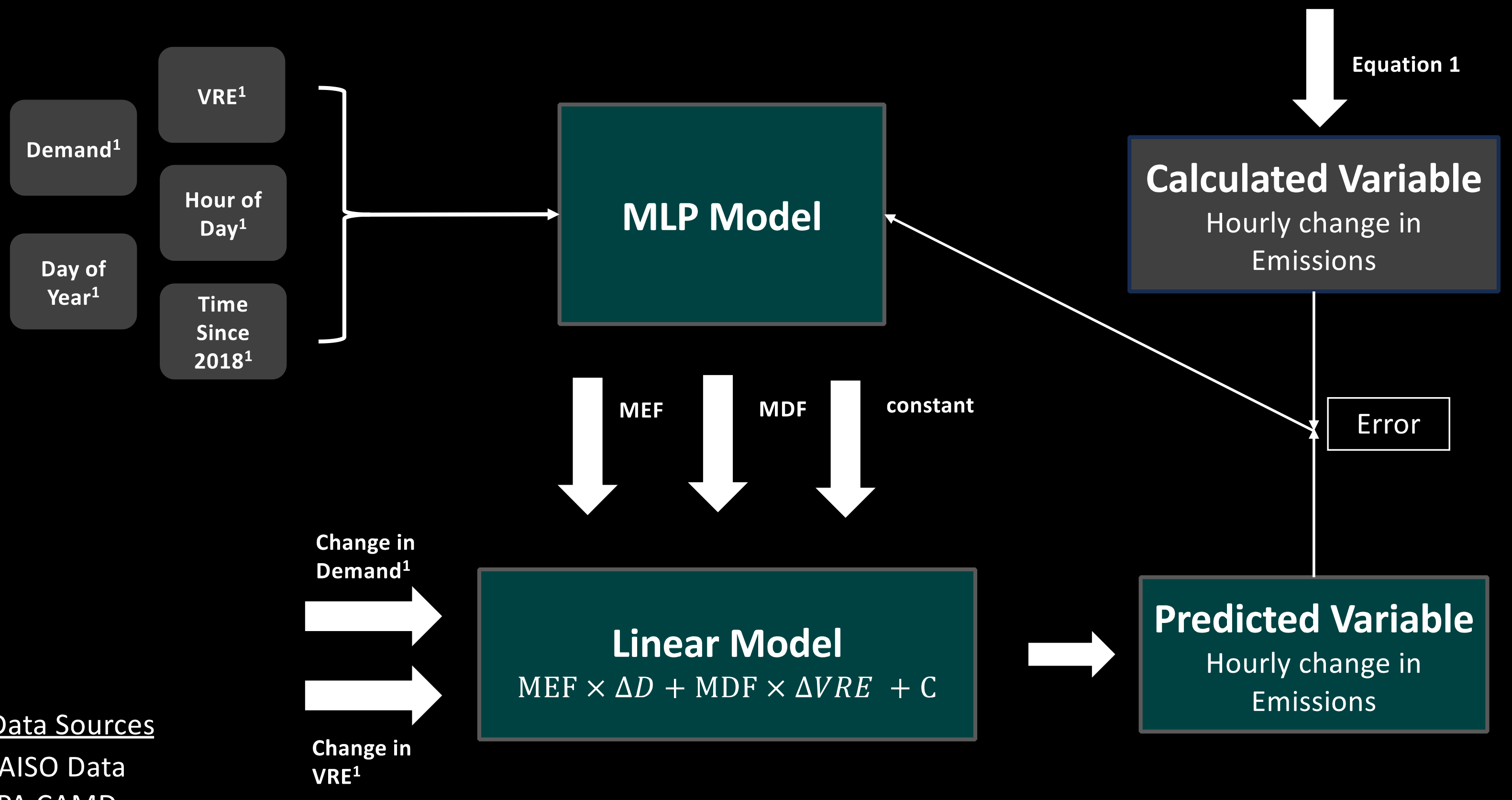
Emissions imported to CAISO depend on the amount of electricity imported and the grid mix of the grid that the electricity is imported from

We introduce a term for the influence of VRE to better isolate the impact of *demand* on emissions

$$\underbrace{\Delta E_t}_{\text{Change in Emissions}} = \underbrace{MEF_t}_{\text{Dependence on }\Delta\text{ demand}} \times \Delta D_t + \underbrace{MDF_t}_{\text{Dependence on }\Delta\text{ variable renewable energy}} \times \Delta VRE_t + C_t$$

- Regression of changes in emissions on changes in demand (with positive coefficient, MEF) and changes in variable renewable energy generation (with negative coefficient, MDF)

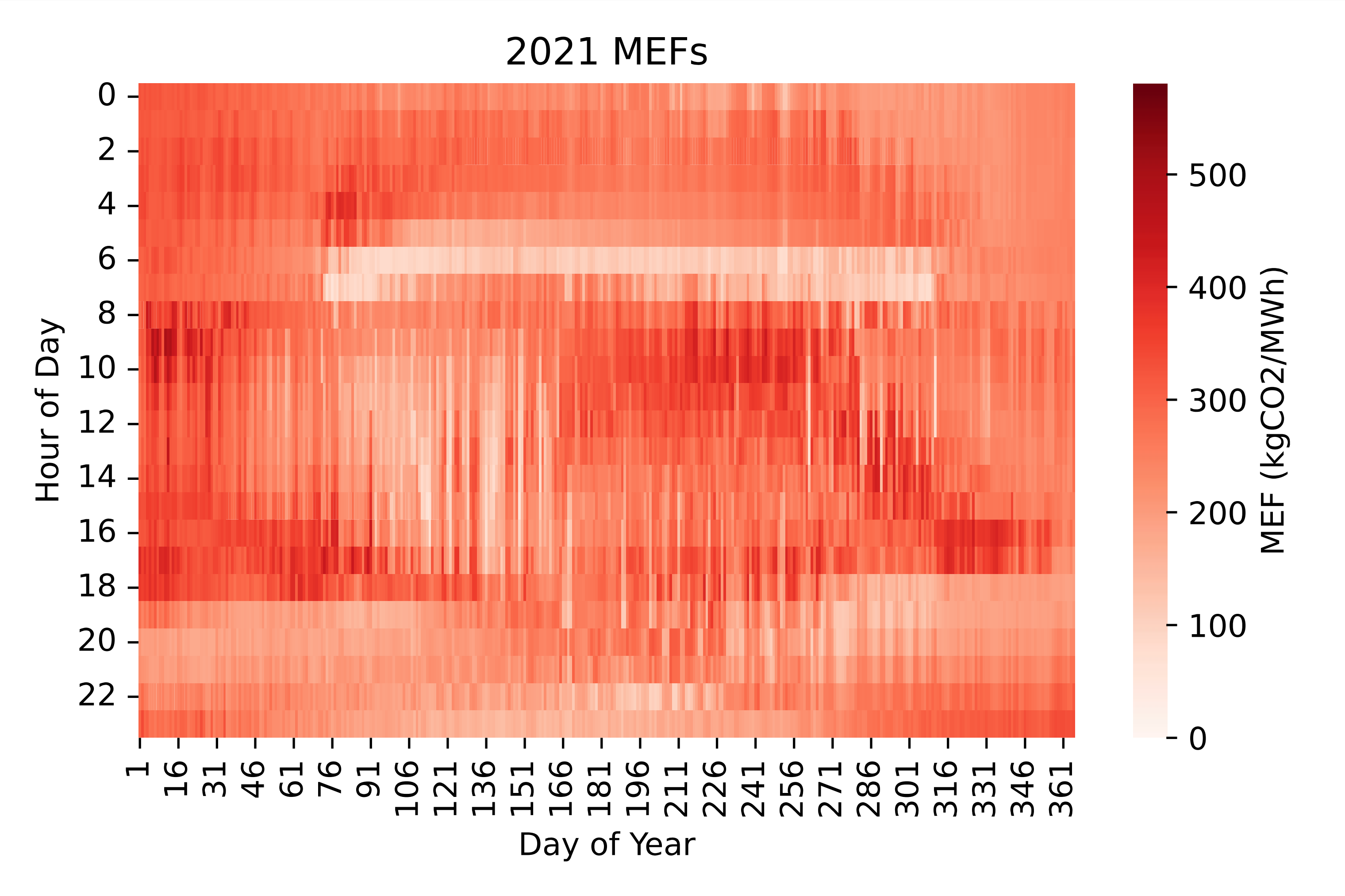
We use an MLP-linear composite model to increase granularity and accuracy



Data Sources

1. CAISO Data
2. EPA CAMD
3. EIA Data

The increased granularity reveals significant fluctuations in MEFs across different time scales



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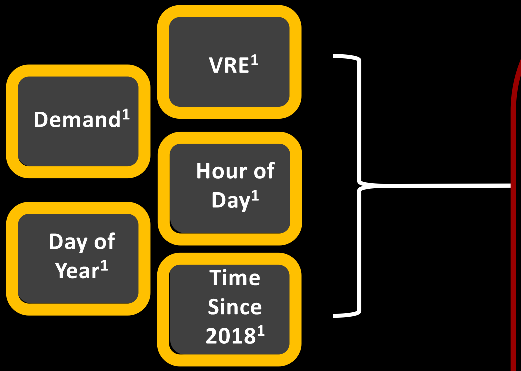
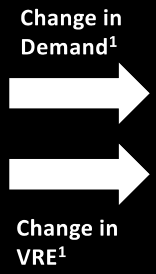


- Demand and VRE are forecasted by CAISO at multiple resolutions (7d, 2d, and 24hr)
- Temporal variables are known ahead of time
- Model fit with real-time values:
  R-squared = 0.91
- Model fit with forecasted values:
  R-squared = 0.88



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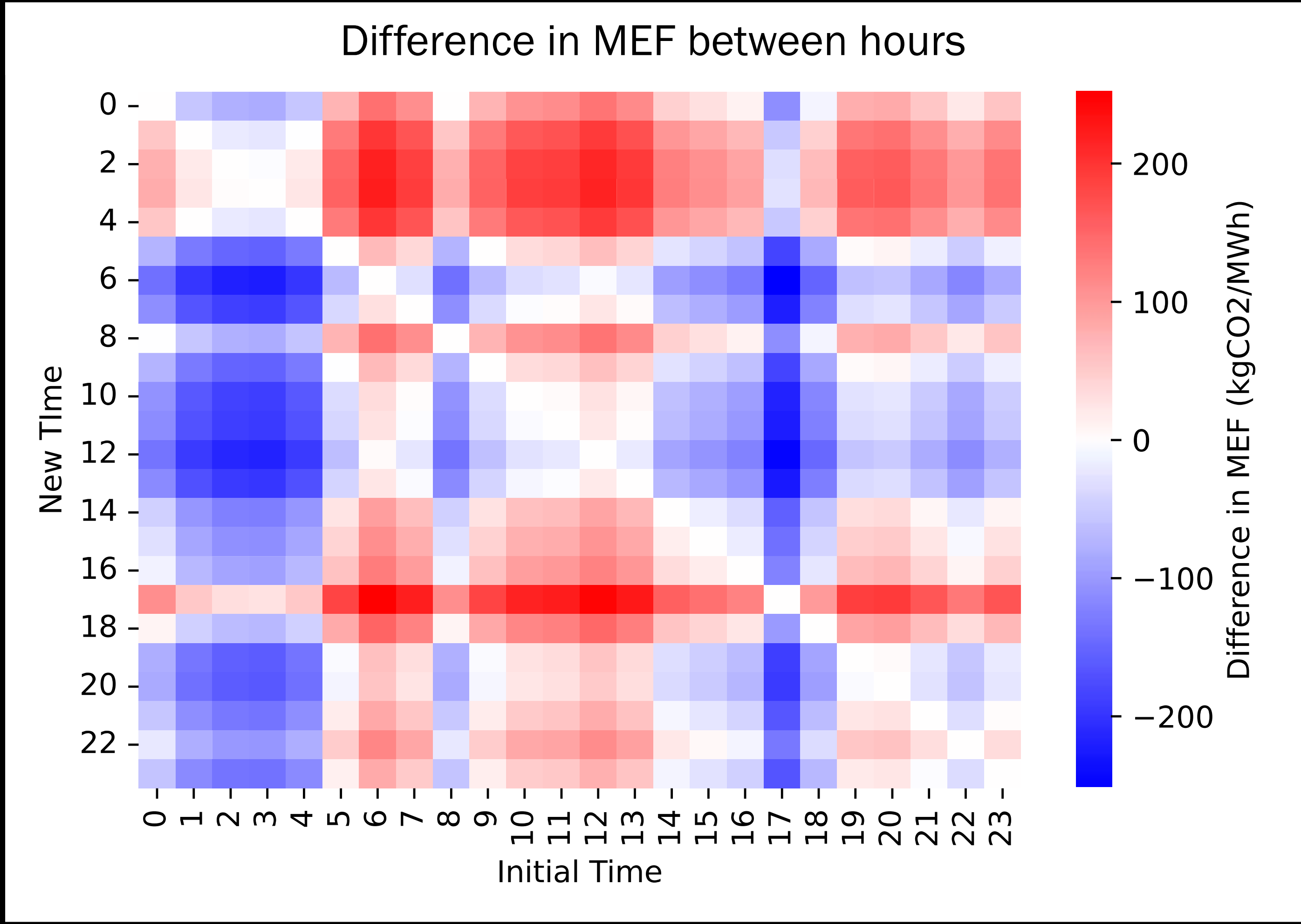
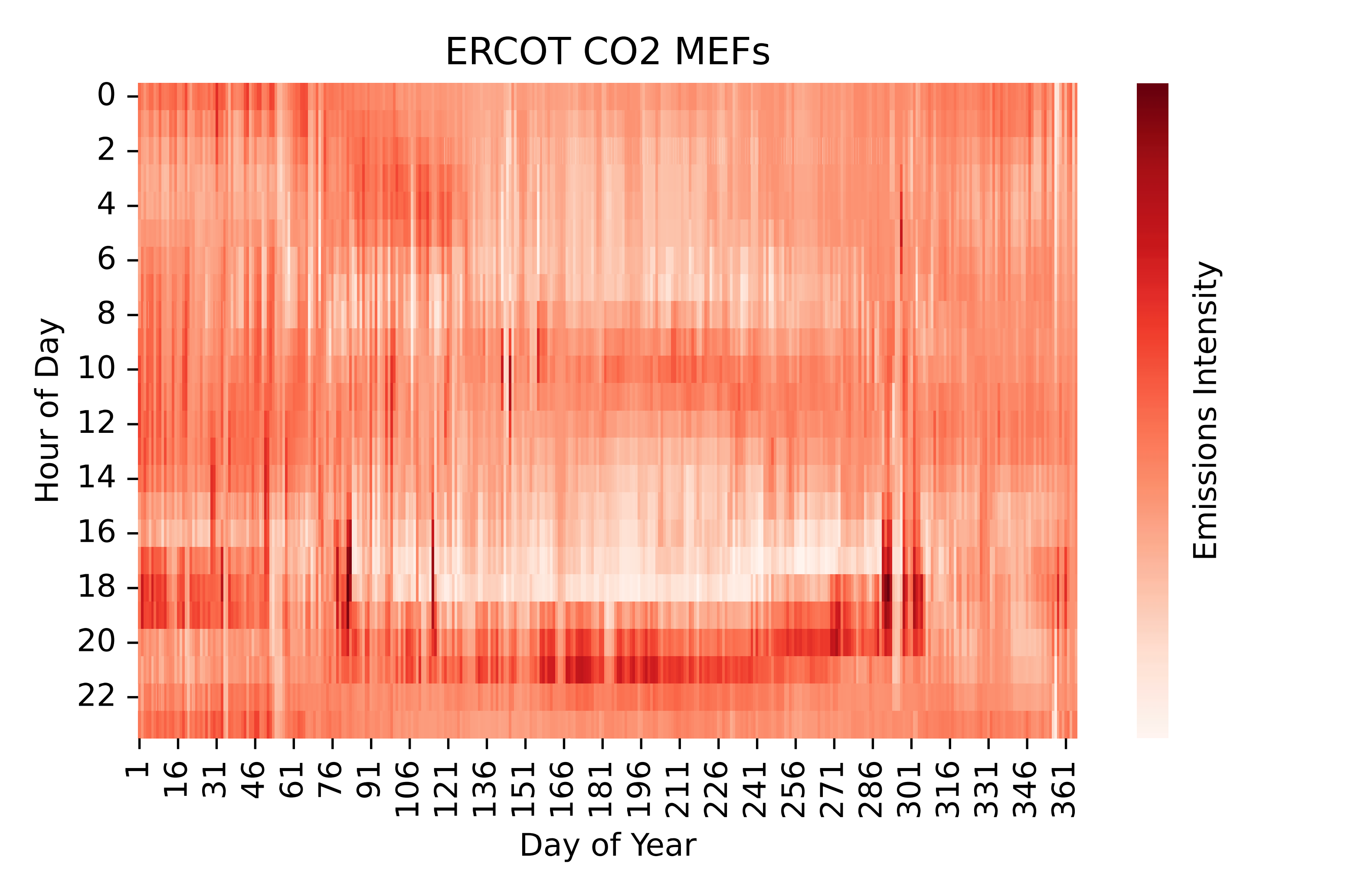
We can design day-ahead, load-shifting programs to help meet carbon mitigation goals



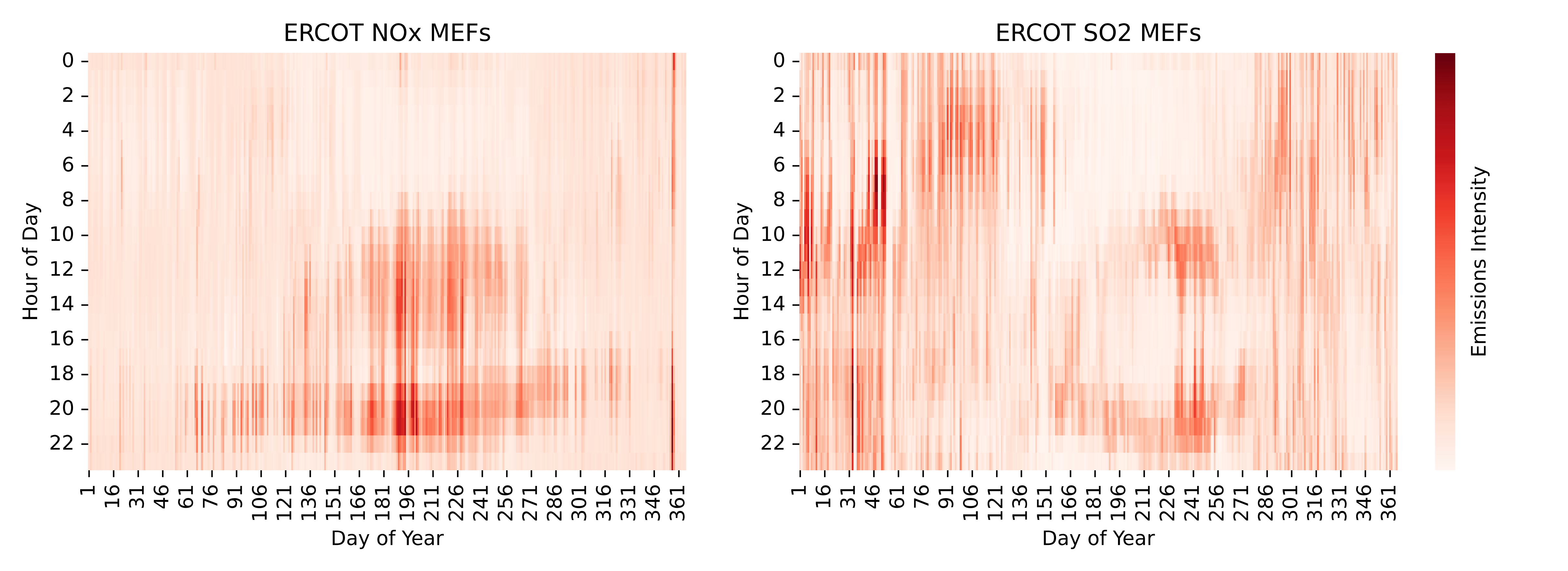
Ongoing work: Expanding to other grids and pollutants

We can repeat this process for other grids



ERCOT has its own set of seasonal and diurnal patterns

We can repeat this process for NOx and SO_2



NOx and SO_2 each have their own distinct patterns

Key findings and implications of this work

- We developed a granular, accurate, forecastable model to estimate MEFs that can be applied to DSM
- Factors such as social costs of carbon and pollutant damage factors quantify the impact of emissions on society
- DSM programs can then be designed to minimize societal impact based on MEFs forecasted by our MLP-linear composite model
- As demand and emissions continue to decouple for grids across the U.S., this framework will become increasingly important

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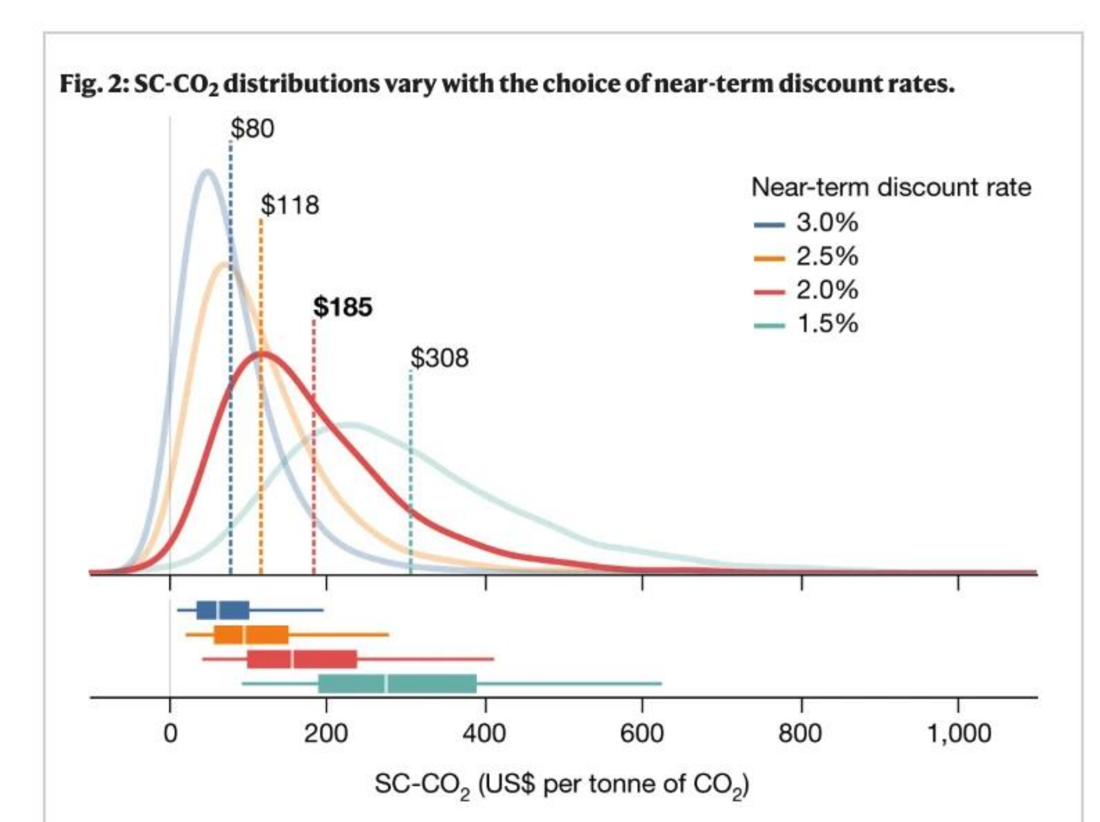
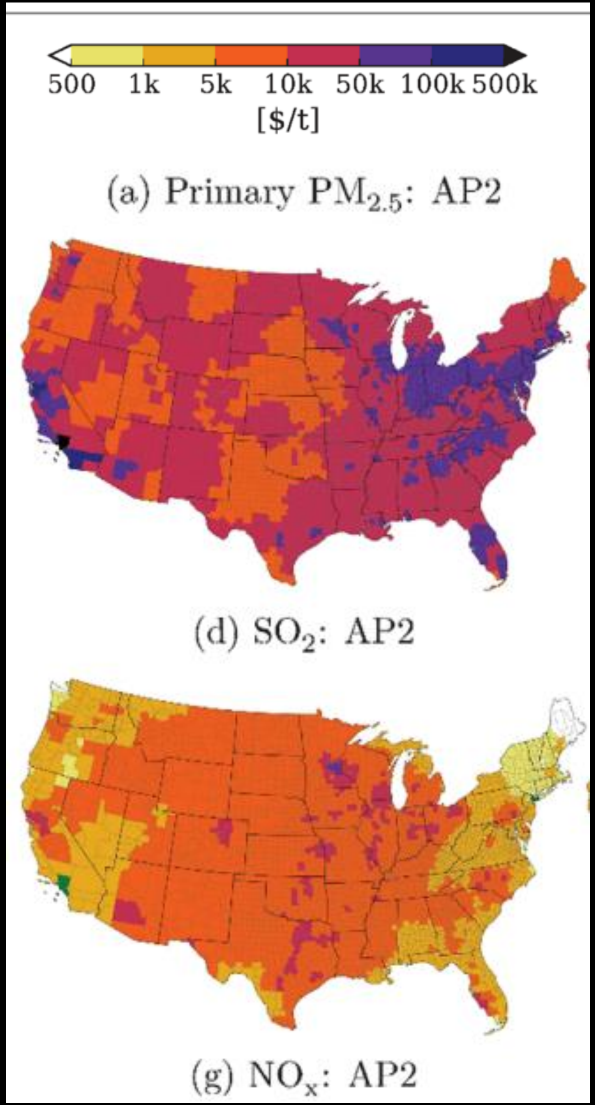
These emissions have an impact on society



Rennert, K et al. 2022 Nature



Elisabeth A Gilmore et al 2019 Environ. Res. Lett.