Scaling Portfolio Decarbonization

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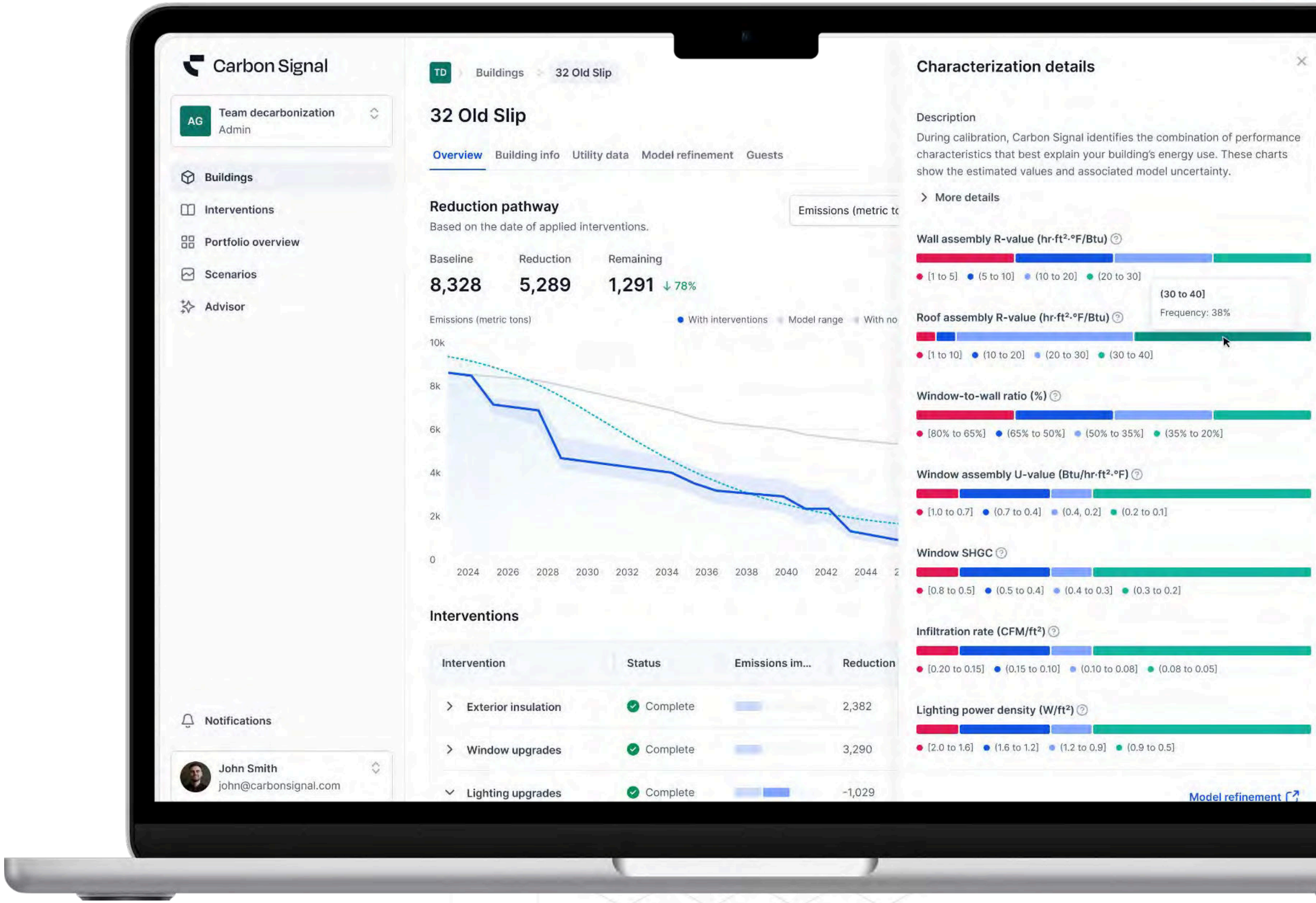
Carbon Signal

Scaling
Portfolio
Decarbonizatio
n

Building Energy Intelligenc e

How do we make it rapid, reliable, and repeatable?



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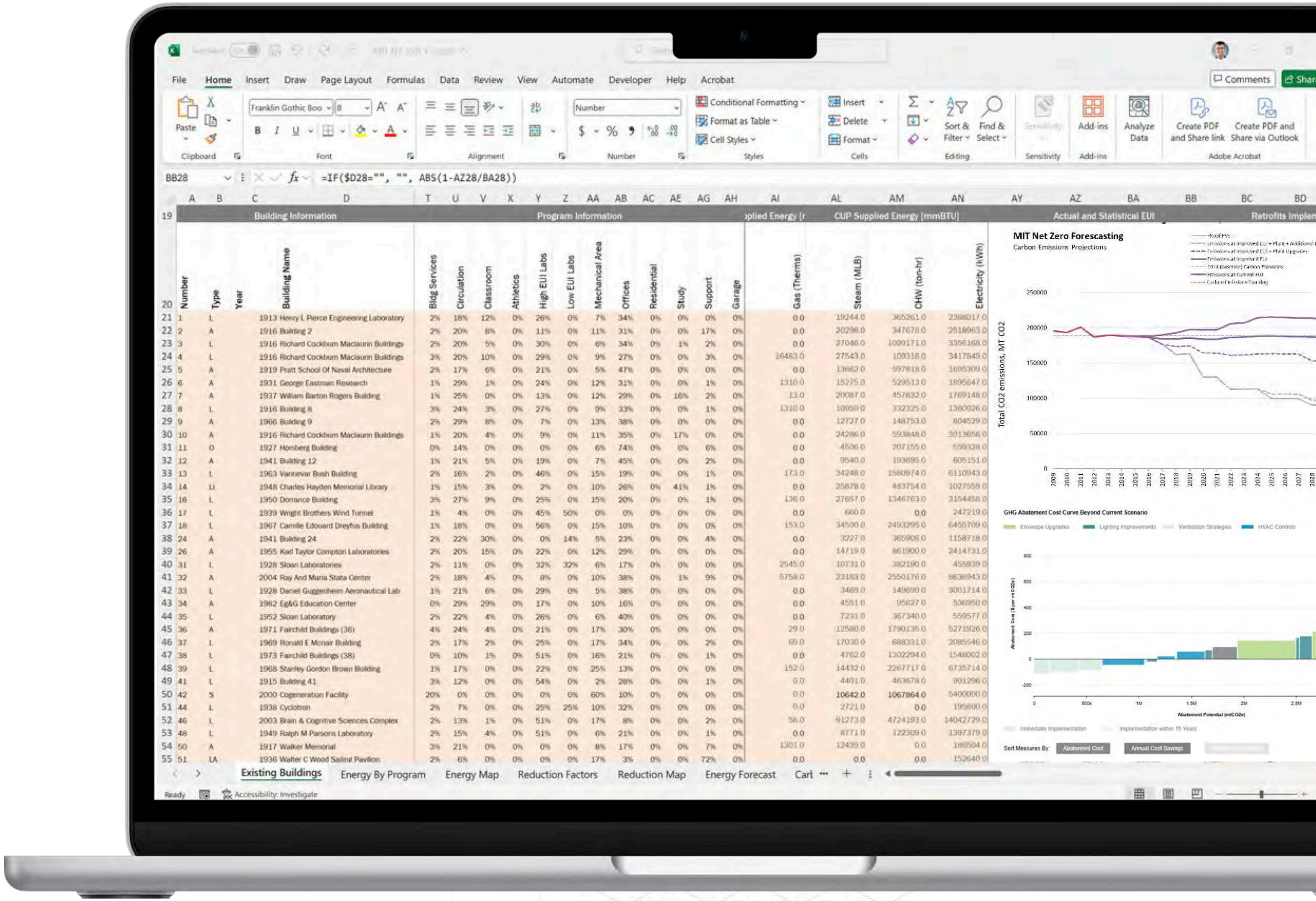
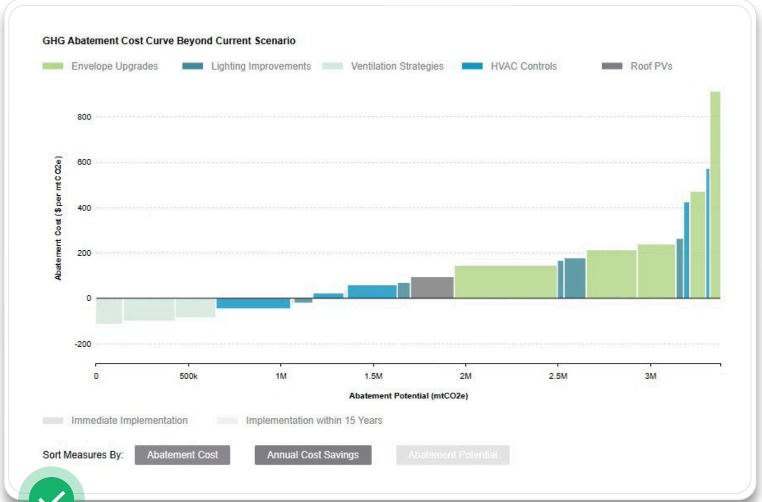
Net Zero Forecastin g Tool [2015]

Statistical energy analysis across program archetypes

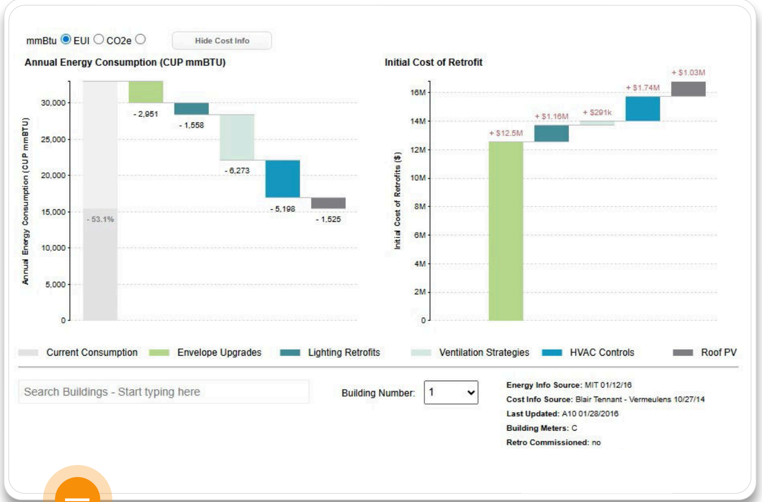


The building energy intelligence gap



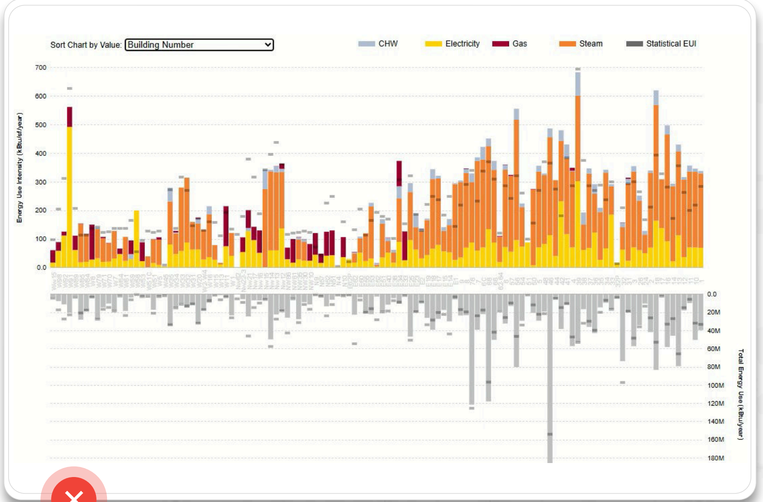
Portfolio-level targets

High confidence in cost abatement curves for high level retrofits across portfolio.



Building-level actions

Low confidence in identifying actionable interventions and their emissions impact.



Archetypical baselines

No confidence in building-specific characteristics that explain energy use.

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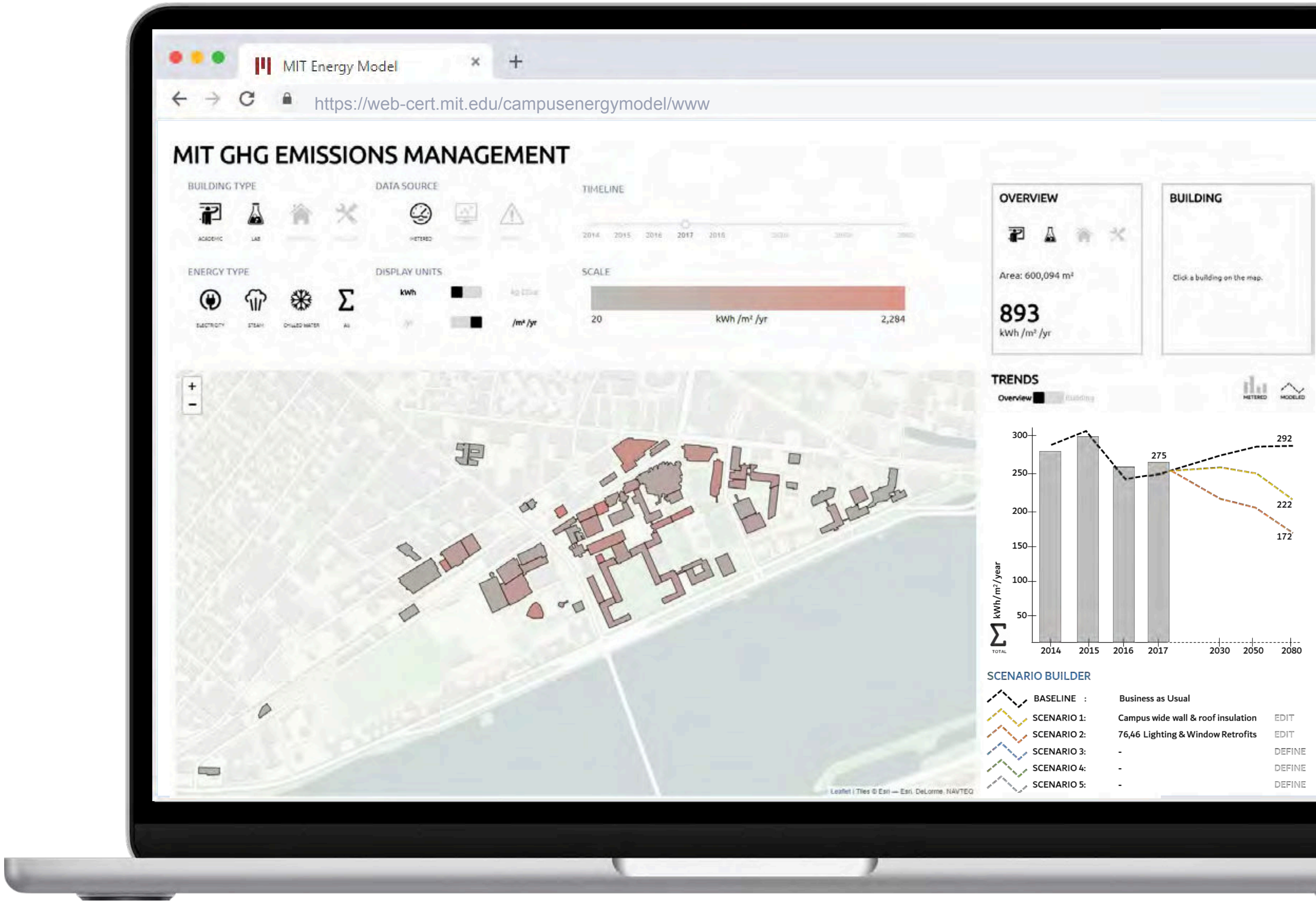
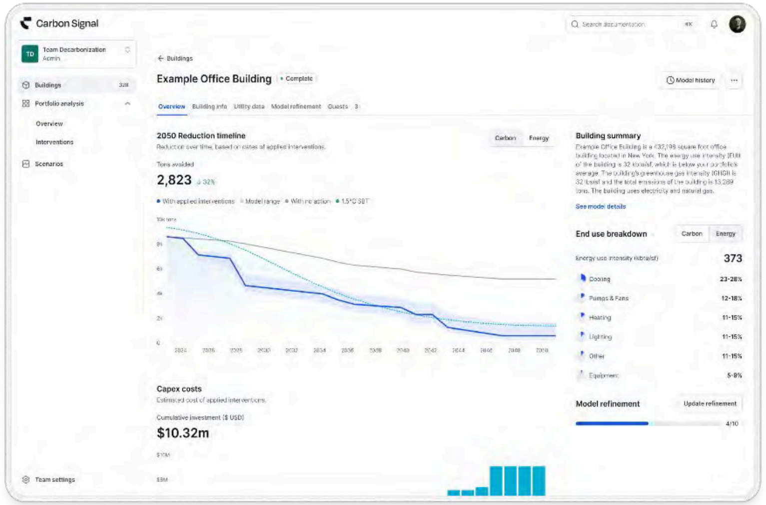
Continuous Planning Framework

Built on auto-calibrated building energy models.

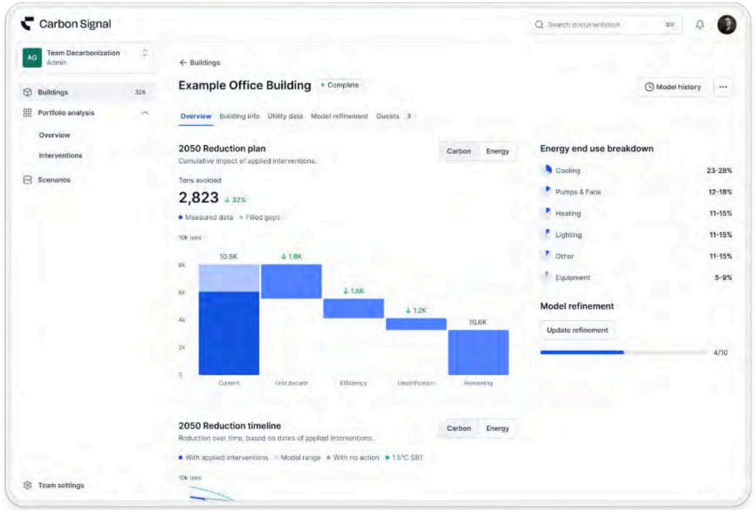


The building energy intelligence gap



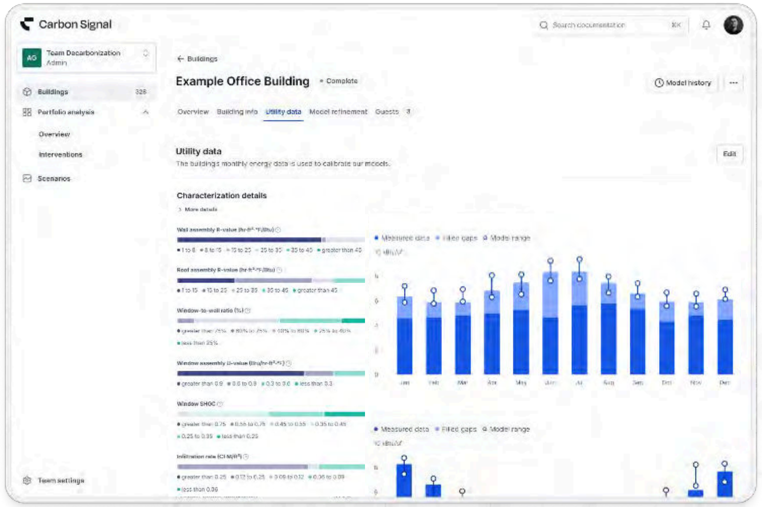
Finding an actionable path

Assigning project timelines, costs based on operational and financial constraints.



Setting realistic targets

Identifying interventions with the biggest cost-effective impact on emissions.

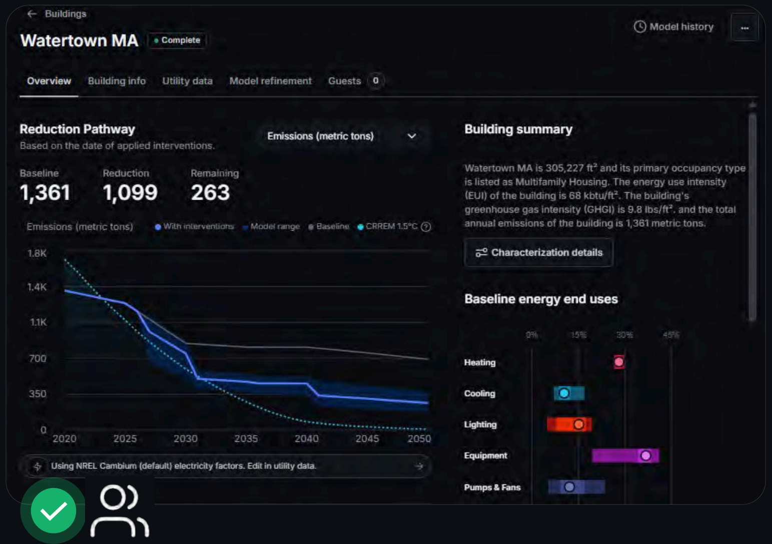


Establishing clear baselines

Understanding building characteristics that explain system energy use.

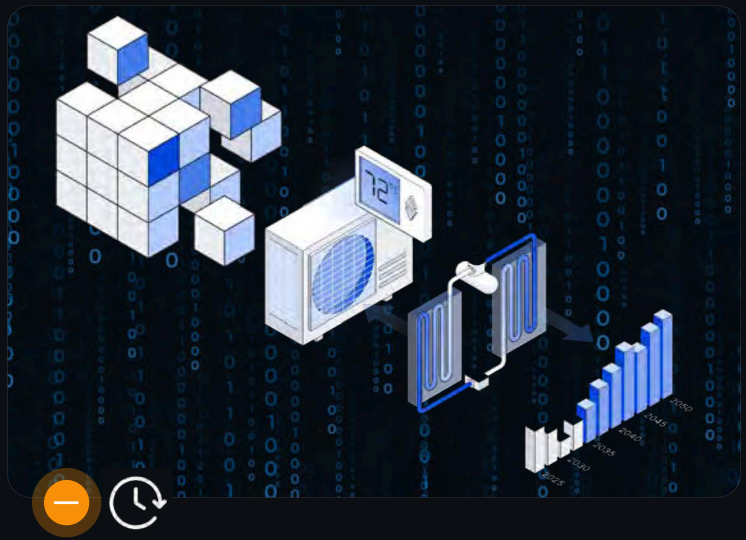
Image generated by OpenAI's DALL·E via ChatGPT

Our expert-consultant model is collapsing under its own weight



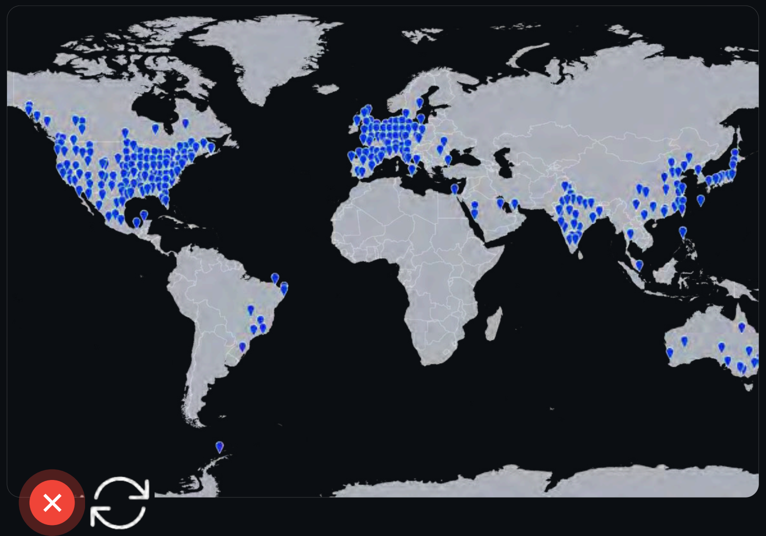
It's not that we lack expertise

We hold immense knowledge, technical experience, and decades of practice.



The real bottleneck... is time

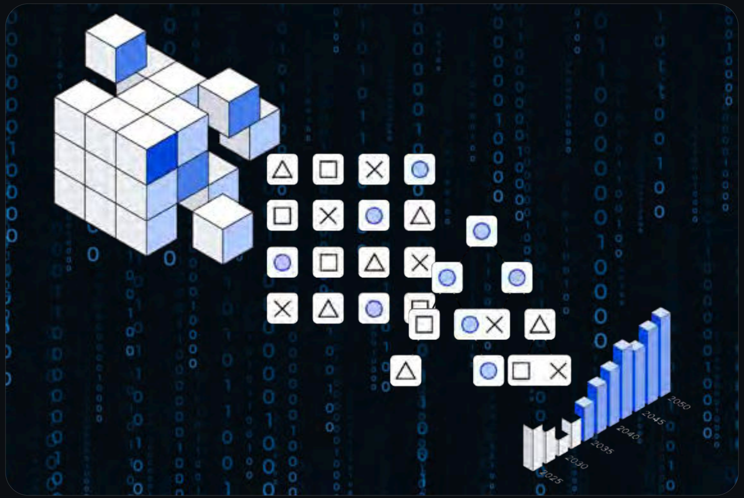
We spend weeks chasing data, running audits and models, and writing reports.

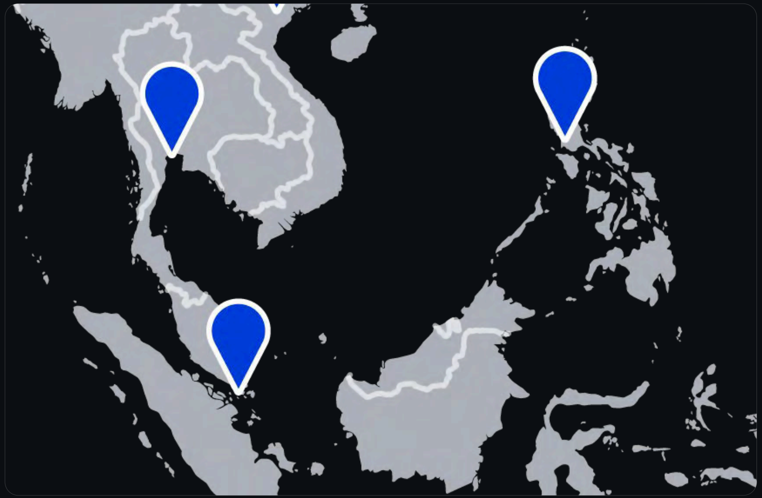


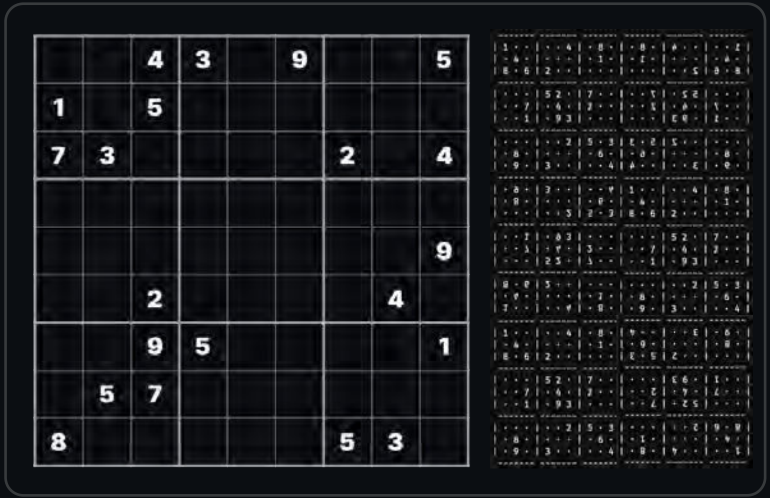
Our model is at its limits

When one building takes weeks, it fails to scale to a campus, portfolio, or a city.

AI pattern-guessing cannot replace established science







Replacing physics with AI

Scalable and automatable. But rely on archetypical patterns without any rigor.

Fast, but no actionable insights

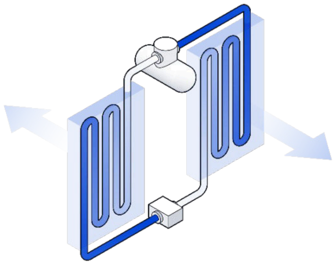
Black-box models can’t guarantee validity outside their training data.

Solve with rules, not patterns

Don’t need a million data points to train AI models when established rules exist.

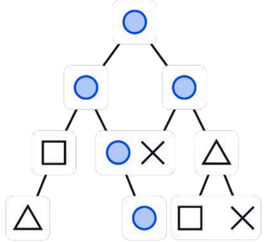

Image generated by OpenAI's DALL·E via ChatGPT

The physics of energy flows accelerated with AI



Engineering analyses

Well established but requires highly skilled consultants. Each building can take weeks to evaluate.



AI-powered exploration

No rigor without physics. Only makes sense to accelerate physics evaluations with smart optimization.

Rigorous and reliable	✓	-	✓
Easy to interpret	✓	-	✓
Can capture uncertainty	✓	✓	✓
Rapid and automatable	-	✓	✓
Repeatable at scale	-	✓	✓

Energy intelligence that scales

First, understand nuances

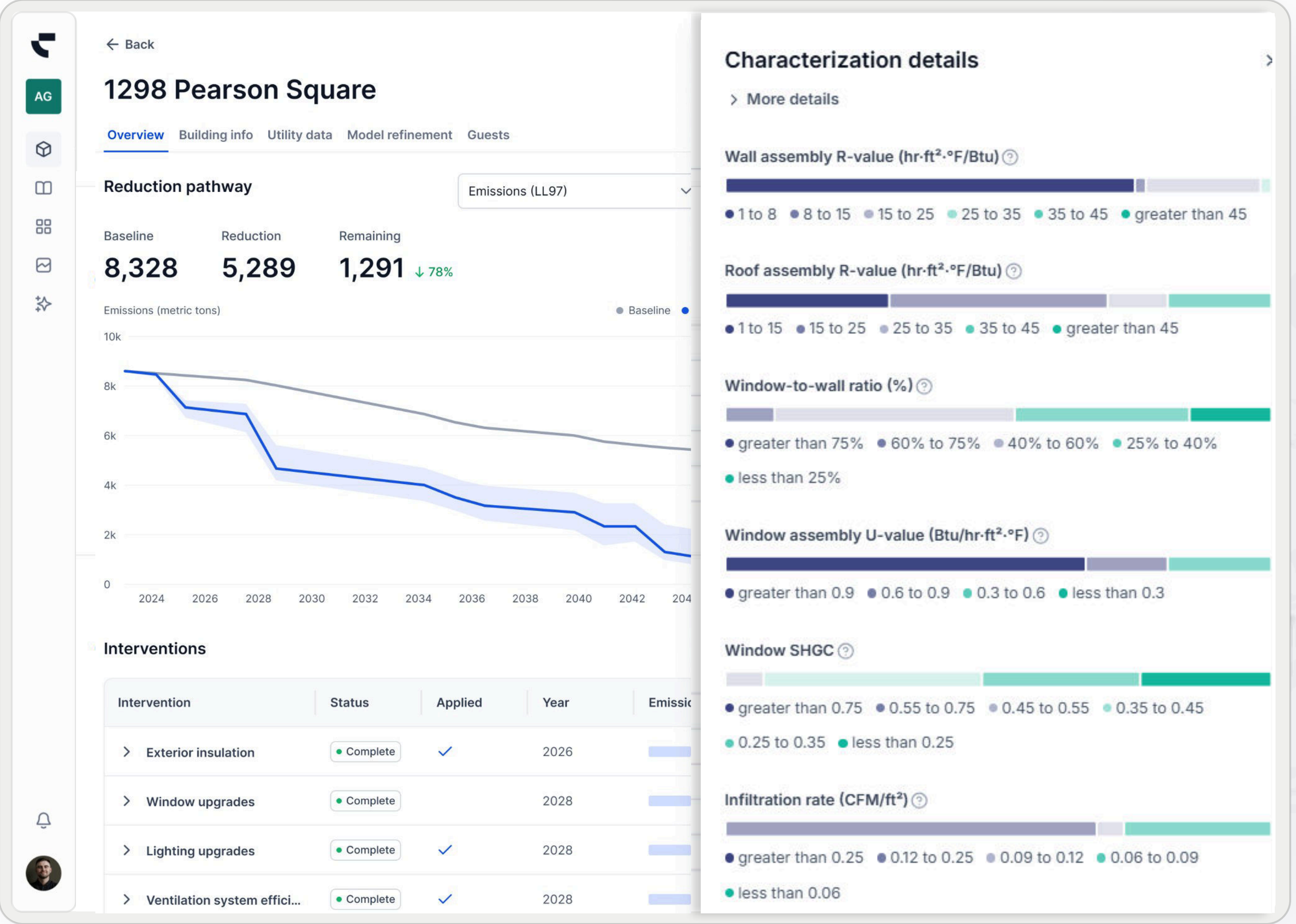
Quickly identify the performance of critical building systems using a few key data points.

Then, simulate interventions

Evaluate any decarbonization intervention utilizing a baseline tailored to that building.

And uncover real savings

Establish realistic roadmaps that account for programmatic, operational, financial constraints.



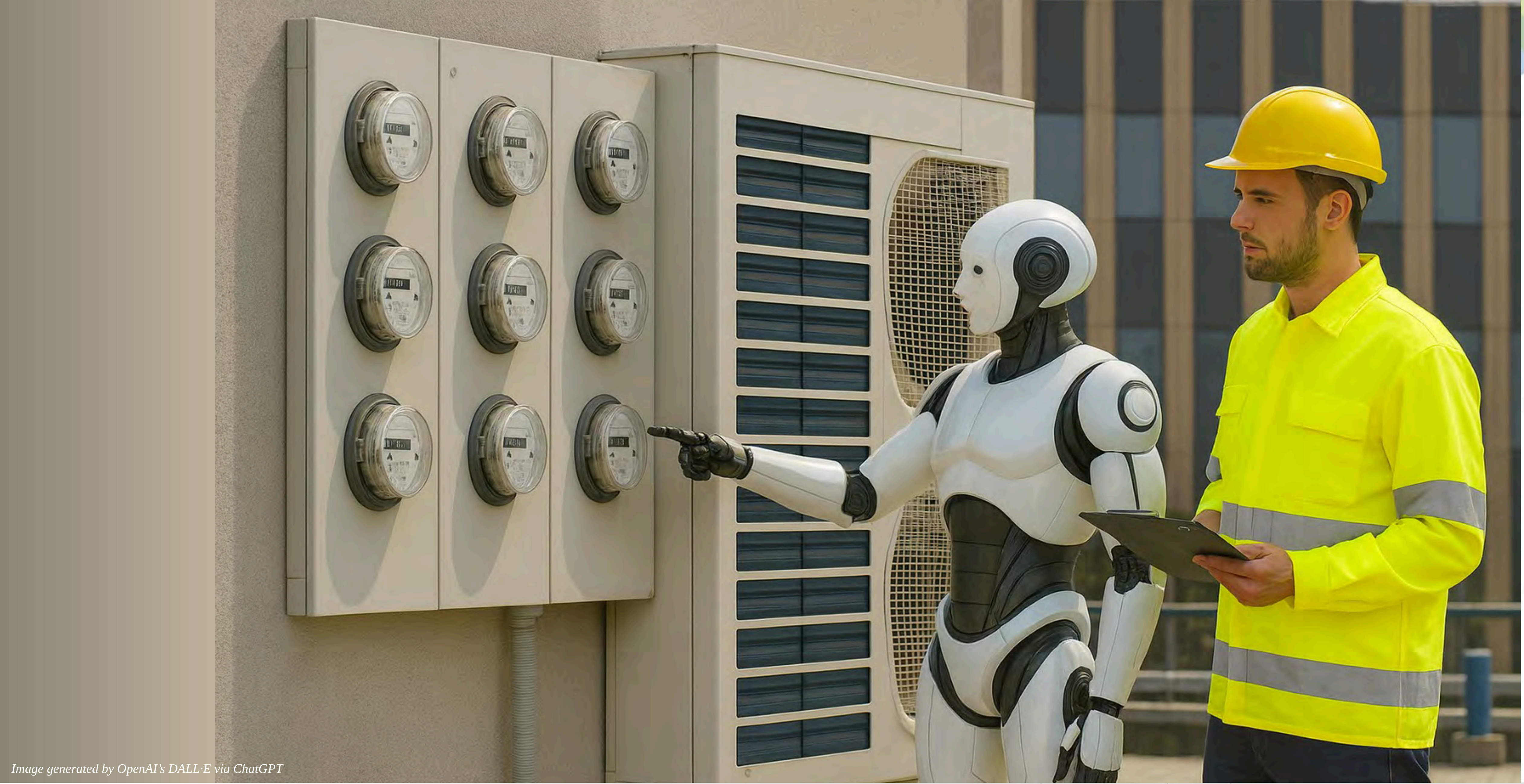
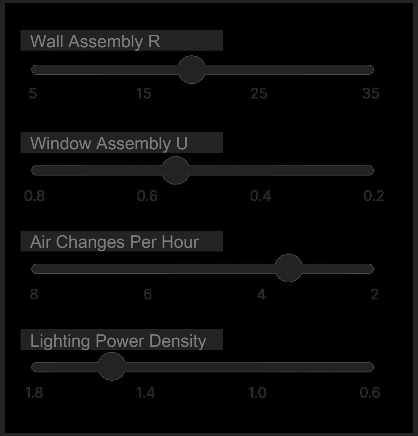
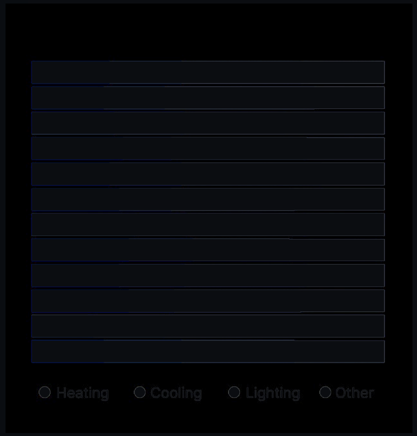


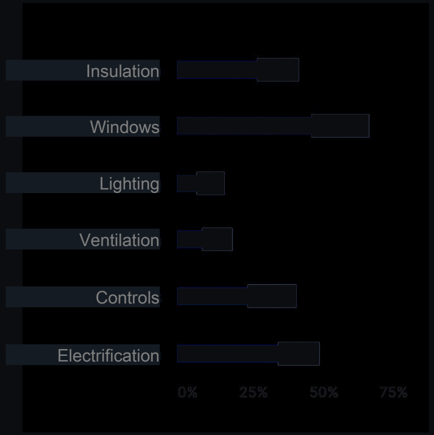
Image generated by OpenAI's DALL·E via ChatGPT

The science behind Carbon Signal

AI Autocalibration







Monthly data

Analyze trends in building energy use given size & climate.

Exploration

Search through all possible building parameters.

Deduction

Identify all parameter values that can explain building energy use.

Baseline

Generate physics-based energy models for building insights.

Scenarios

Quantify confidence levels in projected intervention savings.

Solving with rules, not pattern-guessing

Under-determined problem

E.g., a Sudoku with too few clues can have dozens, even hundreds of valid solutions.

Quantified uncertainty

Use automation to explore all possible solutions to see the full picture. Still solving with rules.

Conditional identifiability

As more clues come in, the uncertainty narrows, giving us confidence in the answer.

		4	3					5
1		5			4			
7	3					2		4
				?				
		2					4	
			5					1
	5	7						
8						5	3	

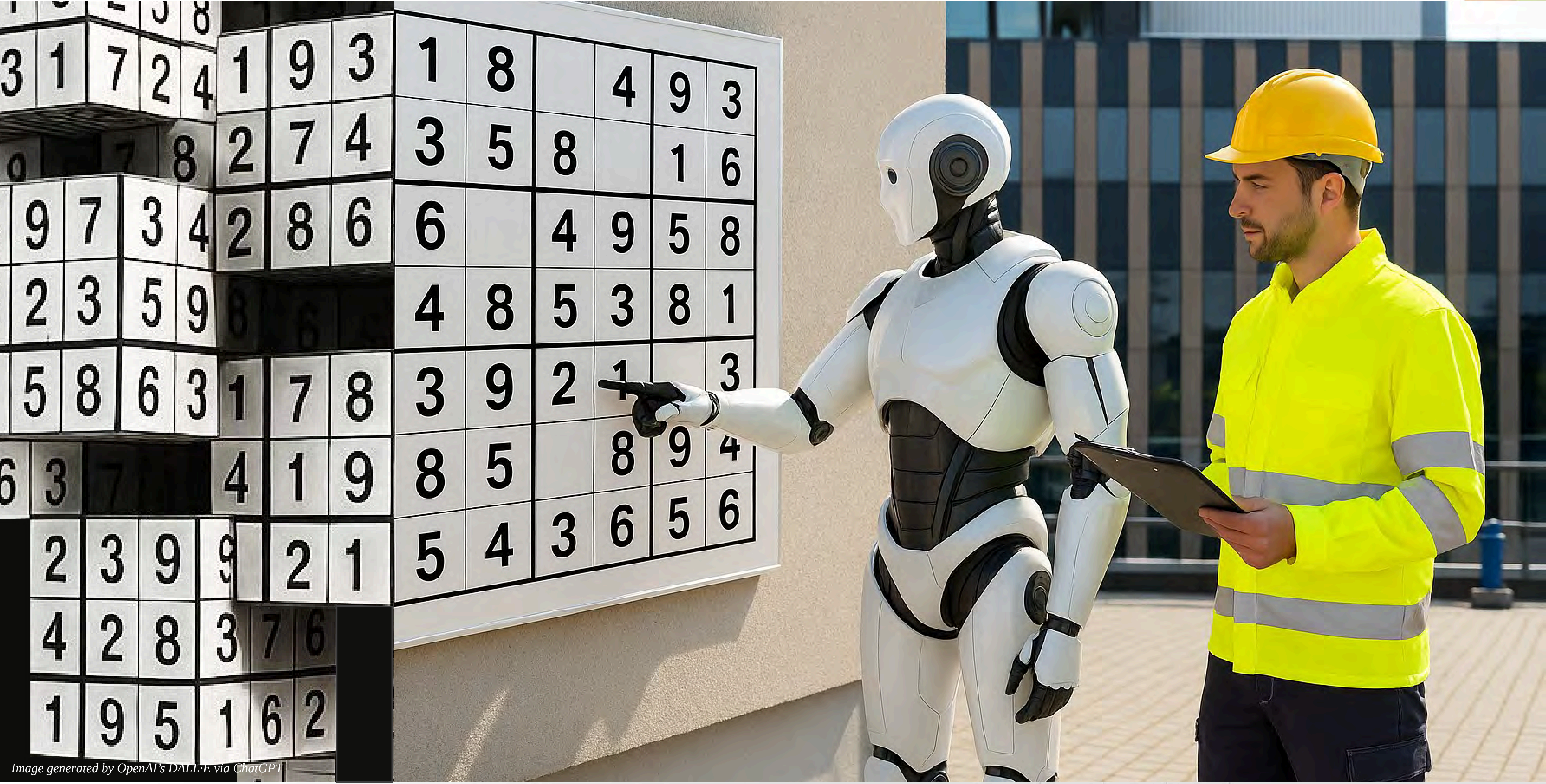


Image generated by OpenAI's DALL·E via ChatGPT

The map of possibilities

The physics is complex

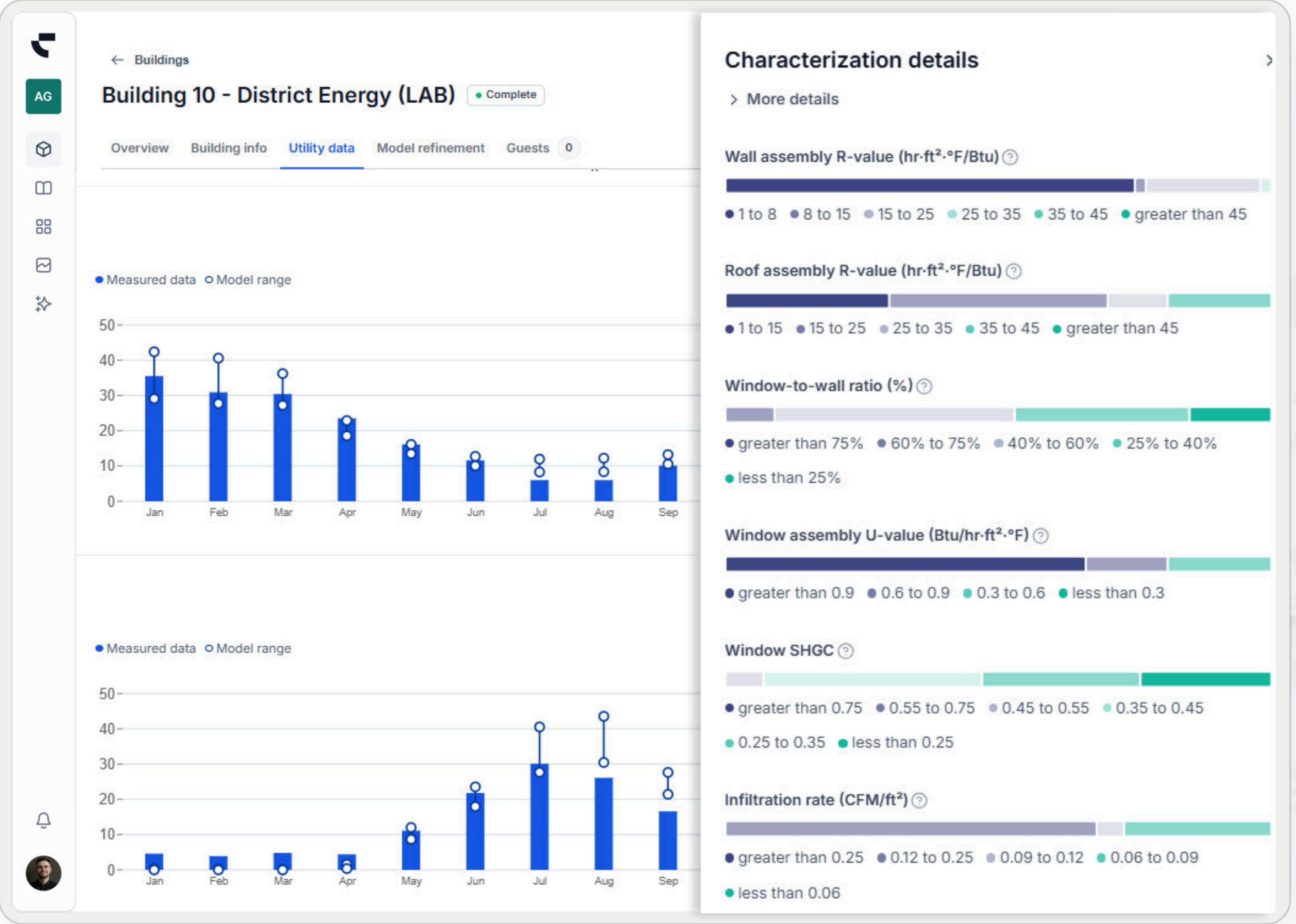
Same principle as Sudoku, but extremely complex. Exploration space is unimaginably larger - in trillions.

No easy patterns to guess

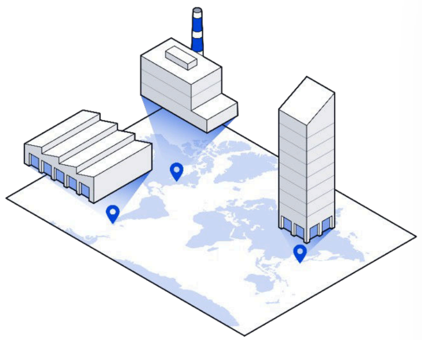
Humans cannot find all reliable solutions without clues. AI can not find patterns with any confidence.

Accelerate physics with AI

Physics constrains the exploration space; AI explores it rapidly. The result is a map of possibilities.

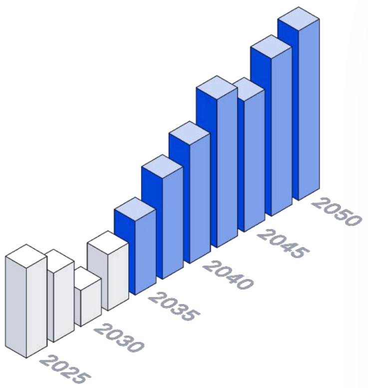


From analysis to action



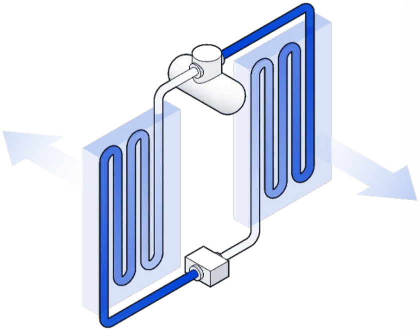
Study any type of building, anywhere in the world

with its own model tuned to its unique energy behavior.



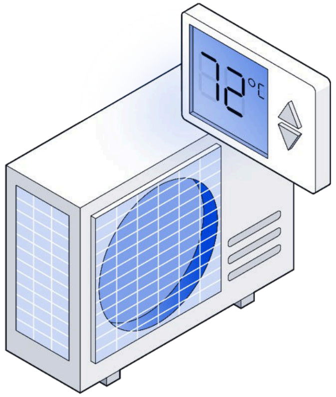
Create project timelines and investment roadmaps

simulated over changes in future climate and grid.



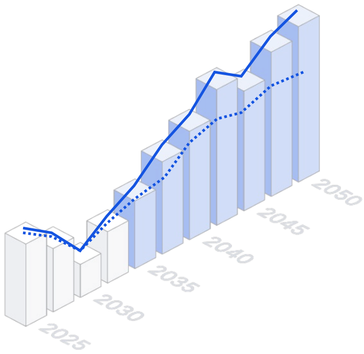
Assess asset-level savings or portfolio-wide ROIs for

any intervention, system upgrade or operational tweak.



Add building details or more energy use data to

refine models and reduce uncertainty if needed.



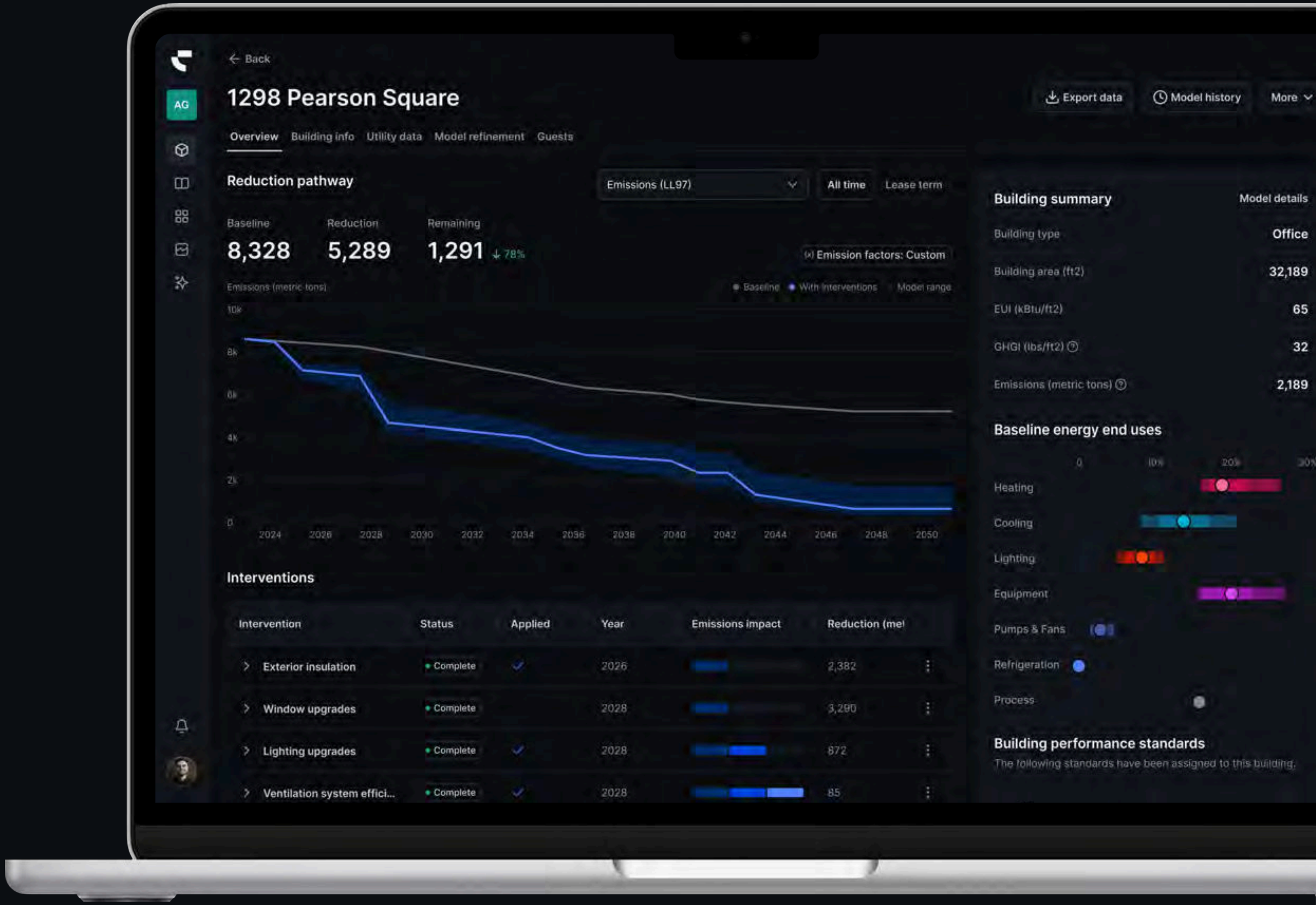
Answer different questions at different stages and

move from analysis to action to tracking its impact.

Scaling Portfolio Decarbonization

Building Energy Intelligence

From 6 months to 6 minutes.



From months to minutes

Introba

Automatically filled data gaps for over 500 buildings and identify top priorities.

Amazon

Scaled 40 audit-fidelity evaluations to 3000 assets of different program types.

MIT

Refined models, fixed misconfigured controls that saved 5000 MTCO2e/yr.

Portfolio decarbonization analytics and planning


MIT


Georgia Tech


Johns Hopkins University


University of Michigan


Yale University


UC Santa Barbara


Amazon


NOAA Fisheries


San Jose State University


Univ of San Francisco


Lawrenceville School


DC DOEE

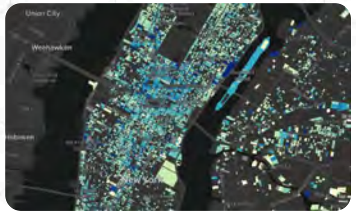

Introba Tech Client


Introba Retail Client


Introba Retail Client


Introba Tech Client


Introba Retail Client


Urban Green NYC

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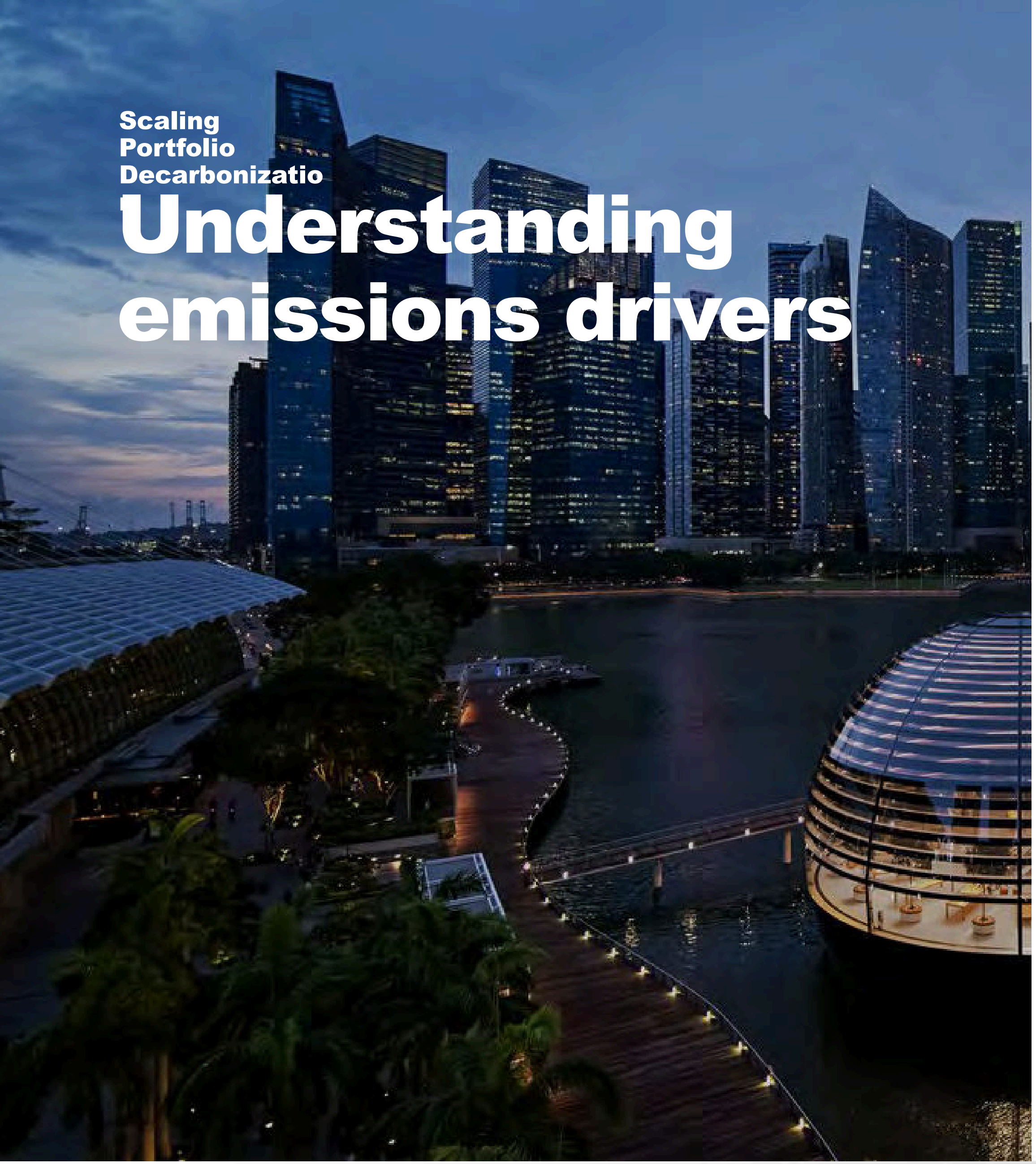
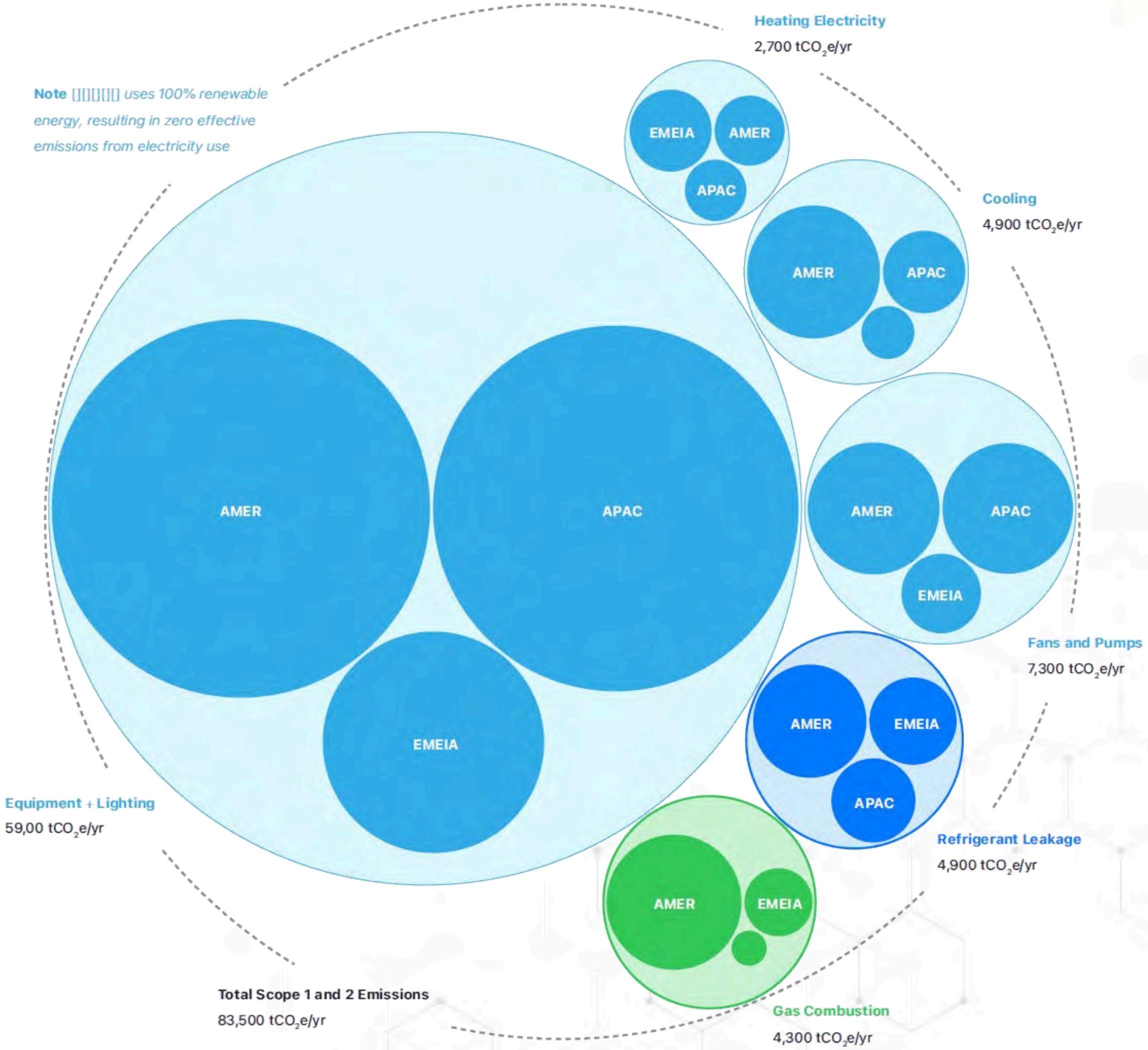
Understanding emissions drivers





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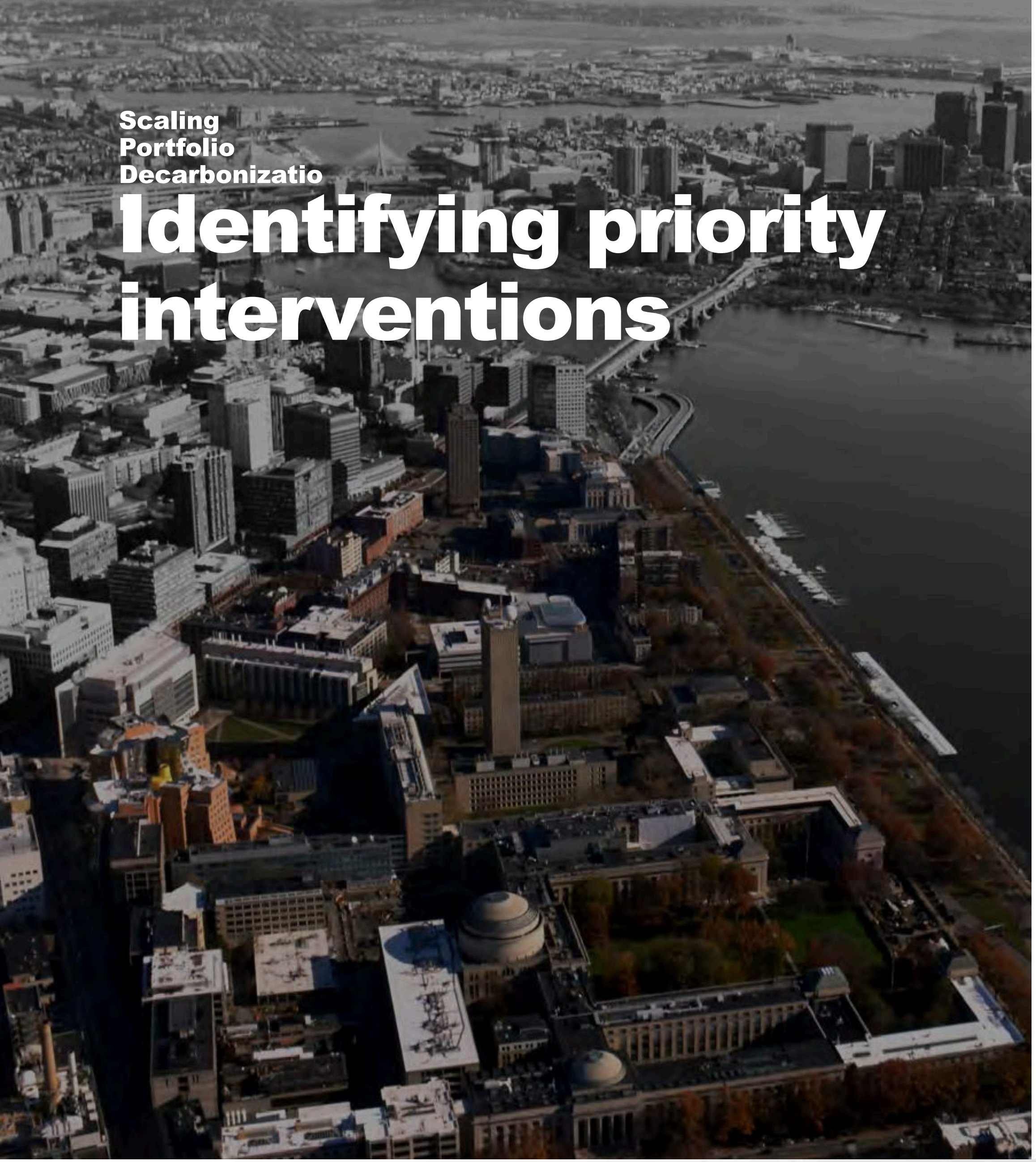
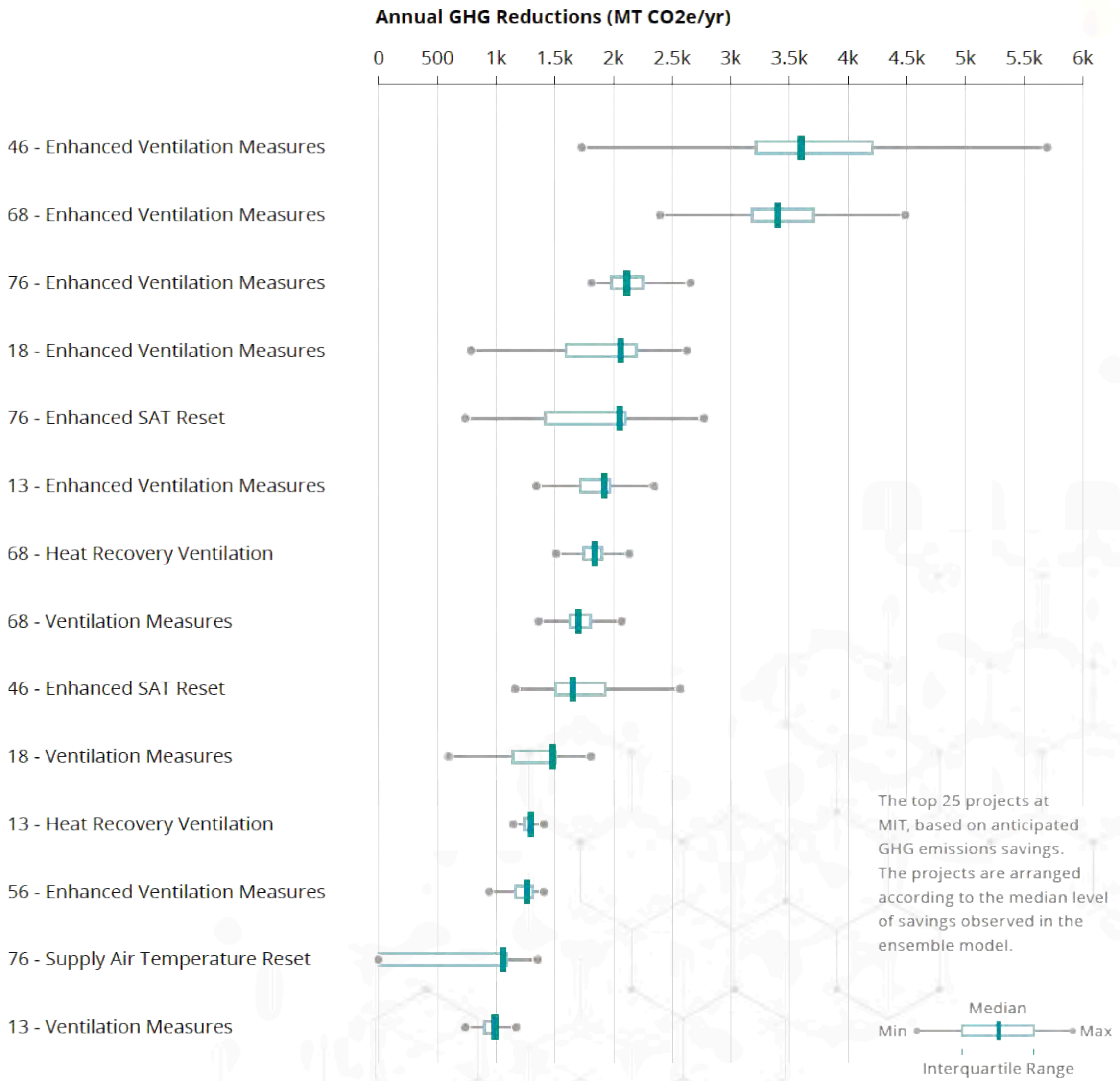
Identifying priority interventions





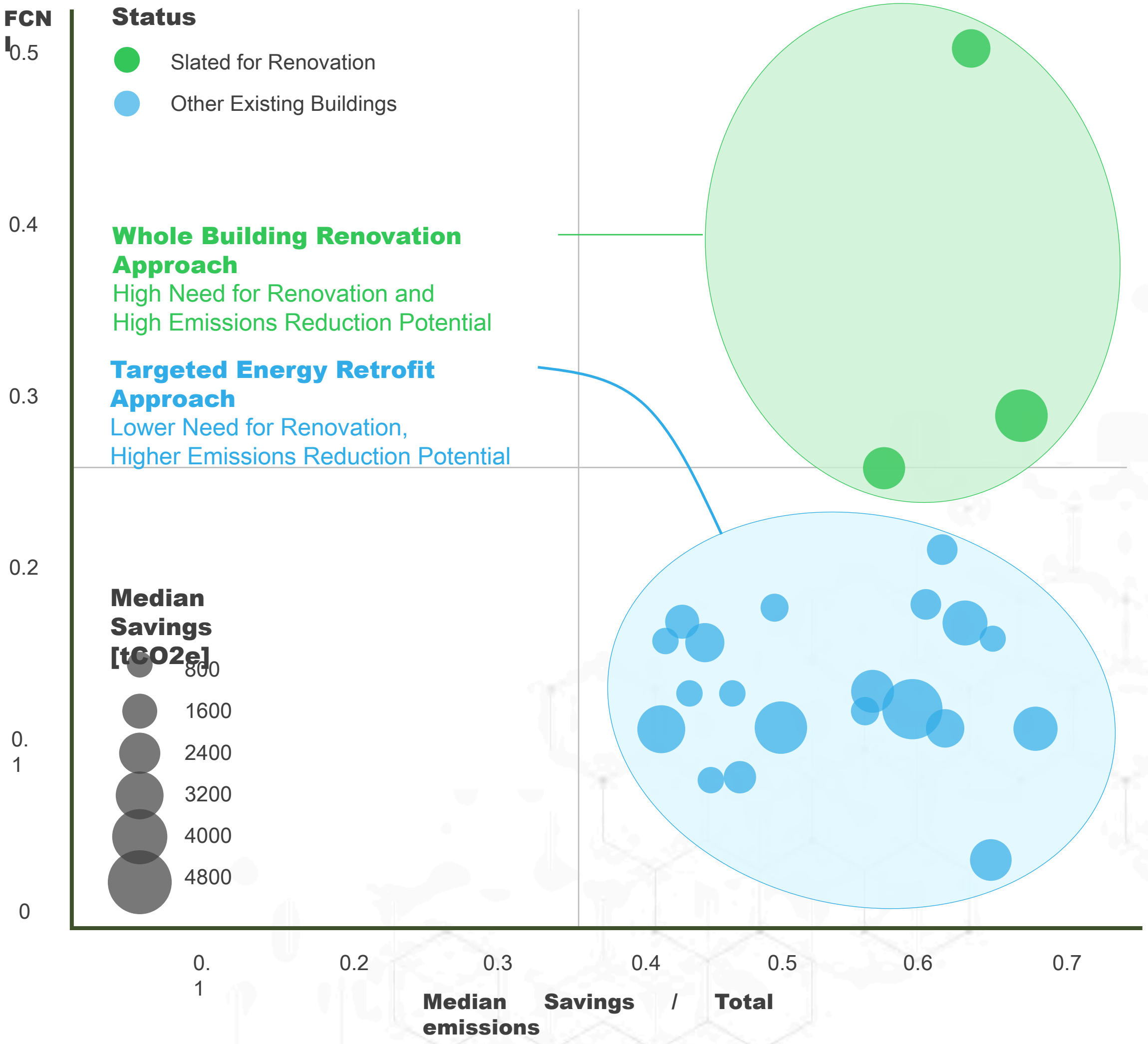
The top 25 projects at MIT, based on anticipated GHG emissions savings. The projects are arranged according to the median level of savings observed in the ensemble model.

Scaling Portfolio Decarbonizatio

Strategizing decarb assessments

Scaling Portfolio Decarbonization

Comprehensive campus planning



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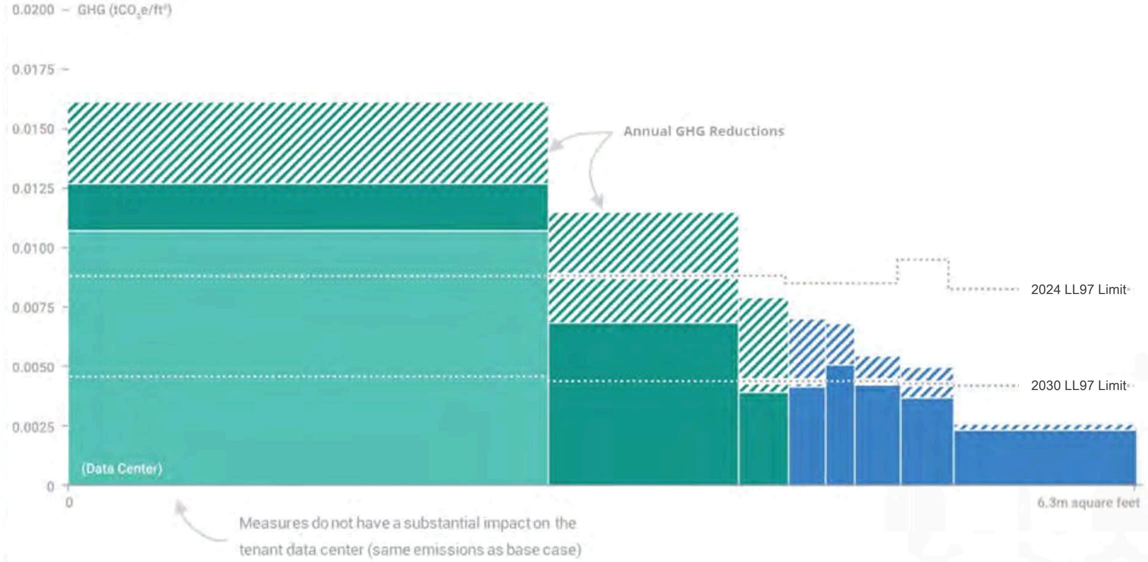
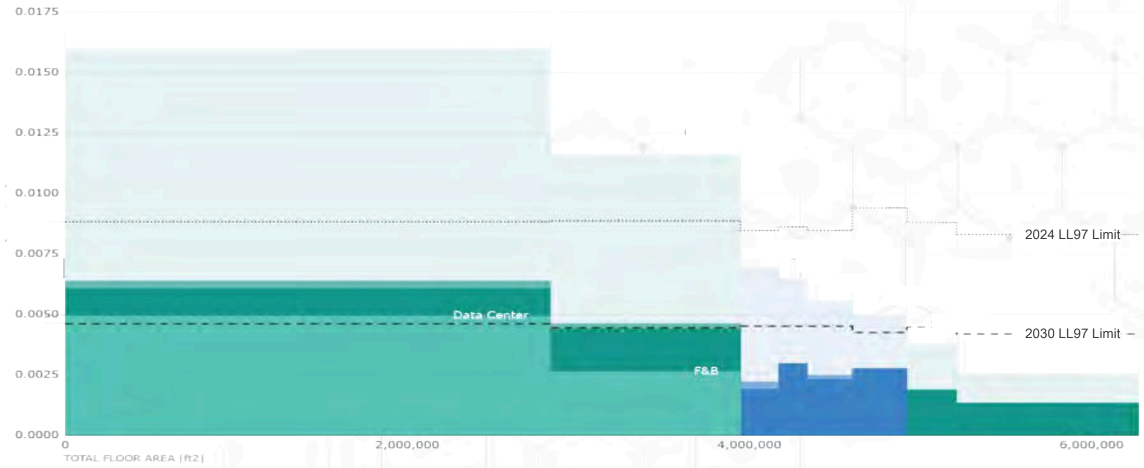
Establishing realistic targets

GHG EMISSIONS INTENSITY



Future State



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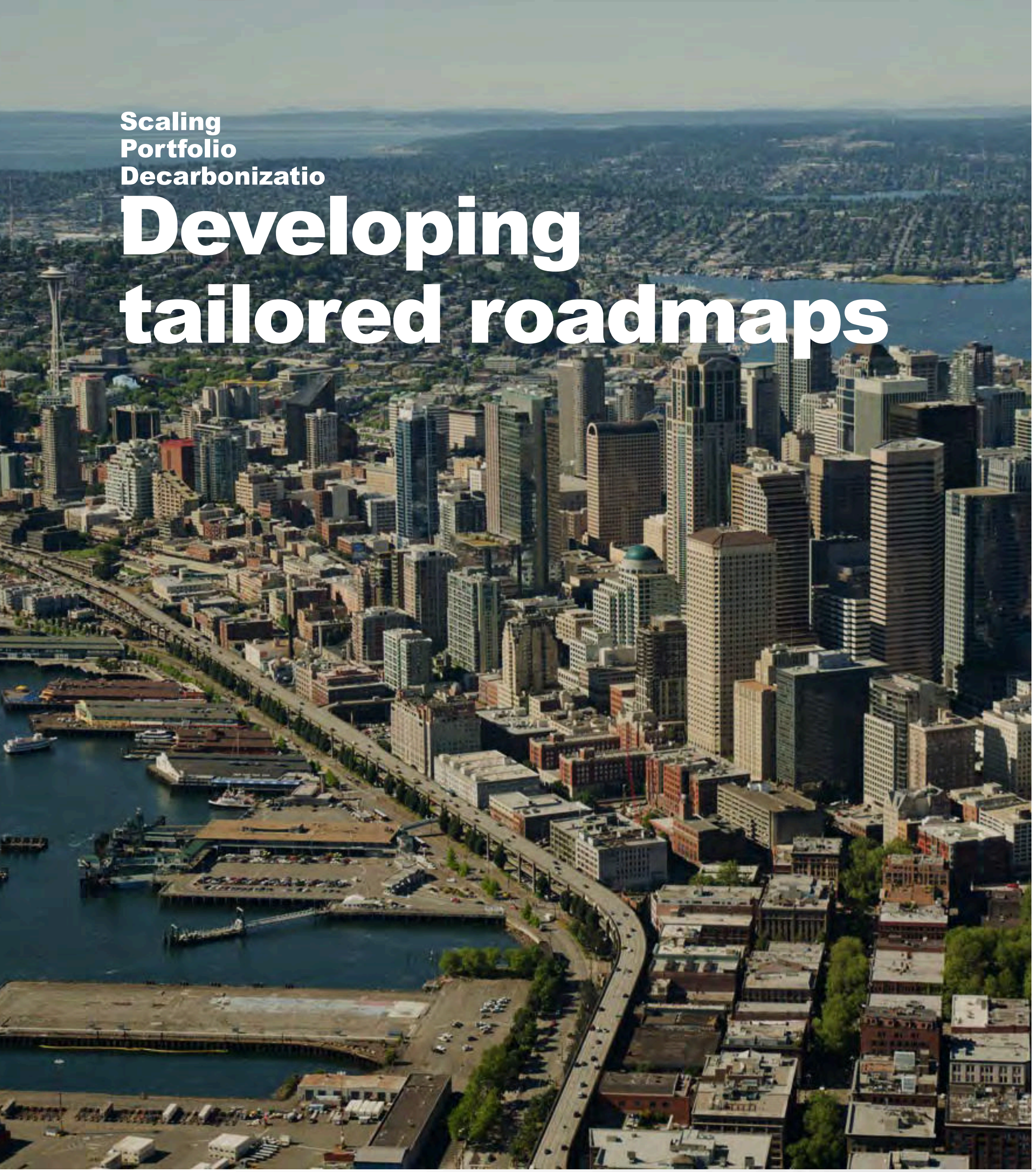
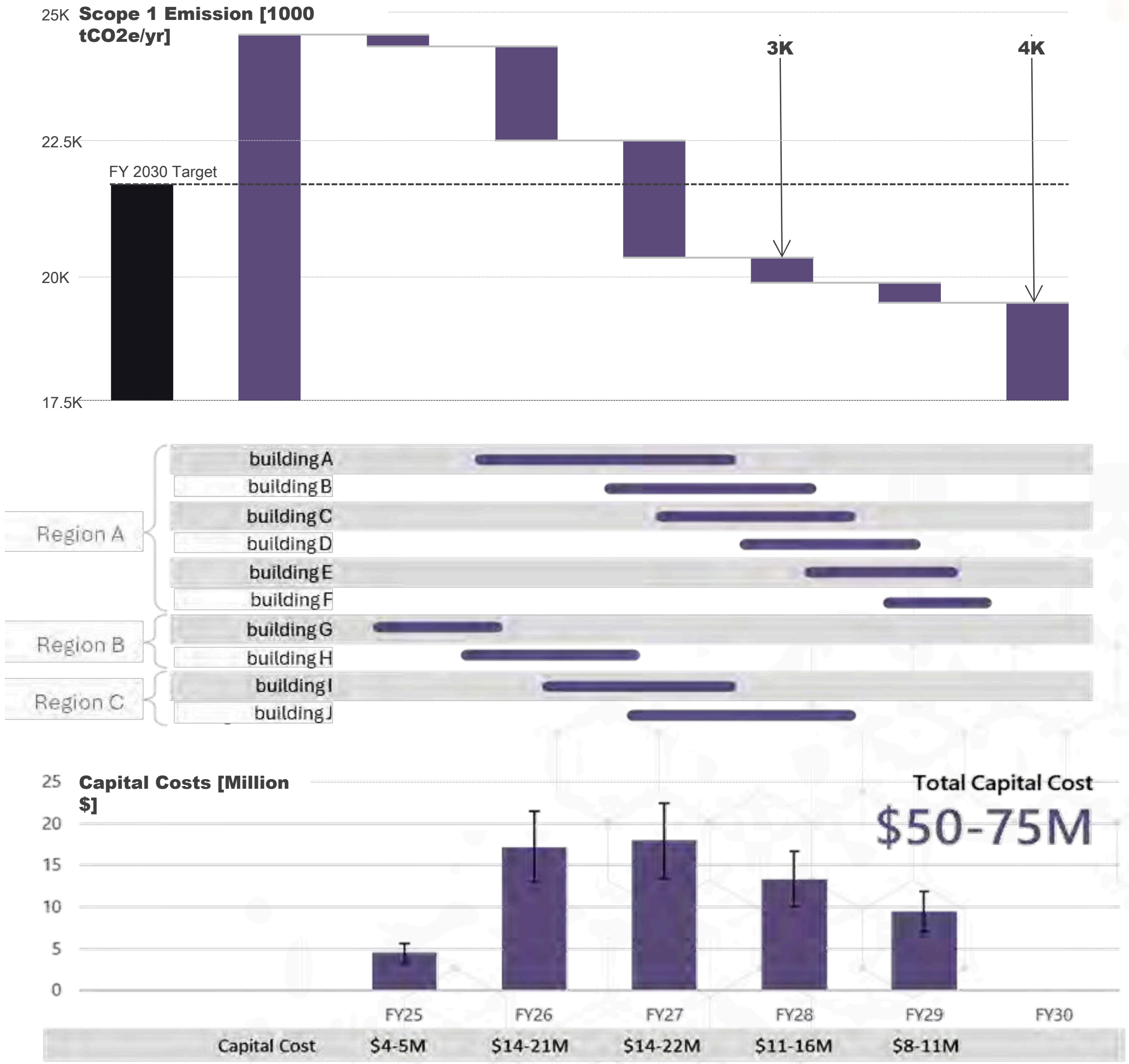
Developing tailored roadmaps





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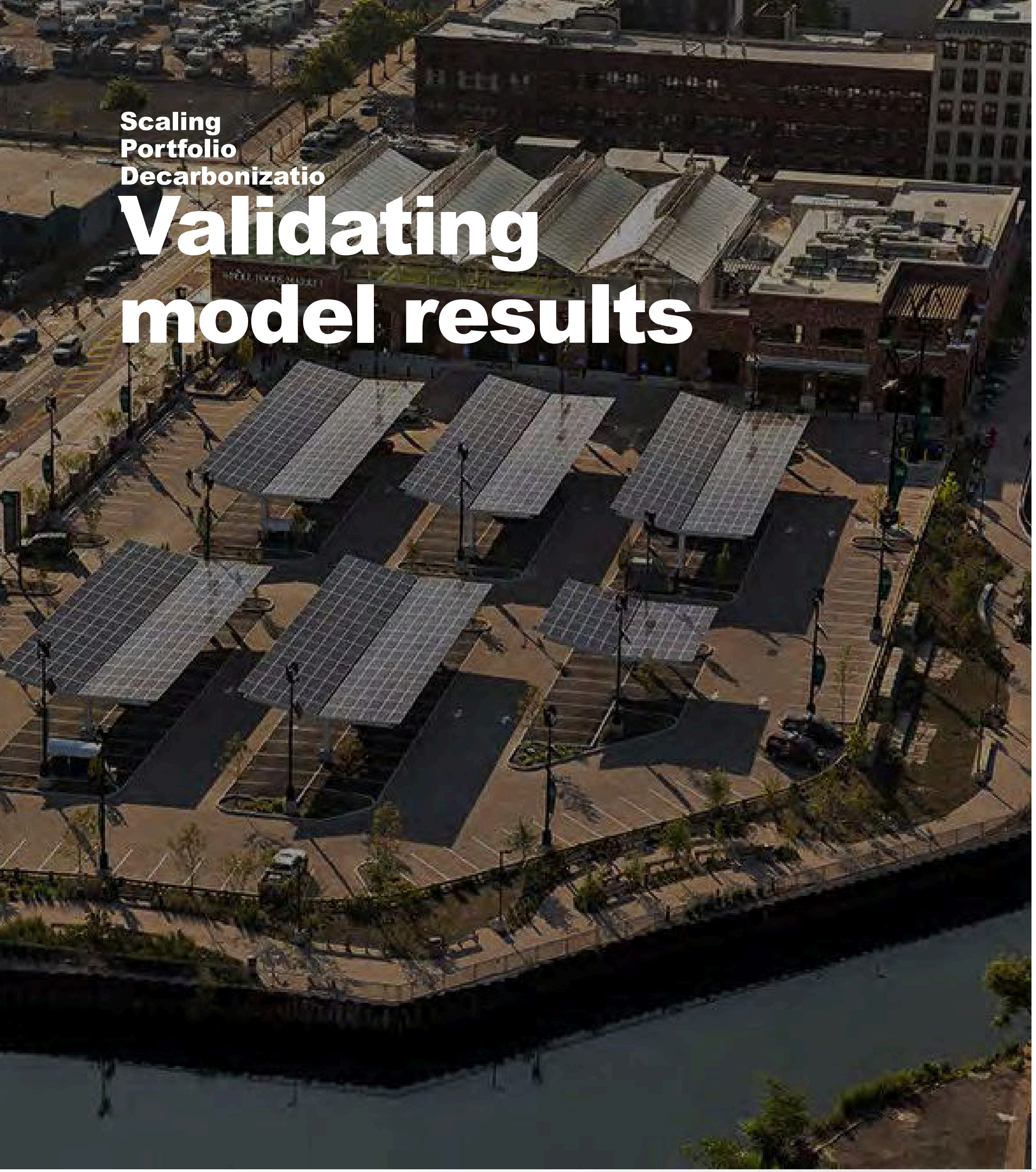
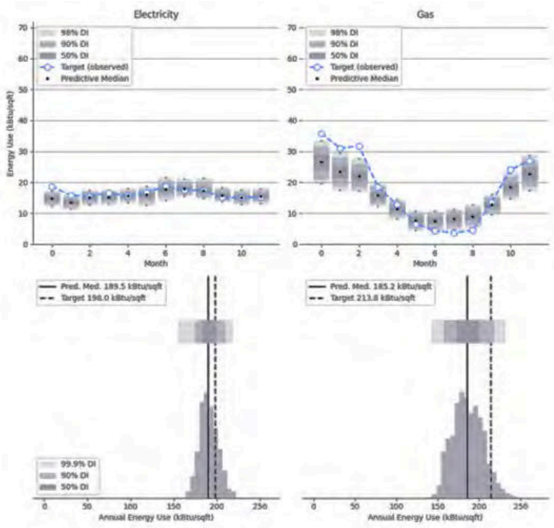
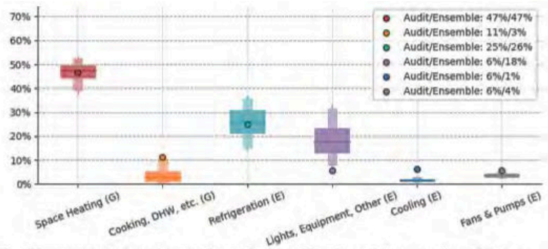
Validating model results

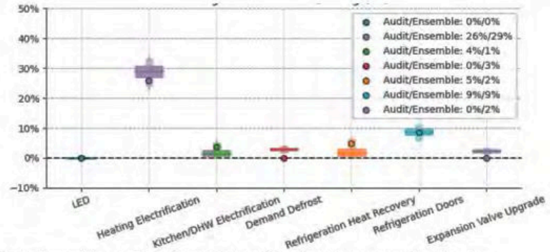




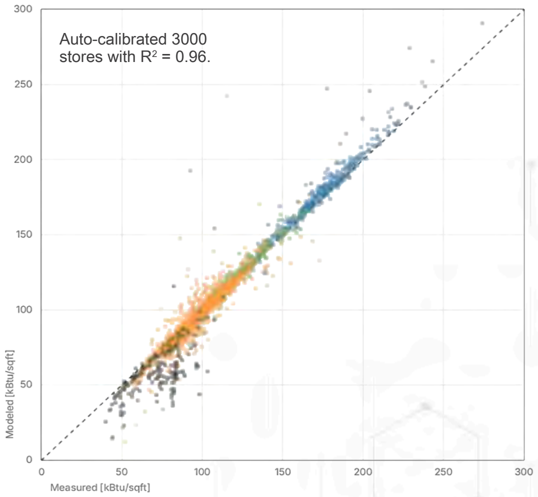
3a. Autocalibration results from Carbon Signal models vs metered data

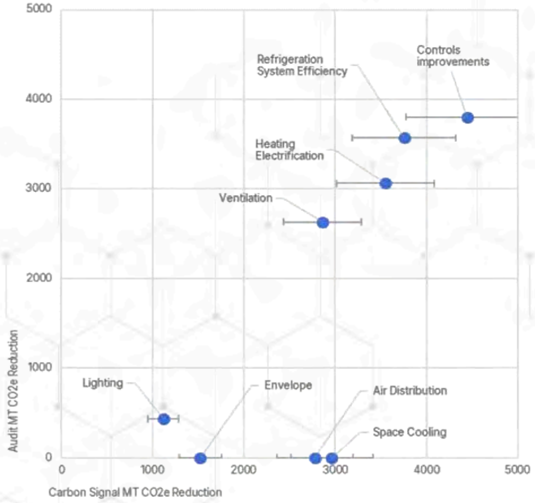


3b. Disaggregation estimates from Carbon Signal models vs audit estimates



3c. Intervention savings from Carbon Signal models vs audit estimates





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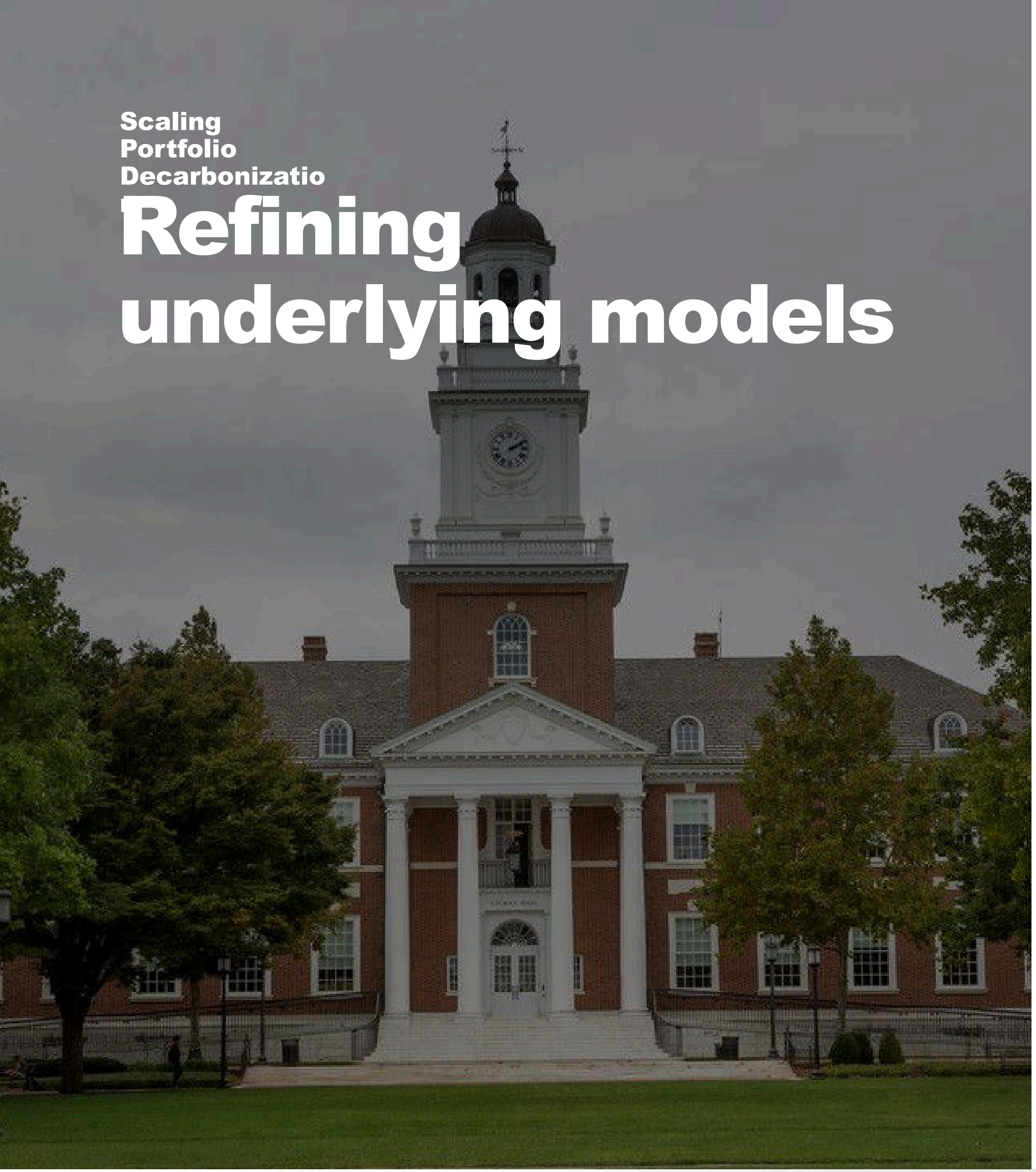
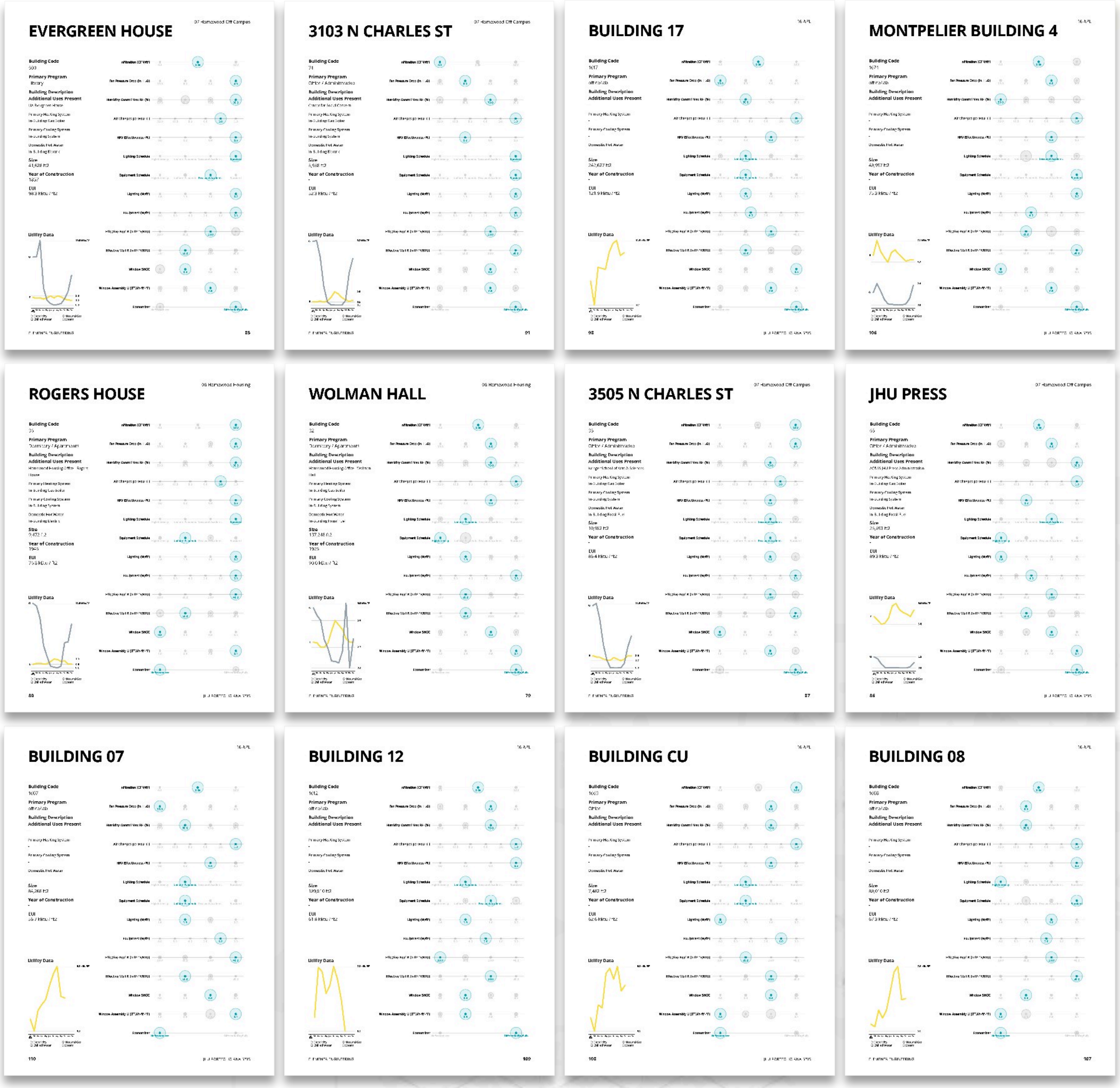
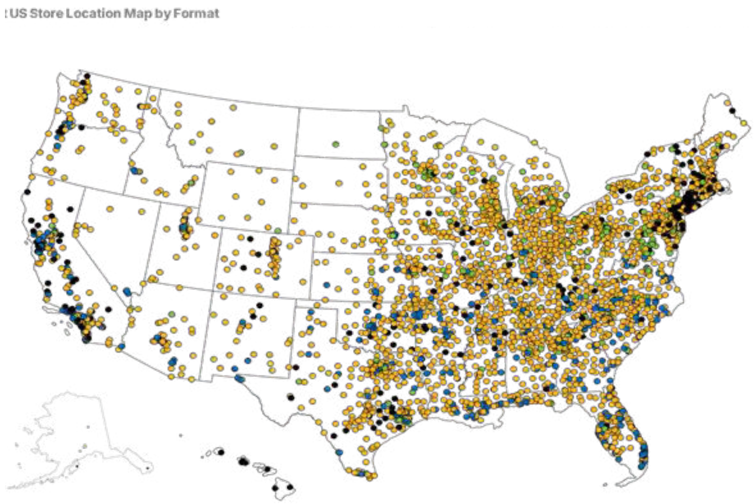
Refining underlying models

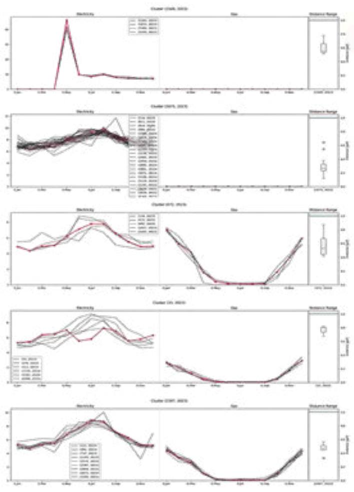




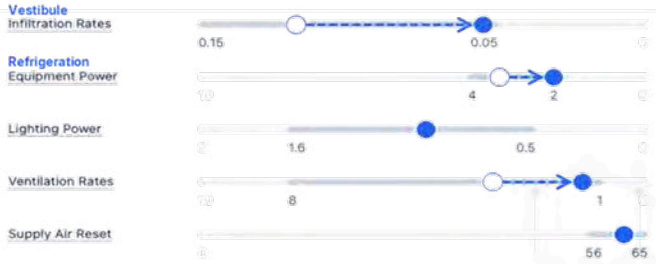
Scaling Portfolio Decarbonization

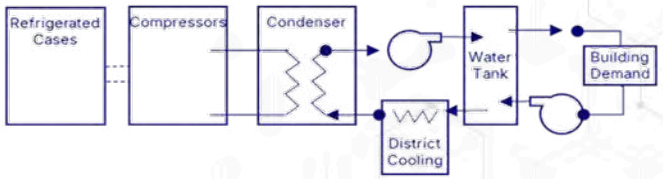
Creating custom interventions



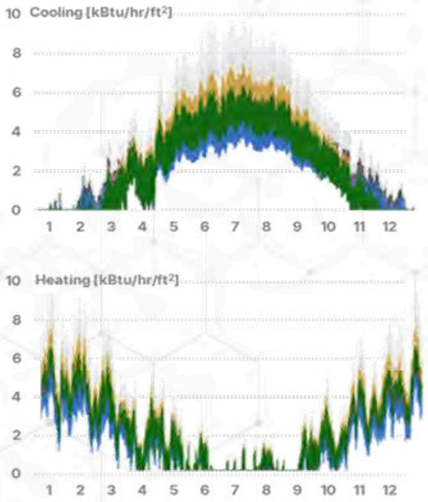


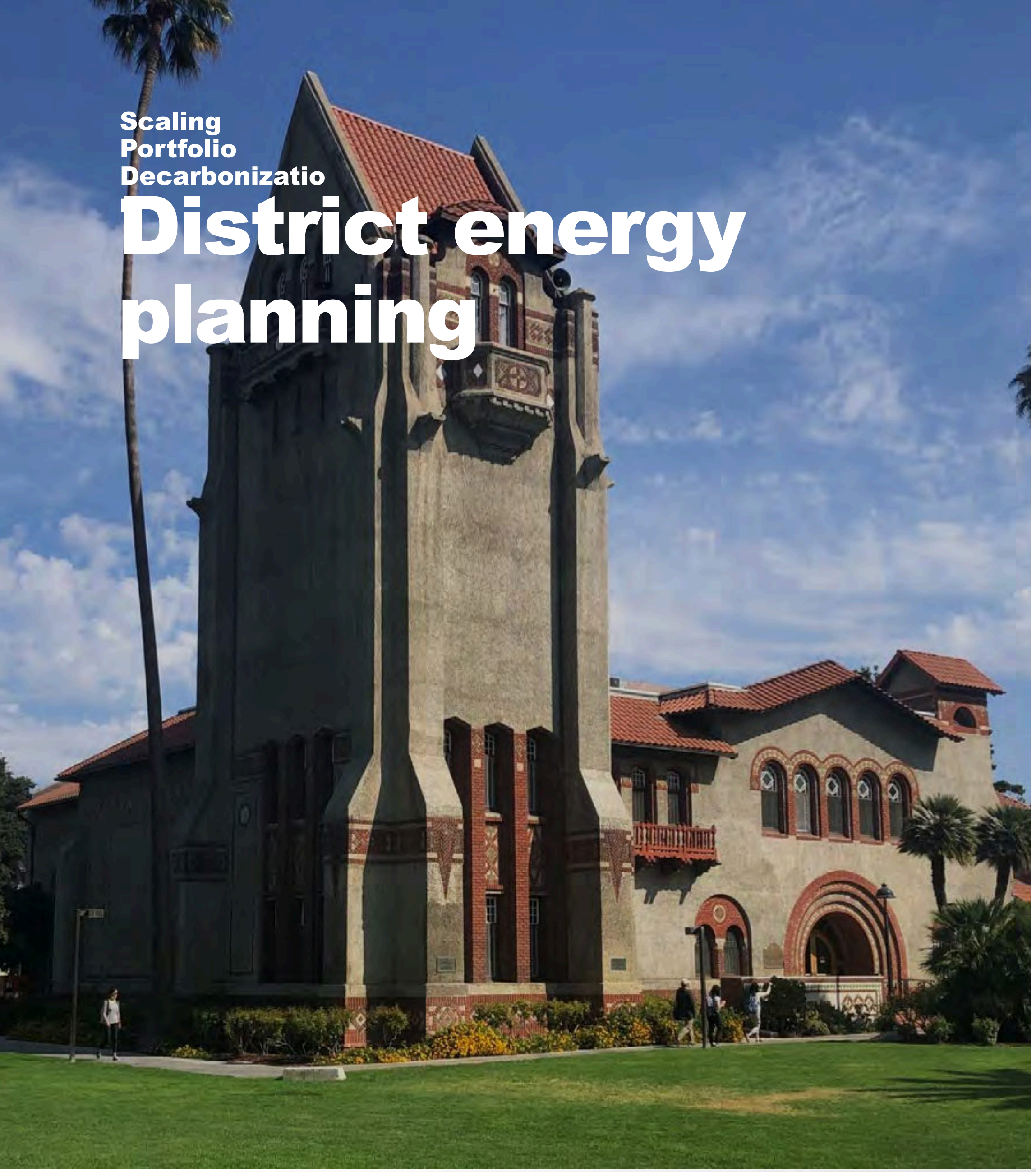
Zone Level Characteristics





Zone Level Demand Profiles





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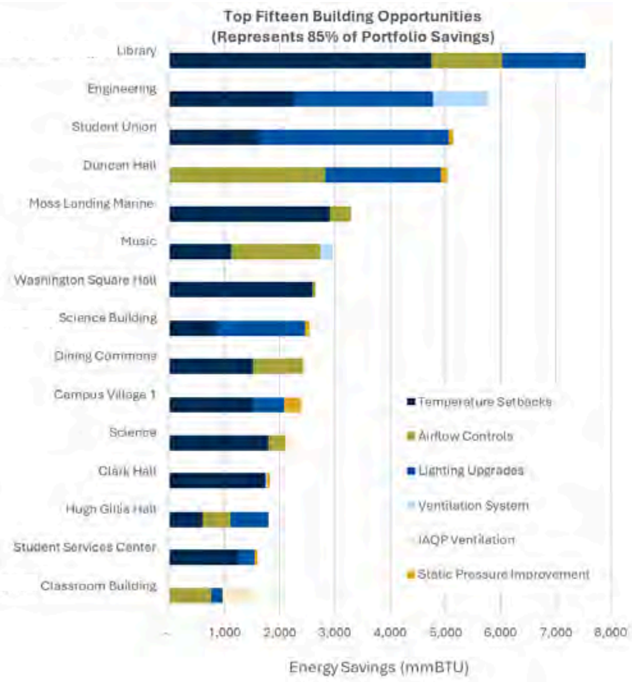
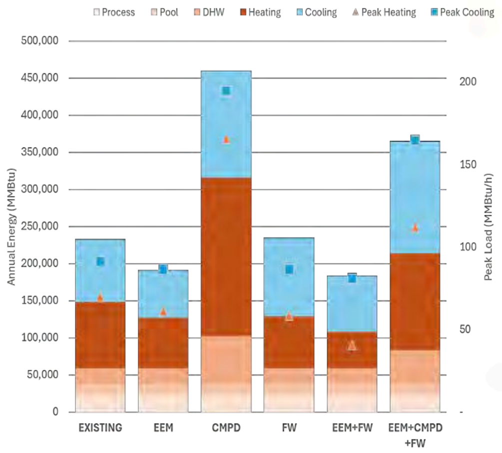
District energy planning





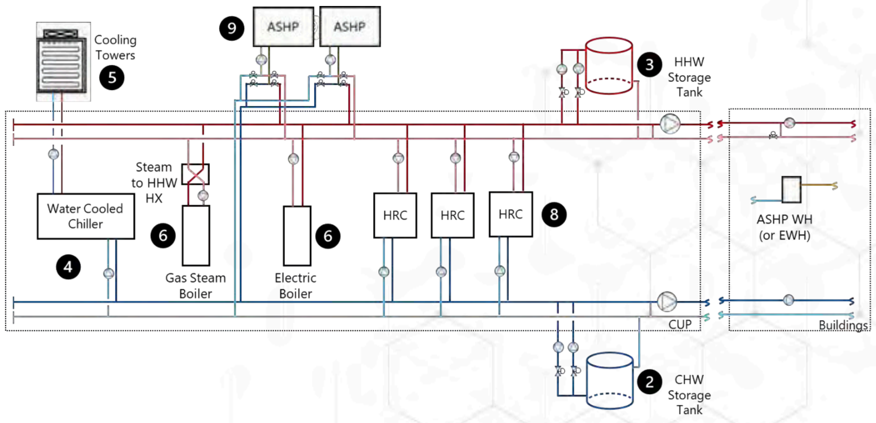
Scenario 0 BAU: Represents the baseline campus energy loads

Scenario 1 EEMs: Reflects the reduced energy loads compared to the baseline due to the implementation of the top 3 EEMs per building

Scenario 2 CMPD: Includes campus expansion

Scenario 3 FC: Based on the baseline model but with a future weather file for 2045

Scenario 4 FC + CMPD: All gas and steam usage is replaced by electrified systems



1	Heat Pump Chillers & Gas Coolers	
2	Chilled Water TES Tank	576,000 Gal
3	Hot Water TES Tank	26,500 Gal
4	Water Cooled Chillers	3000 Tons
5	Cooling Tower	5530 Tons
6	Gas Boilers Electric Boilers	112.5 MMBtu 3960 kW
7	Air Cooled Chiller	
8	Heat Recovery Chiller	1250 Tons
9	Air Source Heat Pumps	1120 Tons
10	Wastewater Heat Recovery Skid + Holding Tank	

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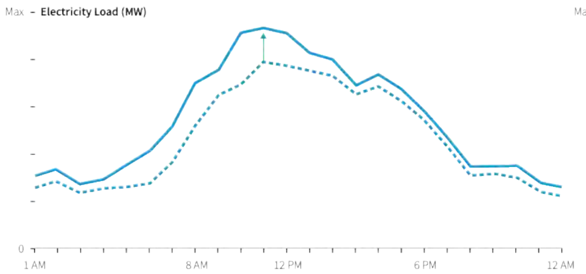
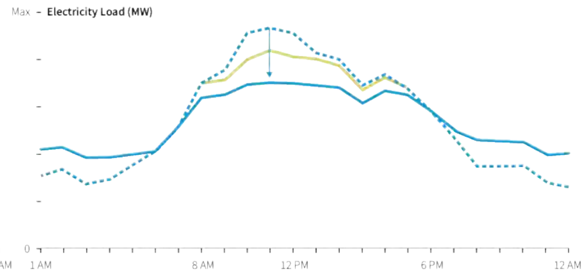
Thermal energy electrification

WINTERTIME DEMAND INCREASE

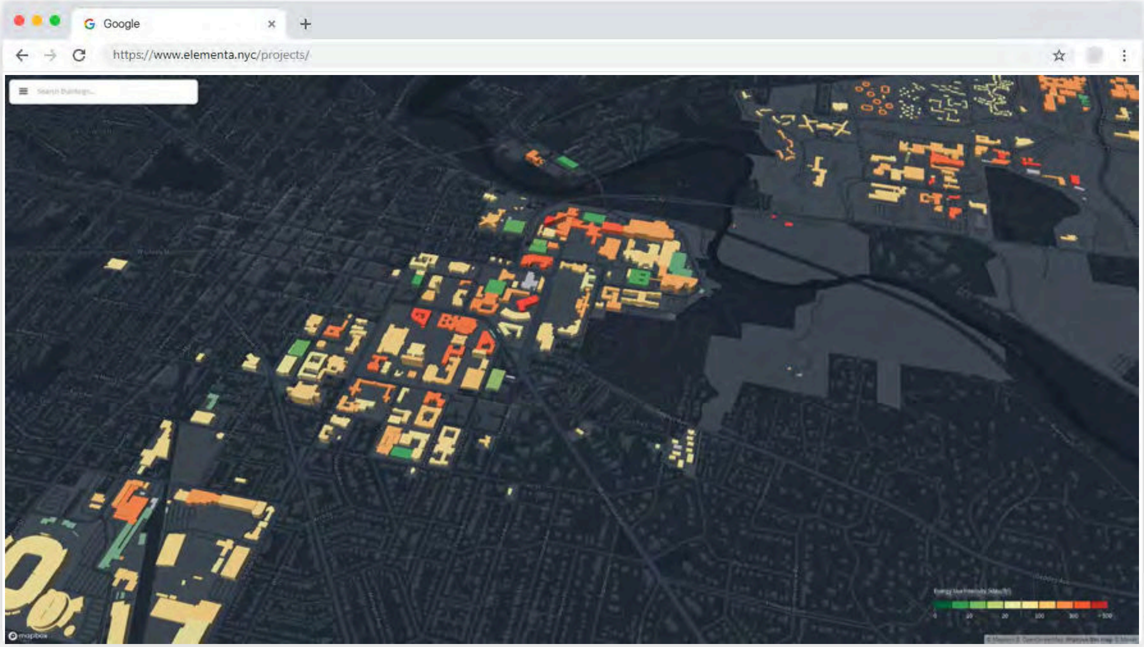


Campus electricity profile after electrification
Current electricity profile

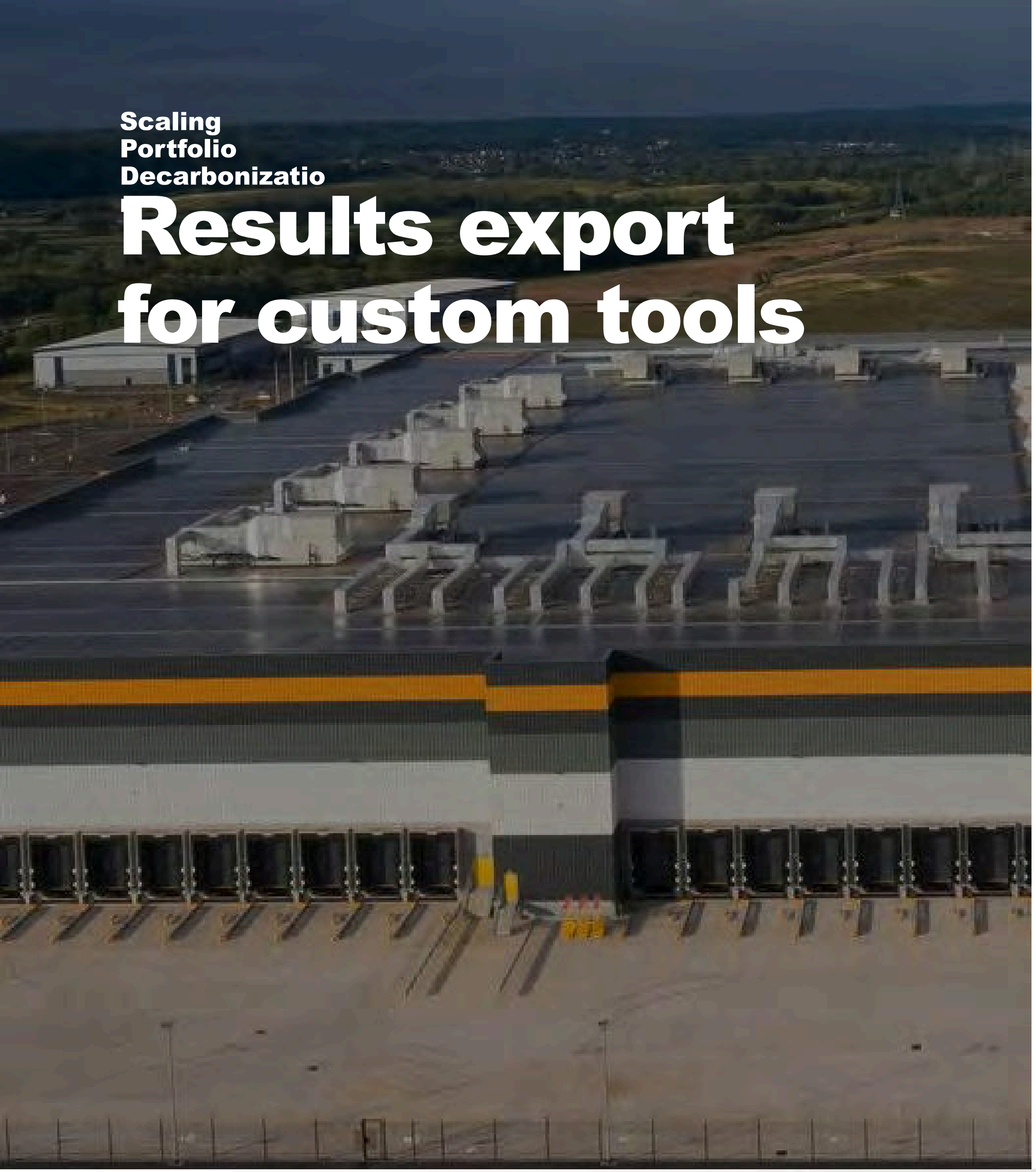
PEAK DEMAND REDUCTION

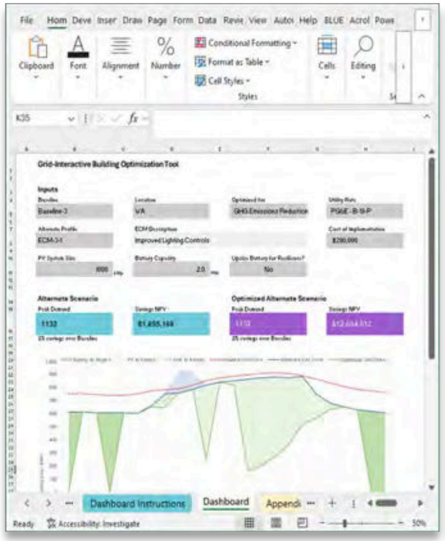


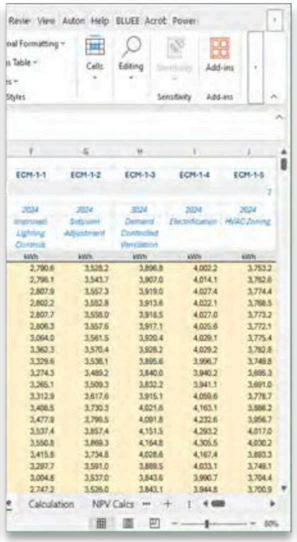
Campus electricity profile after electrification
With solar (estimate)
With solar and battery storage

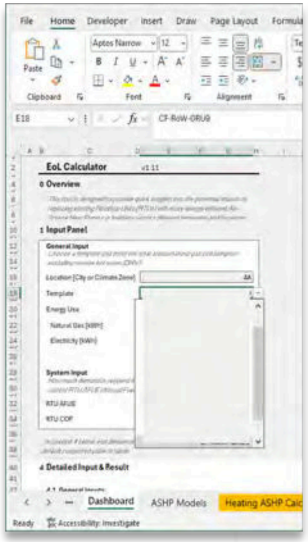


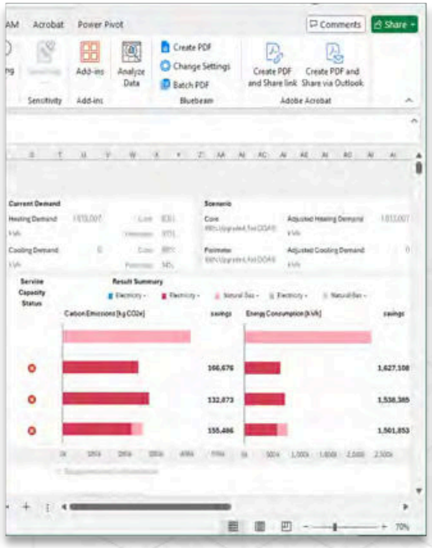
Results export for custom tools

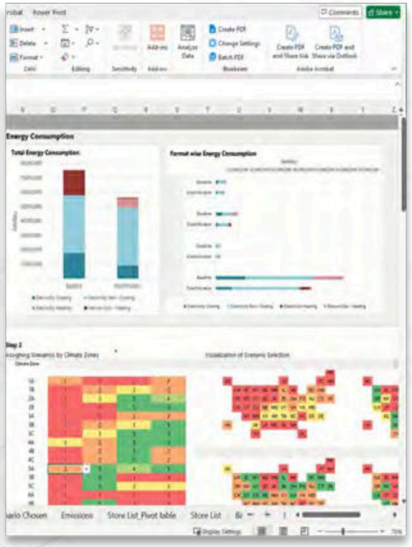












Portfolio decarbonization analytics and planning


MIT


Georgia Tech


Johns Hopkins University


University of Michigan


Yale University


UC Santa Barbara


Amazon


NOAA Fisheries


San Jose State University


Univ of San Francisco


Lawrenceville School


DC DOEE

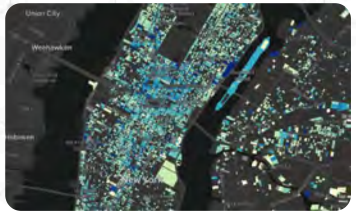

Introba Tech Client


Introba Retail Client

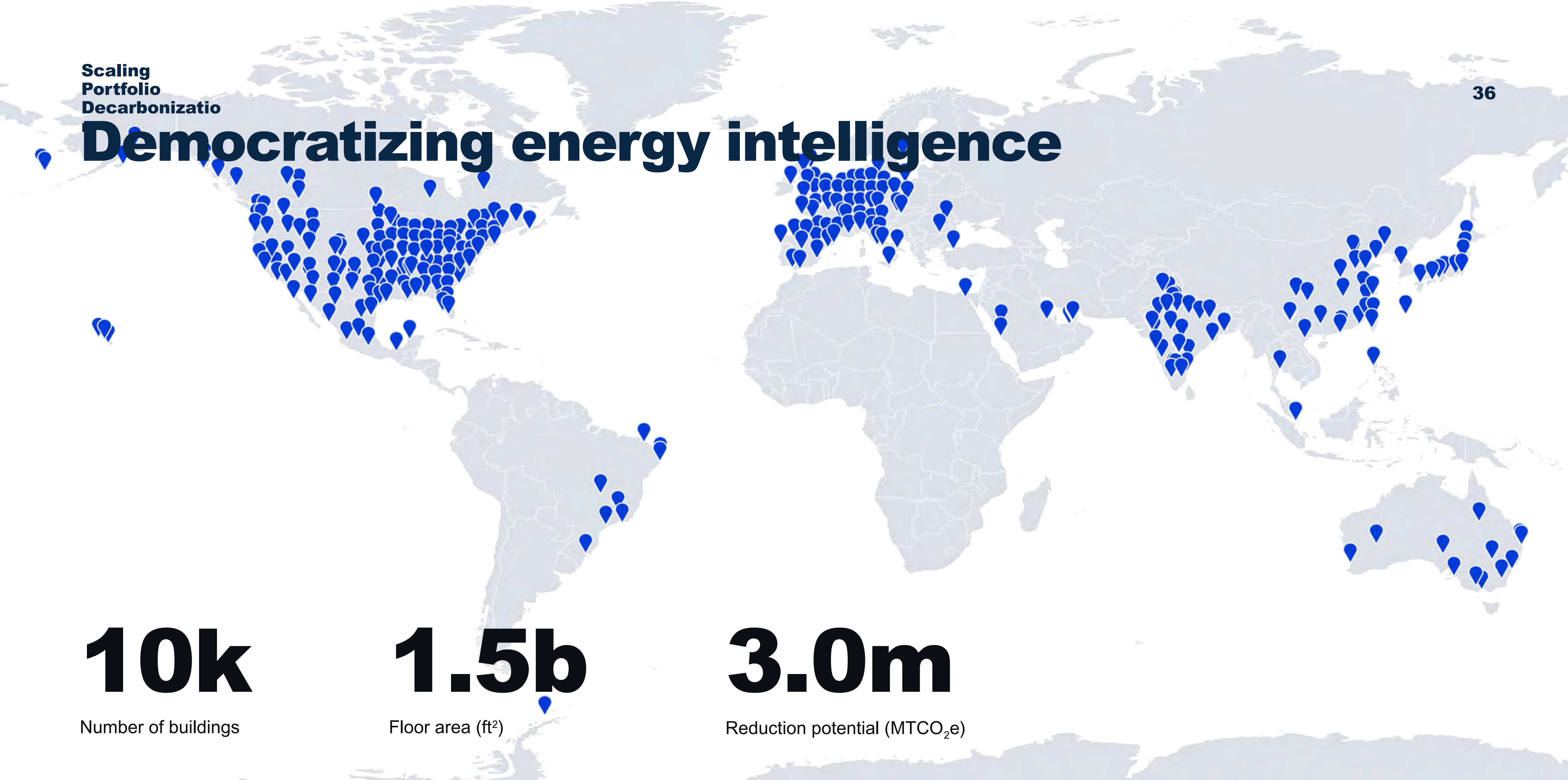

Introba Retail Client


Introba Tech Client


Introba Retail Client


Urban Green NYC

Democratizing energy intelligence



10k

Number of buildings

1.5b

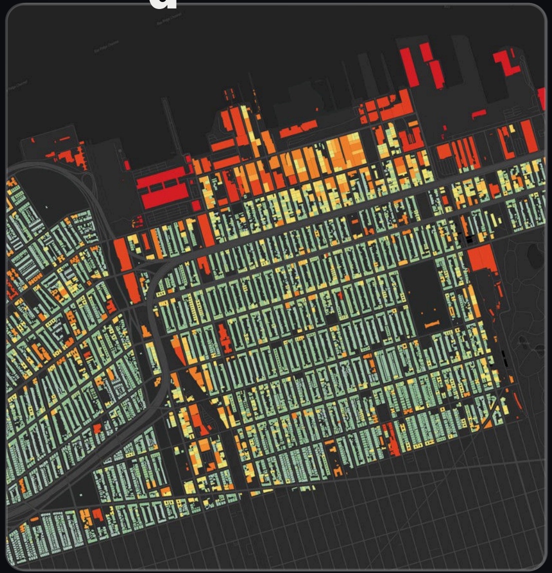
Floor area (ft[2])

3.0m

Reduction potential ($MTCO_2e$)

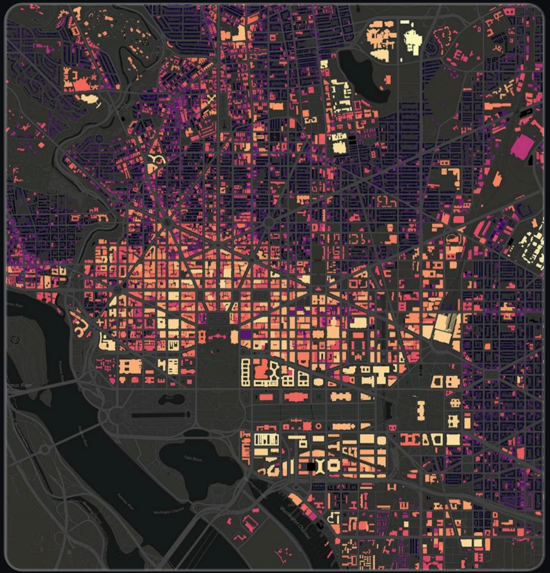
Transformation at scale

1 Neighborhood



Sunset Park Distributed Energy Resource Analysis

2 District

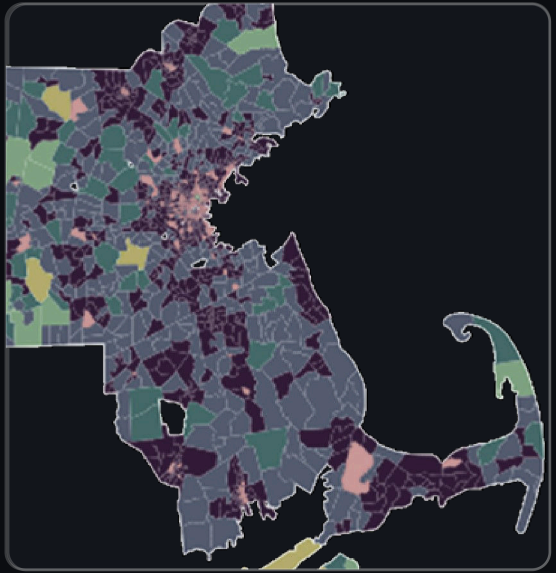


Washington DC Strategic Electrification Plan

3 City

New York City Urban Green Grid Ready

4 State



Massachusetts Building Sector Modeling

A new mindset: rapid + reliable + repeatable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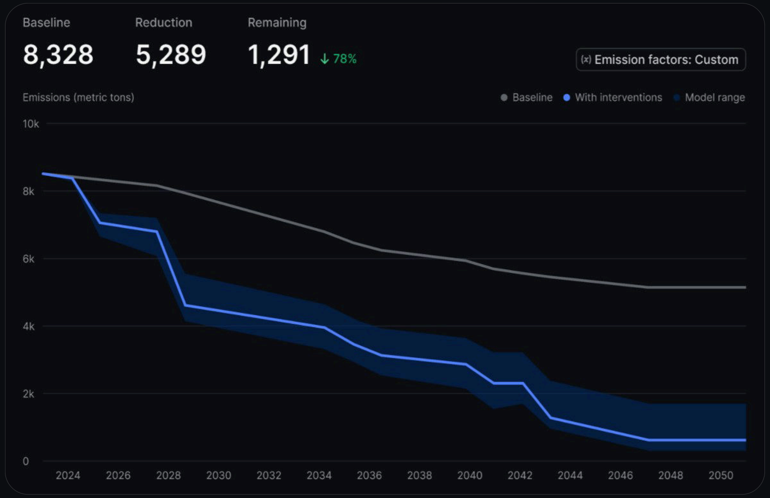


Integrations and connectivity

Plug and play with other platforms to share data and break down silos.

Actionable intelligence

Extensible physics-based models take you further toward implementation.

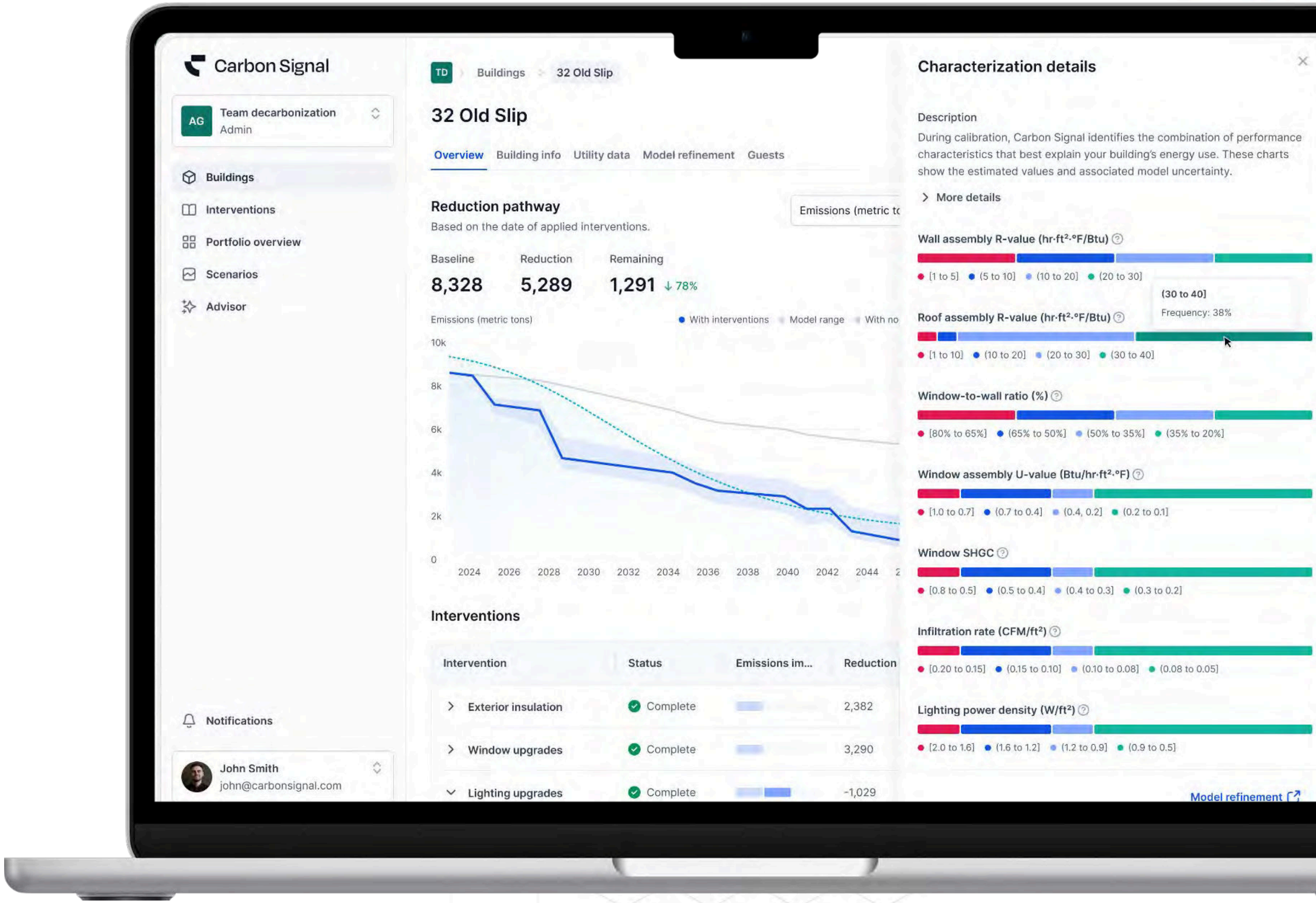
Continual refinement

Probabilistic modeling is continually refined with new information.

**Scaling Portfolio Decarbonizatio
n**

Building Energy Intelligenc
e

From advanced analysis
to bold, confident action.



Carbon Signal

Find your path to lower emissions.

Shreshth Nagpal PhD, CEM, HBDP, BEMP, LEED AP

shreshth@carbonsignal.com

carbonsignal.com