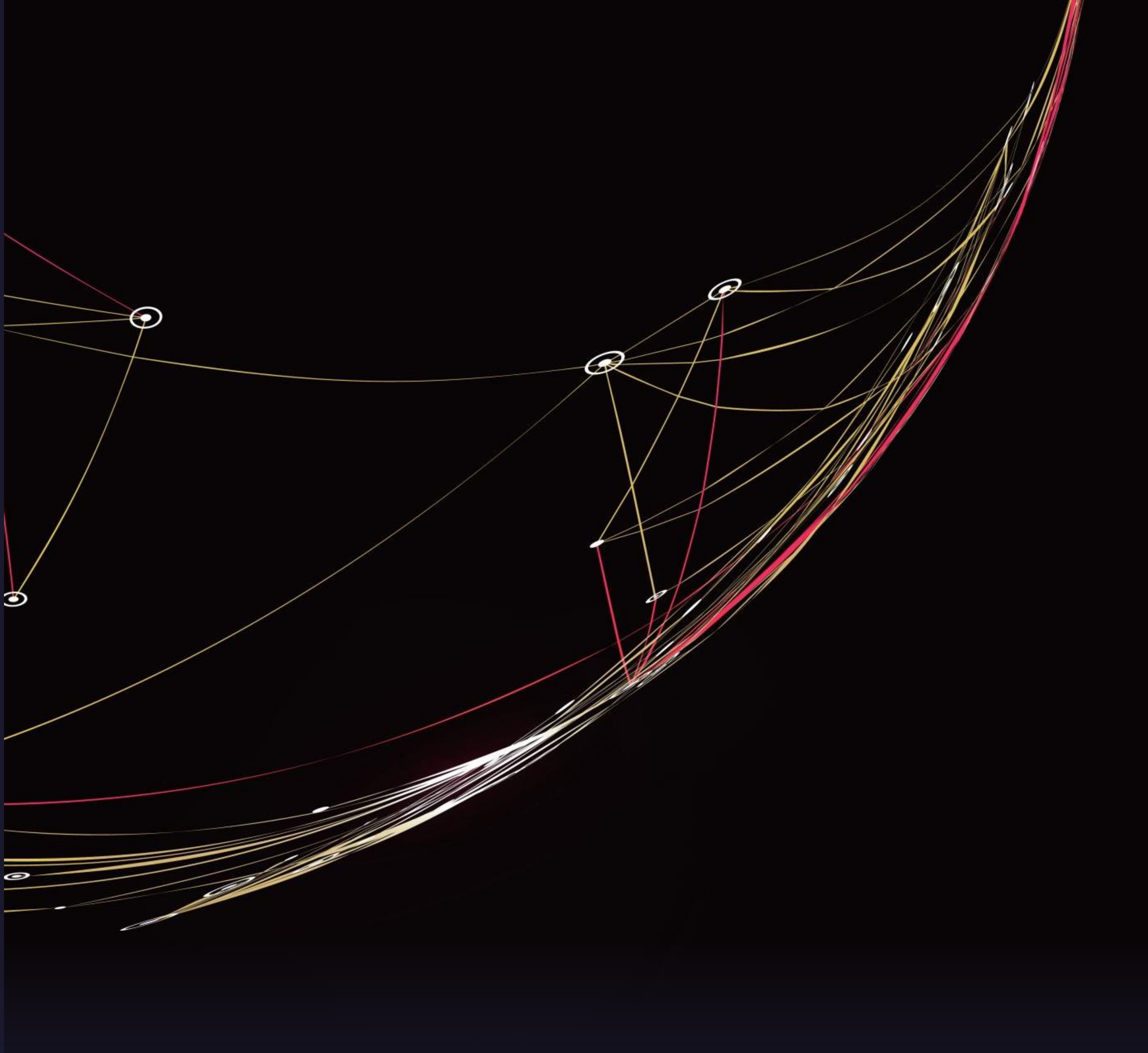
FROM SPARSE TO REPRESENTATIVE: MACHINE LEARNING TO DENSIFY IAM SCENARIO ENSEMBLES FOR POLICY INSIGHT

A proposal




A BRIEF INTRODUCTION TO IAMS

Climate-Economy Models

Designed to help the world understand the impact of socioeconomic policies on the global climate. Often used to help understand potential alignment with the Paris agreement target of limiting warming to no higher than 1.5C above pre-industrial levels by mid-century.

How do Integrated Assessment Models work?

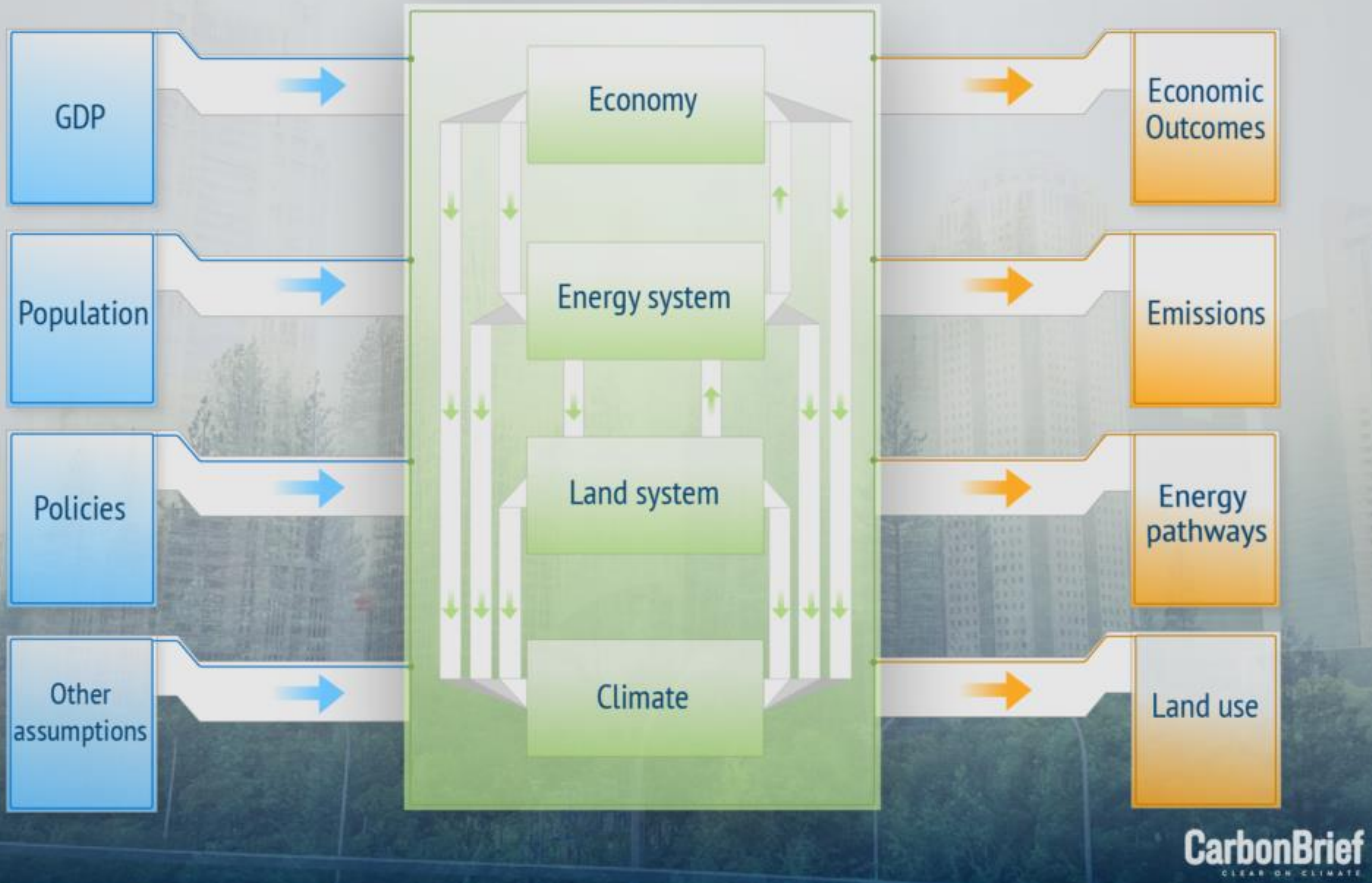
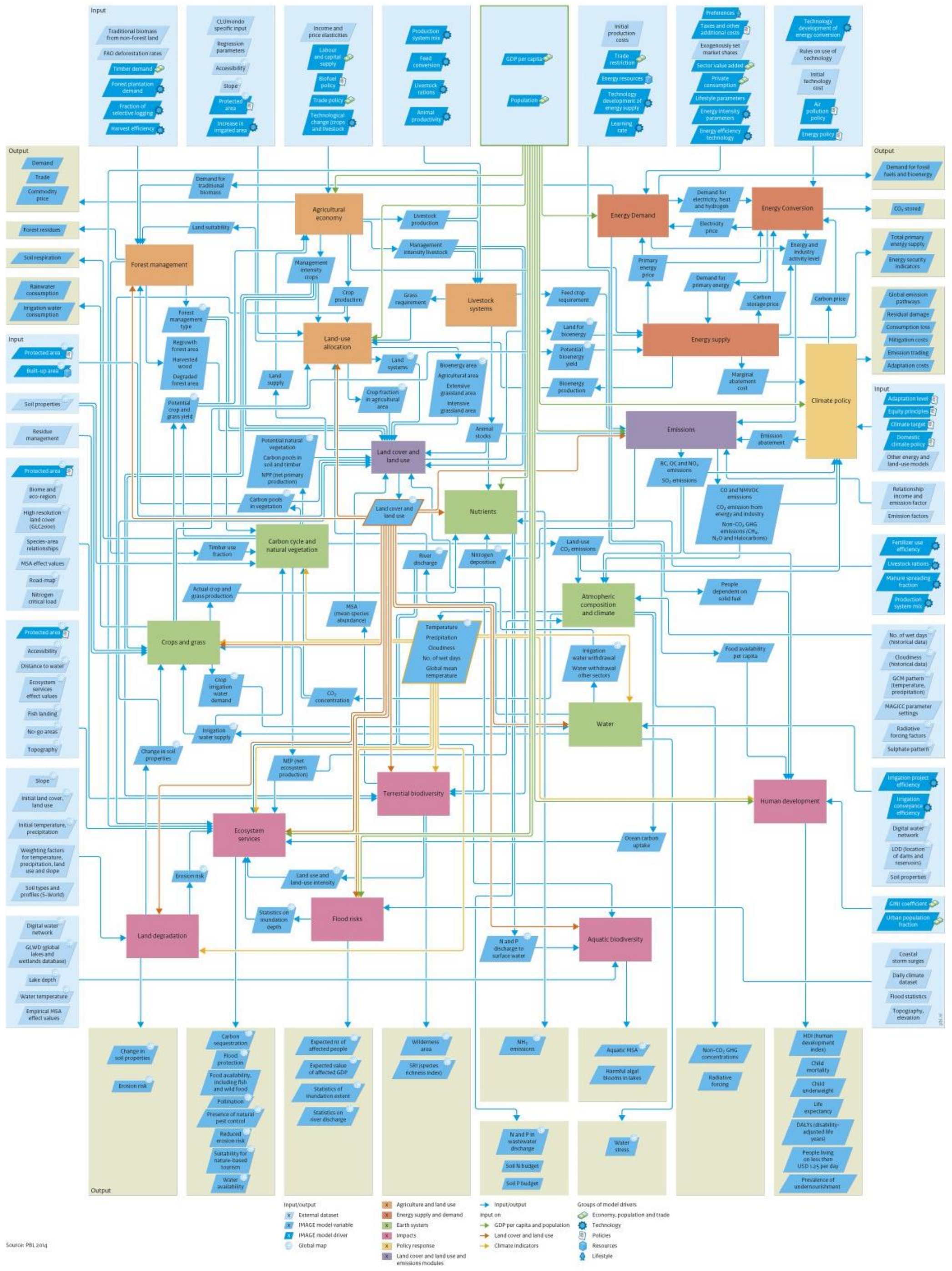


IMAGE 3.0 IN DETAIL

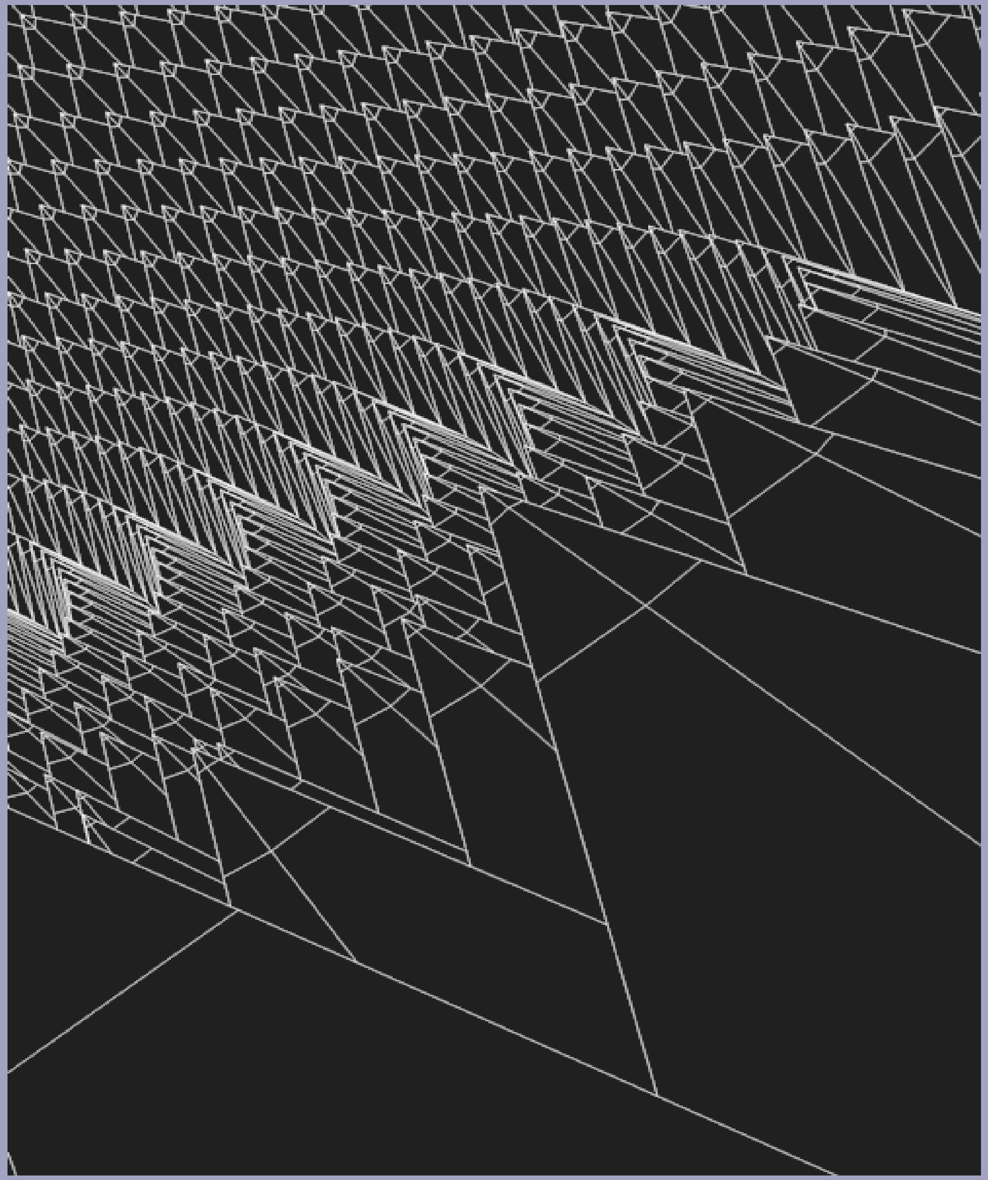


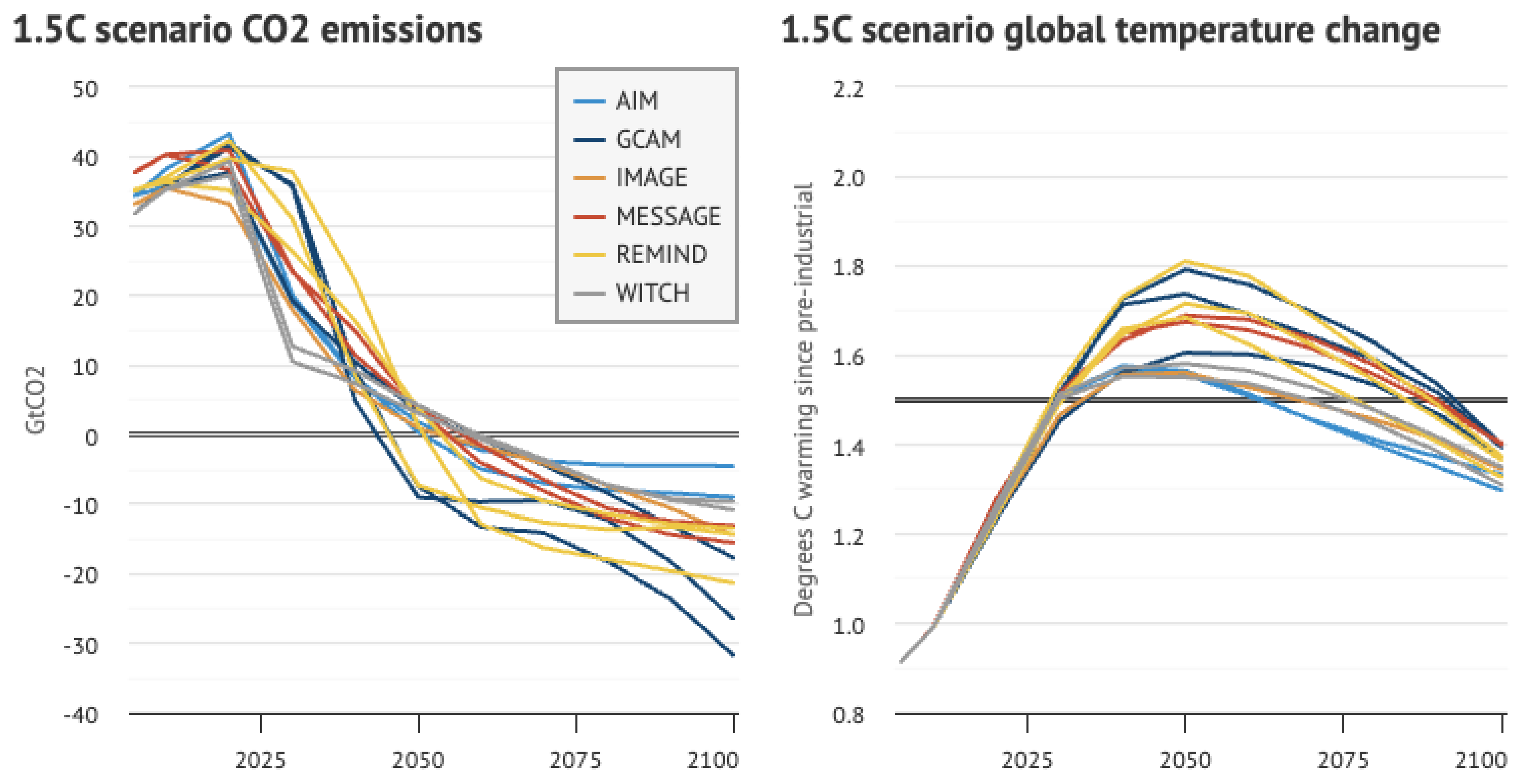
Source: PBL 2014

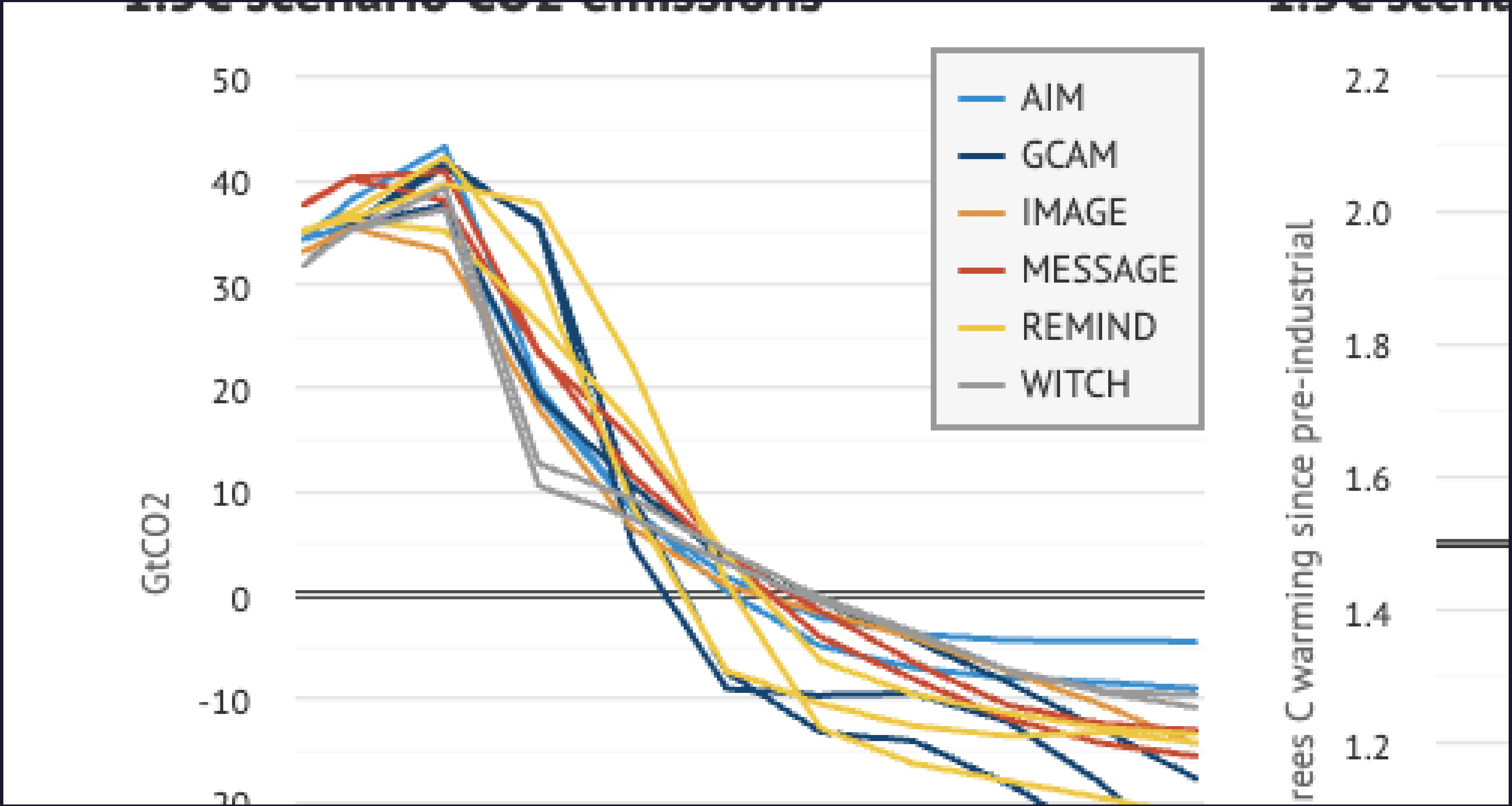
THE CHALLENGE

IAM outputs are not a statistical sample

There are infinitely many futures. The project of modellers is to predict and compare feasible futures for consensus but the outputs should not be taken as a statistical sample of potential futures but a selected subset.




1.5C scenario CO2 emissions
50
40
30
20
10
0
-10
-20
-30
-40
GtCO2
2025
2050
2075
2100
AIM
GCAM
IMAGE
MESSAGE
REMIND
WITCH
1.5C scenario global temperature change
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.8
Degrees C warming since pre-industrial
2025
2050
2075
2100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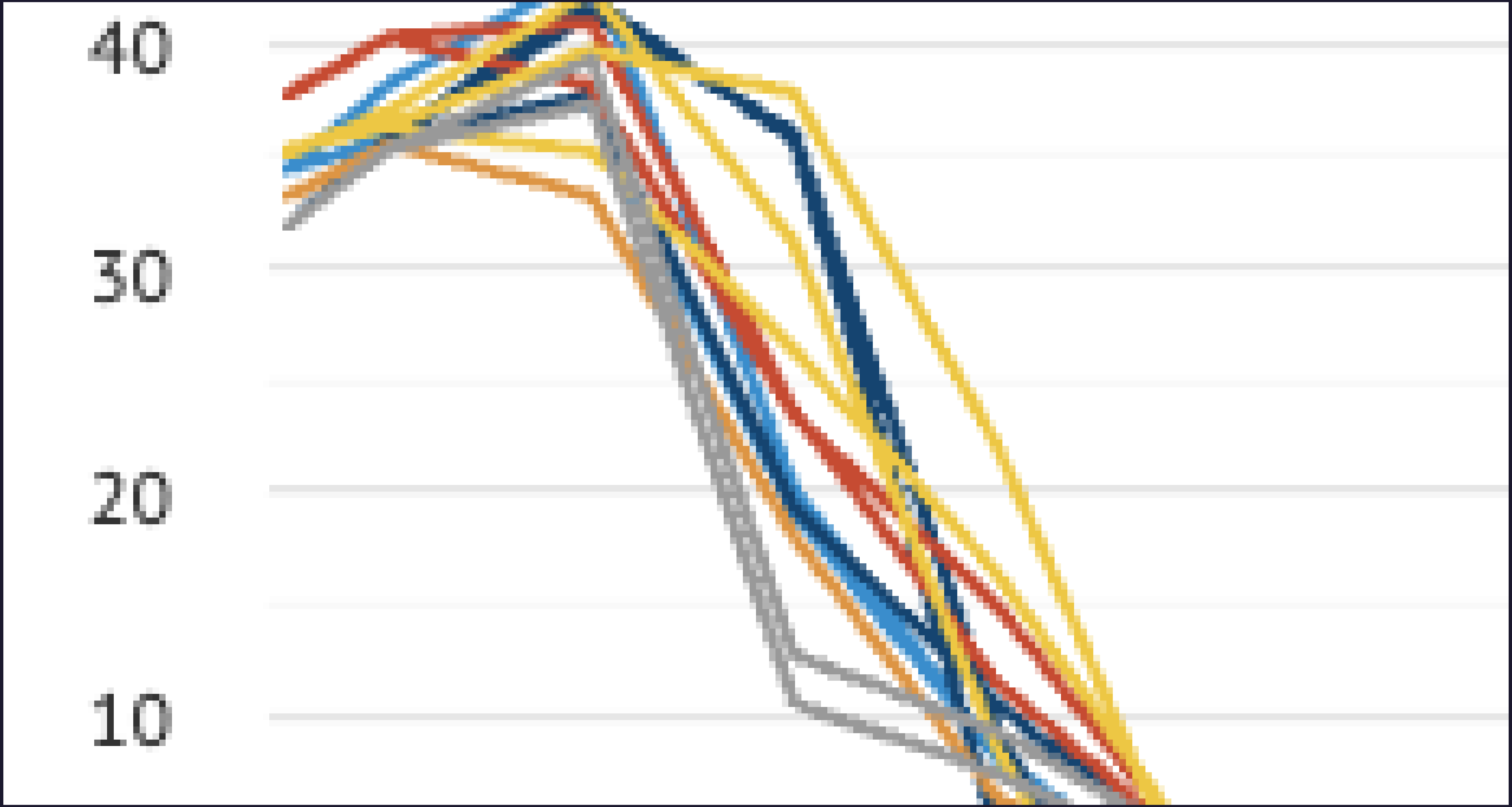

40
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20
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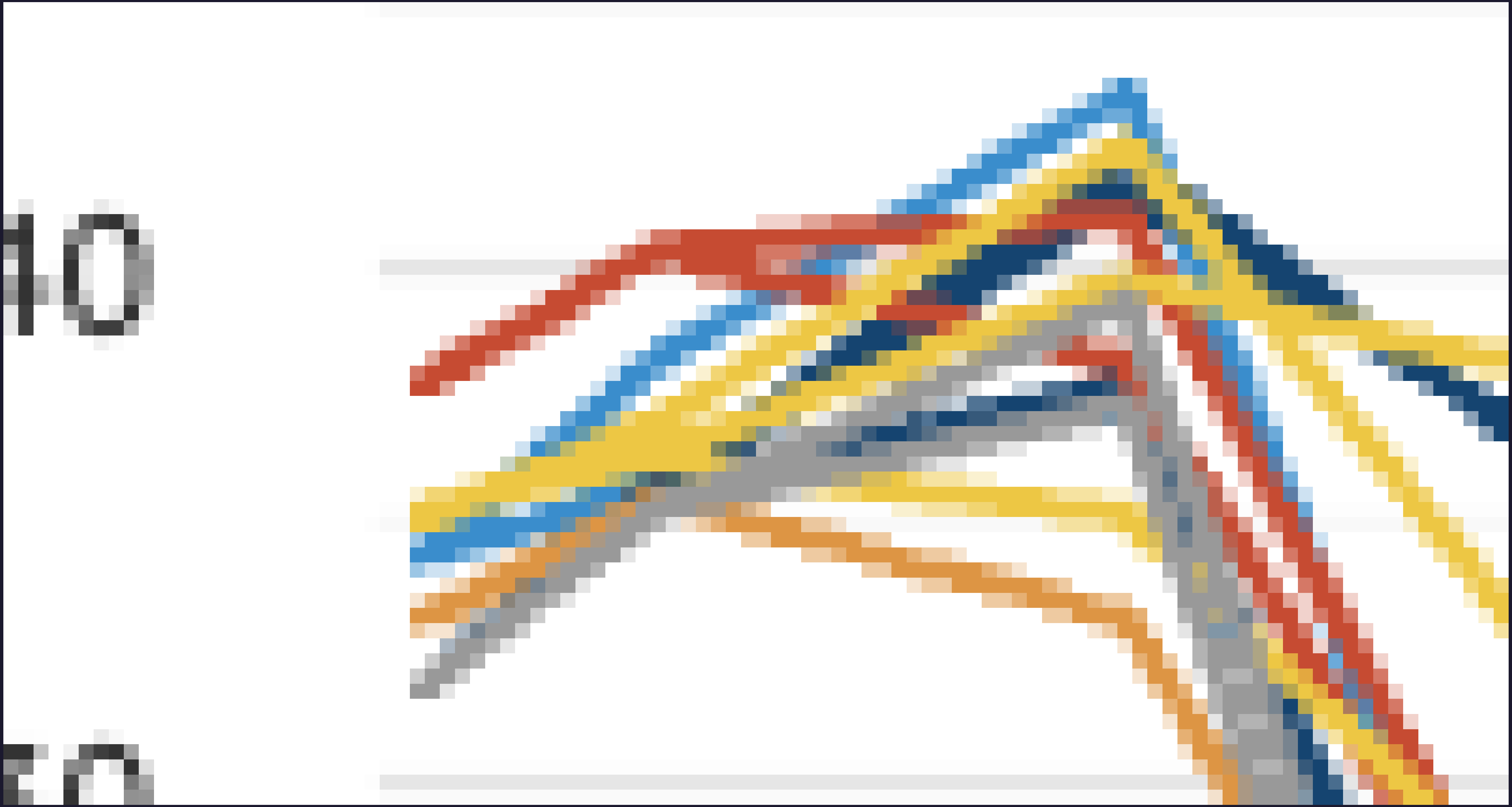
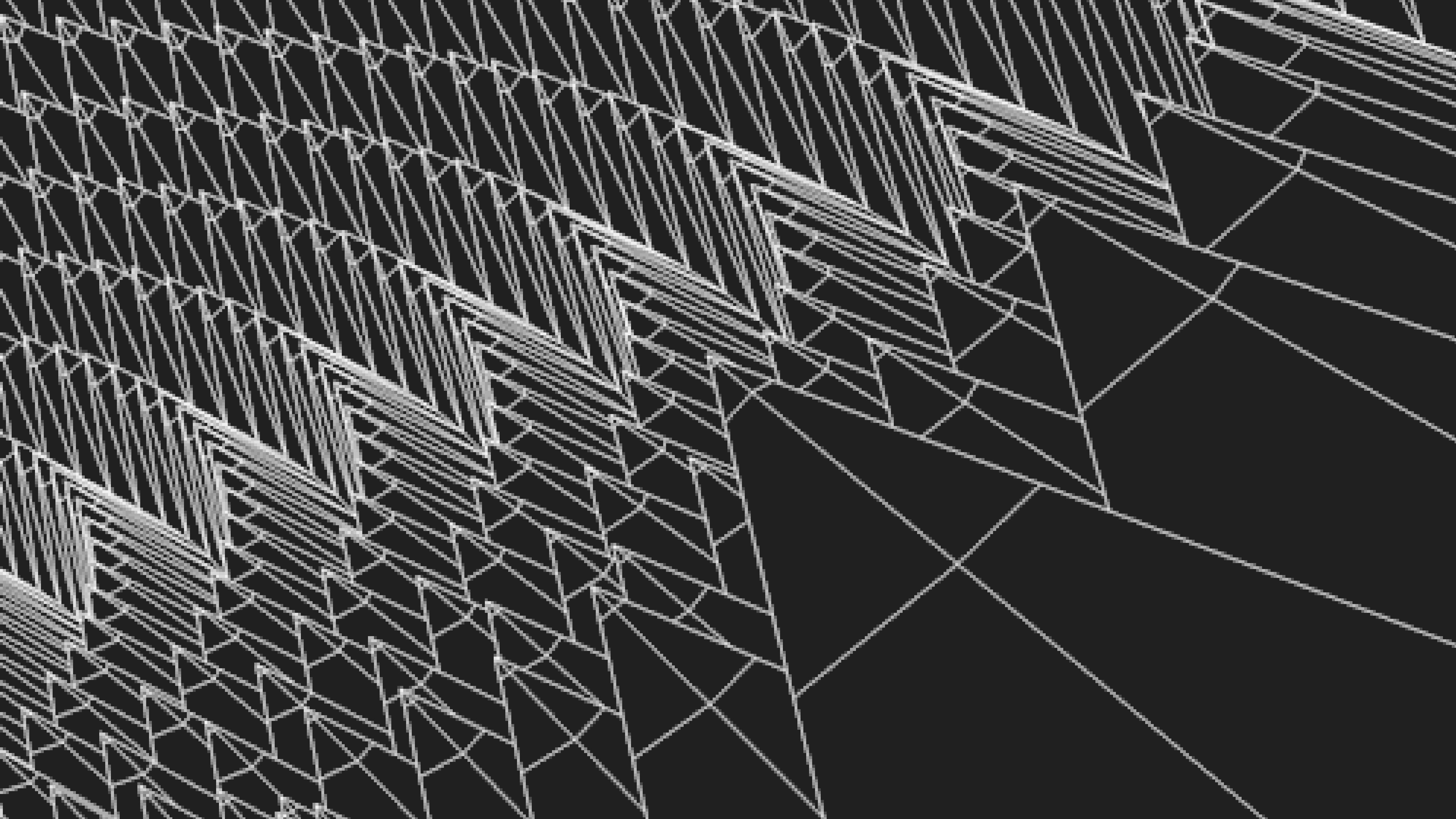




PROPOSED SOLUTION: Machine Learning for Interpolation within Existing Scenario Output Space

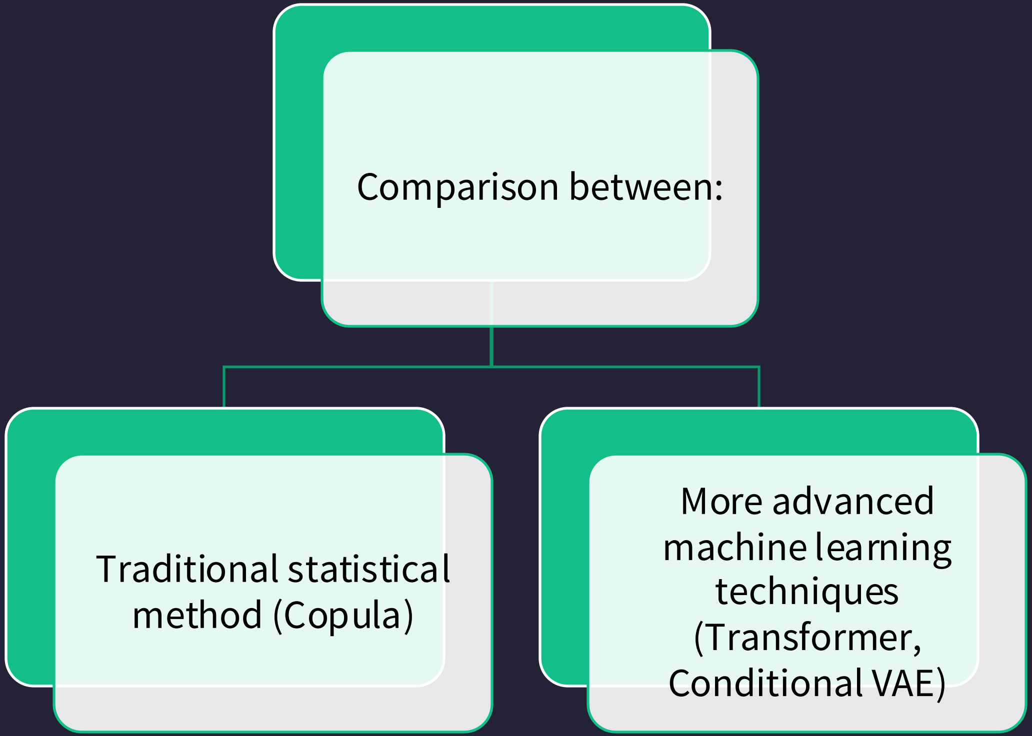
Intended outcomes

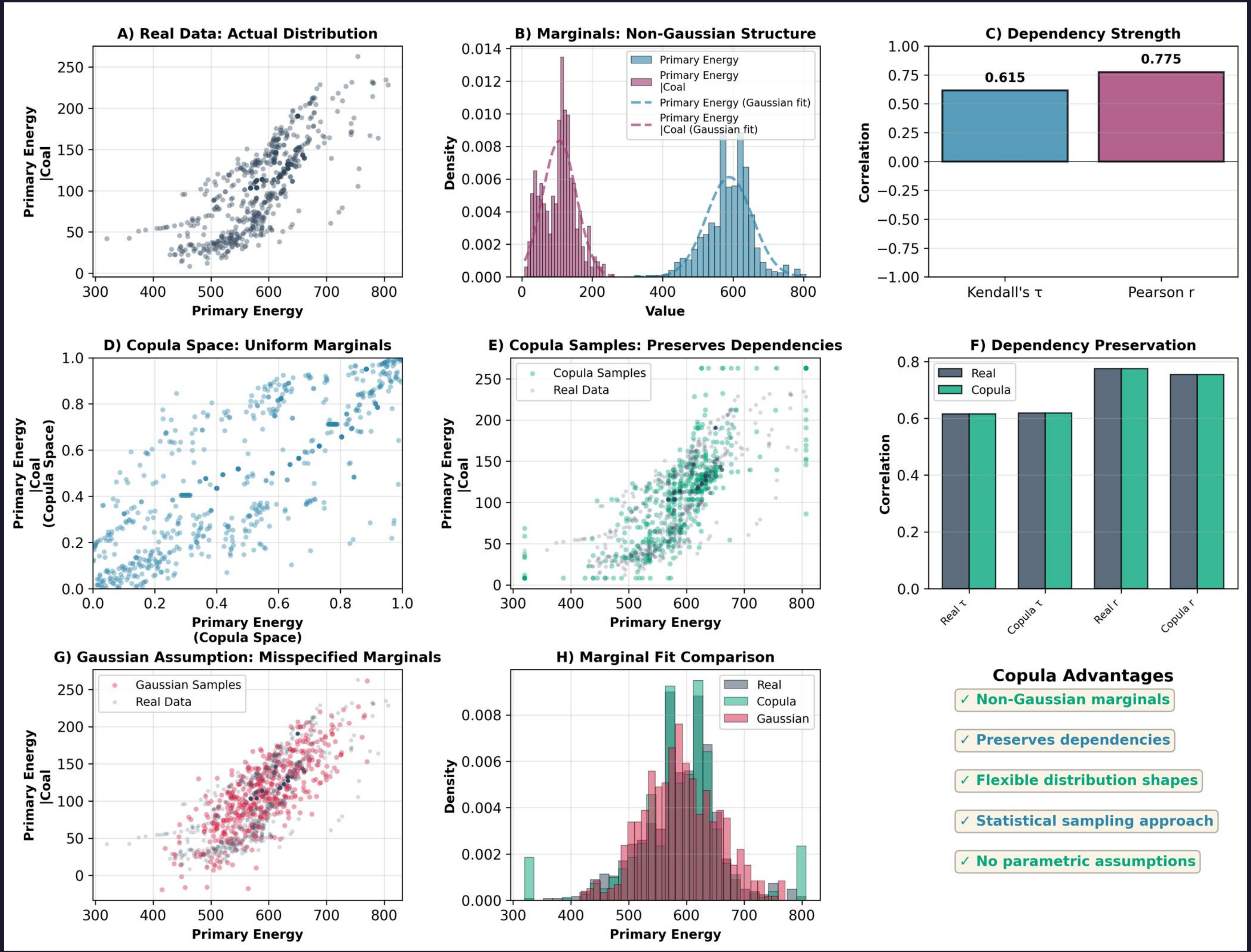
A LEARNED REPRESENTATION OF THE CONSTRAINED, MULTI-VARIABLES RESPONSE STRUCTURE OF THE SCENARIO SPACE, SUCH THAT A USER CAN INTERPOLATE WITHIN A FEASIBLE DOMAIN (RESPECTING JOINT DEPENDENCIES AND PLAUSIBLE OUTCOMES)

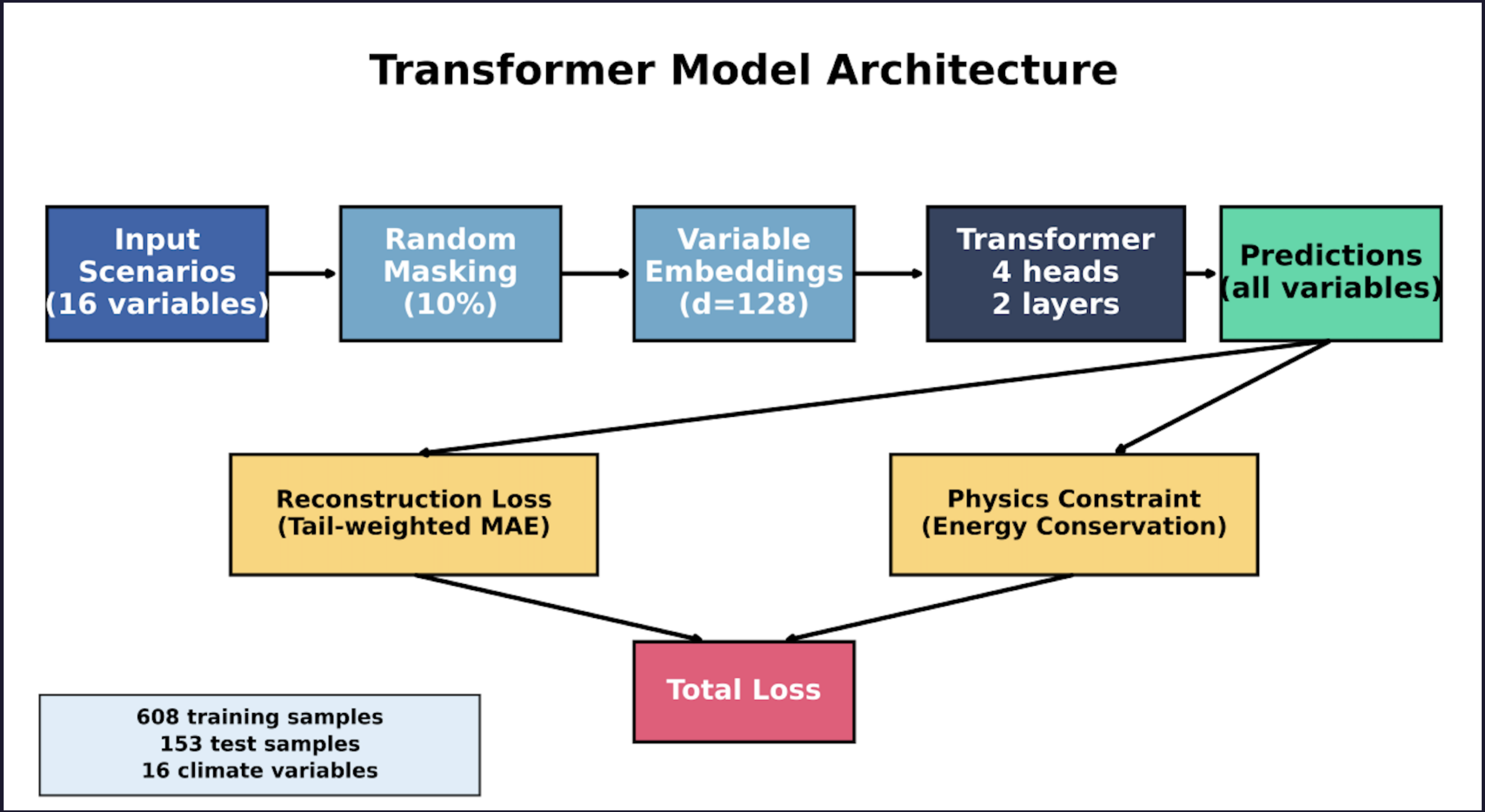
THE ABILITY TO ANSWER QUESTIONS LIKE WHAT HAPPENS IF X INDUSTRY DOES Y

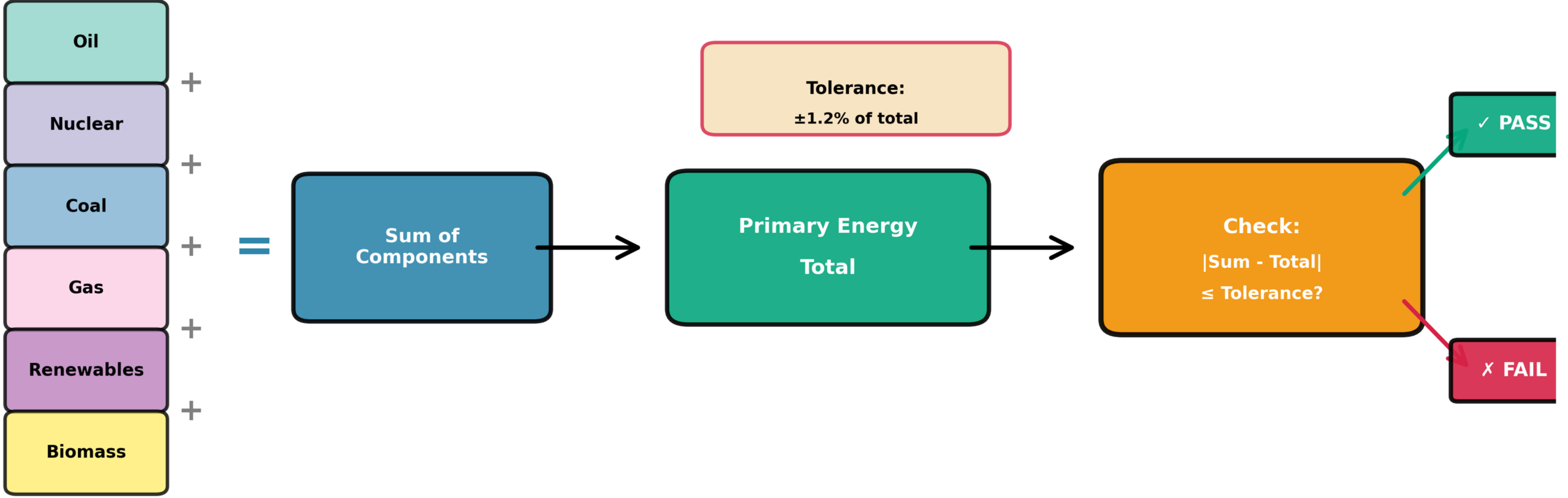
A FIRST STEP TOWARDS ‘FILLING IN THE GAPS’ SO THAT WE CAN UPSCALE/DOWNSCALE FROM THE EXISTING IAM SPACE

Methods


Comparison between:
Traditional statistical method (Copula)
More advanced machine learning techniques (Transformer, Conditional VAE)


A) Real Data: Actual Distribution
Primary Energy
Primary Energy |Coal
B) Marginals: Non-Gaussian Structure
Primary Energy
Primary Energy |Coal
Primary Energy (Gaussian fit)
Primary Energy |Coal (Gaussian fit)
Density
Value
C) Dependency Strength
0.615
0.775
Correlation
Kendall's τ
Pearson r
D) Copula Space: Uniform Marginals
Primary Energy |Coal (Copula Space)
Primary Energy (Copula Space)
E) Copula Samples: Preserves Dependencies
Copula Samples
Real Data
Primary Energy |Coal
Primary Energy
F) Dependency Preservation
Real
Copula
Correlation
Real τ
Copula τ
Real r
Copula r
G) Gaussian Assumption: Misspecified Marginals
Gaussian Samples
Real Data
Primary Energy |Coal
Primary Energy
H) Marginal Fit Comparison
Real
Copula
Gaussian
Density
Primary Energy
Copula Advantages
✓ Non-Gaussian marginals
✓ Preserves dependencies
✓ Flexible distribution shapes
✓ Statistical sampling approach
✓ No parametric assumptions


Transformer Model Architecture
Input Scenarios (16 variables)
Random Masking (10%)
Variable Embeddings (d=128)
Transformer 4 heads 2 layers
Predictions (all variables)
Reconstruction Loss (Tail-weighted MAE)
Physics Constraint (Energy Conservation)
Total Loss
608 training samples
153 test samples
16 climate variables



A Note on Internal Consistency

Easy to generate scenarios; difficult to generate scenarios that align with implicit relationships between variables (Li et al. 2025)

INITIAL RESULTS

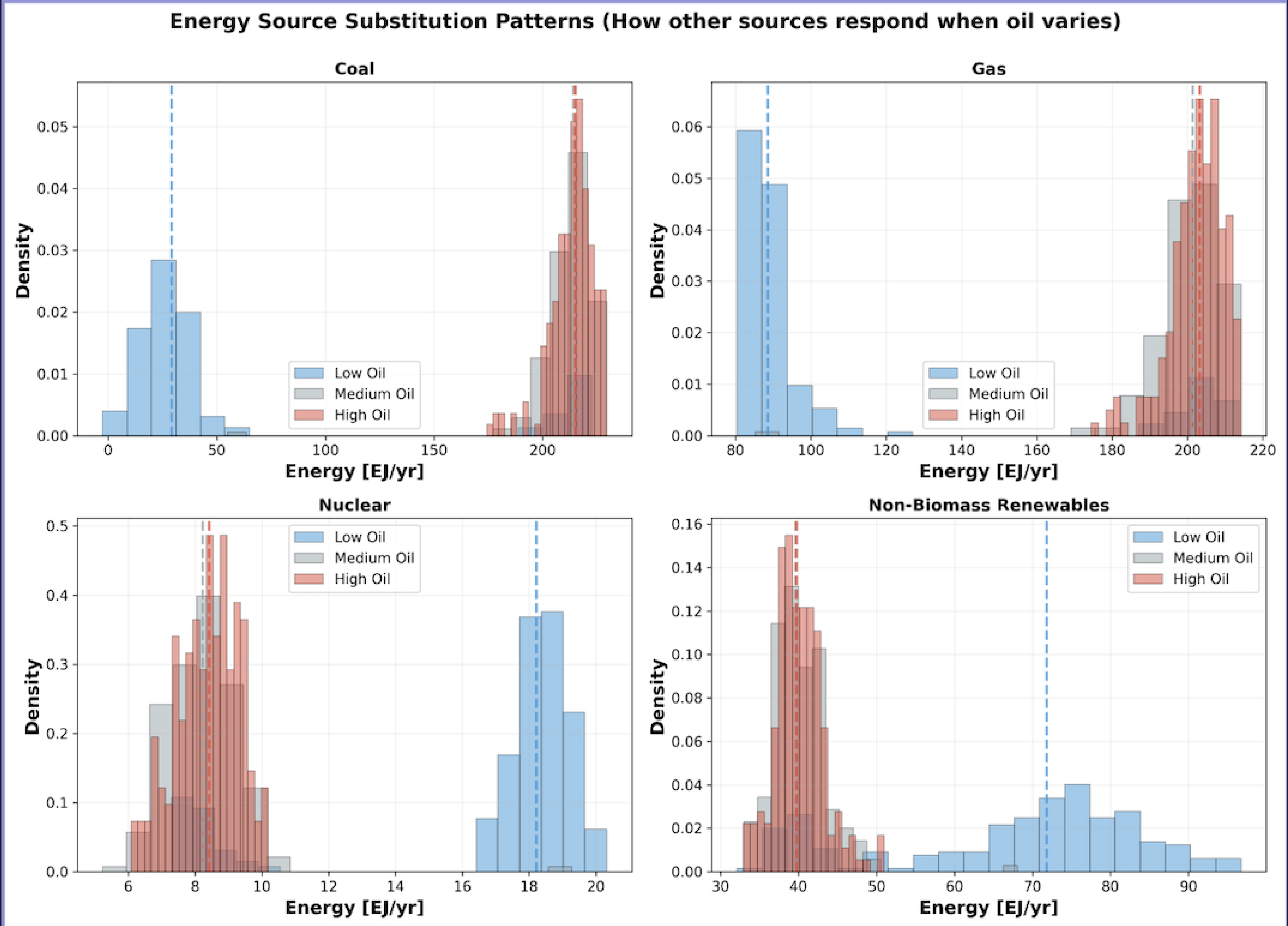


Figure 2. The changes in other variables based on constraints to oil; represented via percentile designations of low, medium, and high (25, 50, 75)

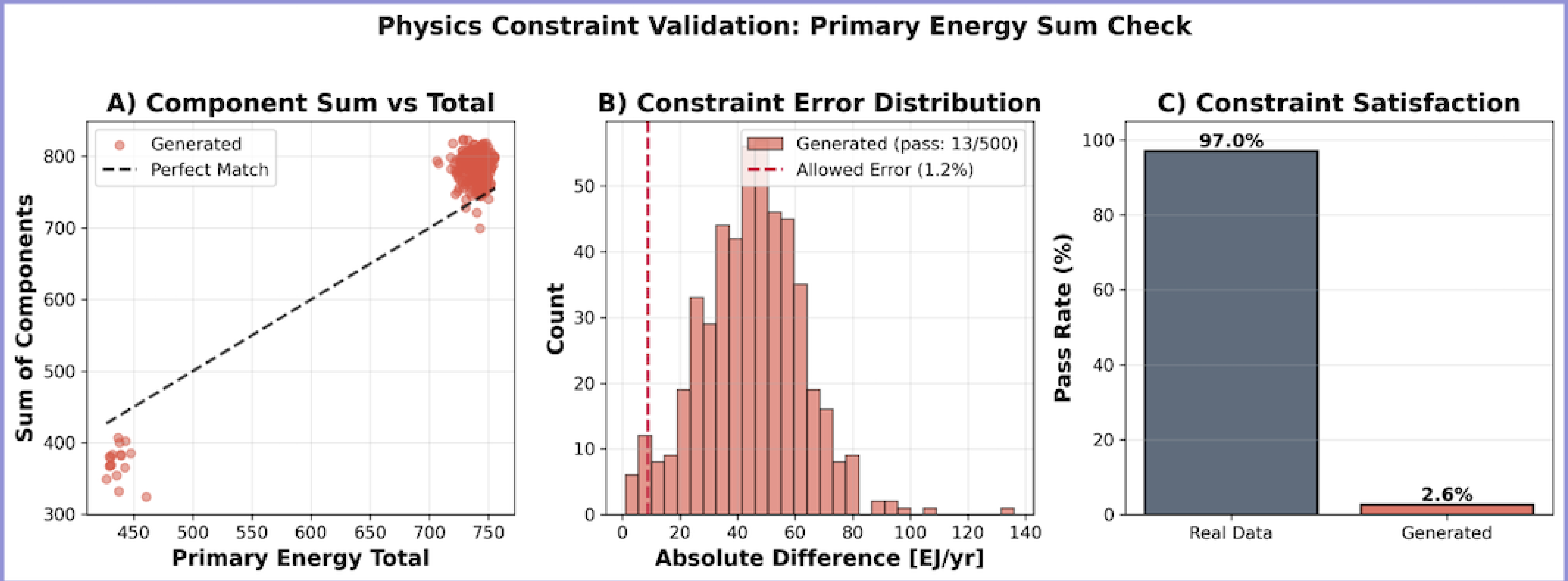


Figure 3. A representation of how well generated scenarios are passing a simple sum check; poor performance is aligned with other generative attempts and a direction for ongoing work

POTENTIAL USE CASES

More efficient downscaling of global climate targets for both state and non-state actors

Exploration space for multi-agent reinforcement learning

Increased ability to embed equity considerations into IAM constraints

Instead of taking the uncertain outcomes from the IAMs, maybe we could work from more real-world, past data from industry and align that to IAM outputs


What would happen
if the transportation
sector invested $1
billion in EVs
worldwide by 2030?

REFERNCES

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[2] Dekker, et al., Identifying energy model fingerprints in mitigation scenarios. Nature Energy 2023 8:12, 8:1395–1404, 11 2023. ISSN 2058-7546. doi: 10.1038/s41560-023-01399-1. URL https://www.nature.com/articles/s41560-023-01399-1.

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[4] Krabbe et al., Aligning corporate greenhouse-gas emissions targets with climate goals. Nature Climate Change, 5:1057–1060, 12 2015. ISSN 17586798. doi: 10.1038/NCLIMATE2770;TECHMETA=129;SUBJMETA=106,66,682,694,703,704, 706;KWRD=BUSINESS,CLIMATE-CHANGE+MITIGATION. URL https://www.nature.com/articles/nclimate2770.

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[6] Multiple Authors, Q&A: How 'integrated assessment models' are used to study climate change, Carbon Brief, 10 2018. URL **https://www.carbonbrief.org/qa-how-integrated-assessment-models-are-used-to-study-climate-change/**.