

# Uncertainty exploration with GCAM

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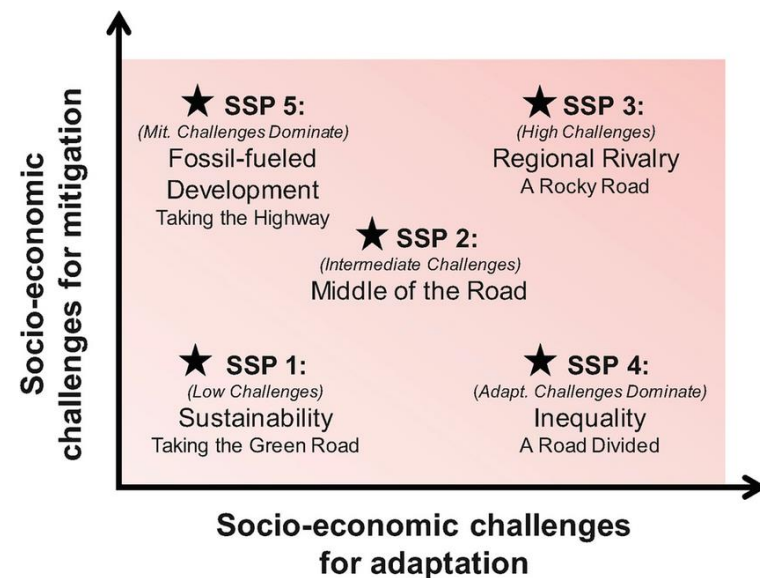
On behalf of the GCIMS Team



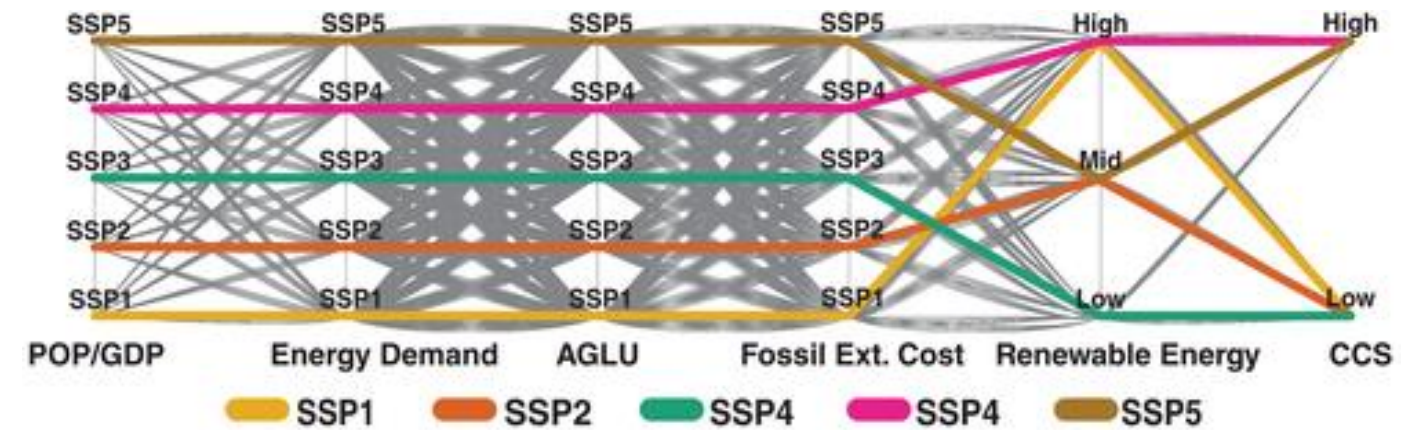


# Scenarios have long played a critical role in exploring uncertainty in multisectoral modeling

**SSPs:** Targeted scenarios based on expert opinion.



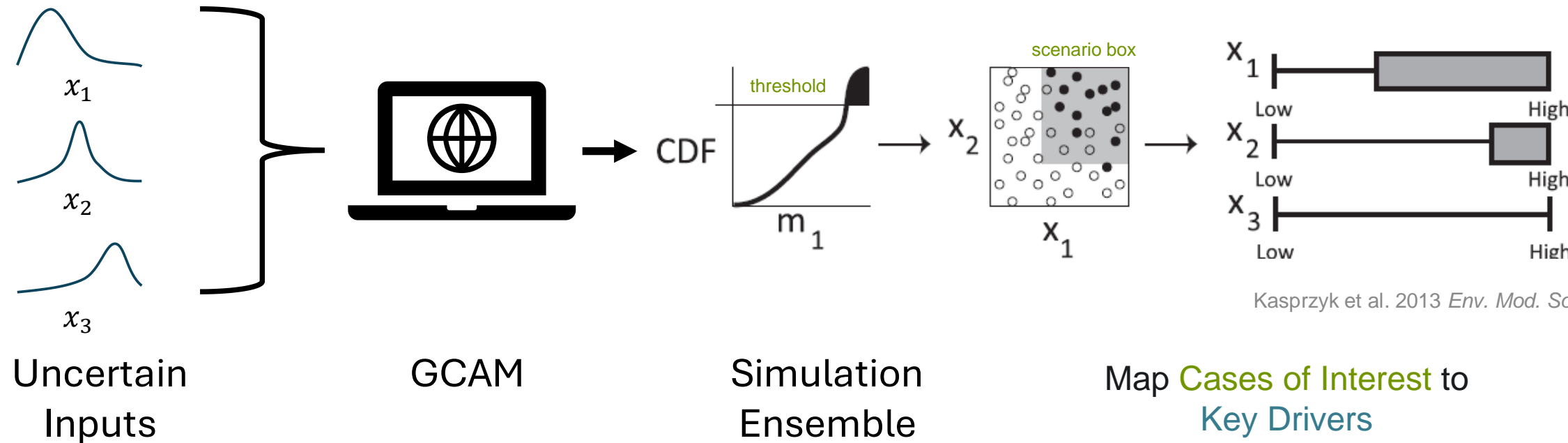
**Scenario Discovery:** Expansive search to identify critical drivers.



GCIMS has pushed the envelope on this style via our collaboration with the Lamontagne Lab at Tufts.

**Concern:** Expert elicited scenarios may miss critical drivers, **but** scenario discovery can be inefficient (many factors don't matter).

**Proposal:** Deep learning models can emulate GCAM, to help us target our search for interesting outcomes and get there more efficiently.



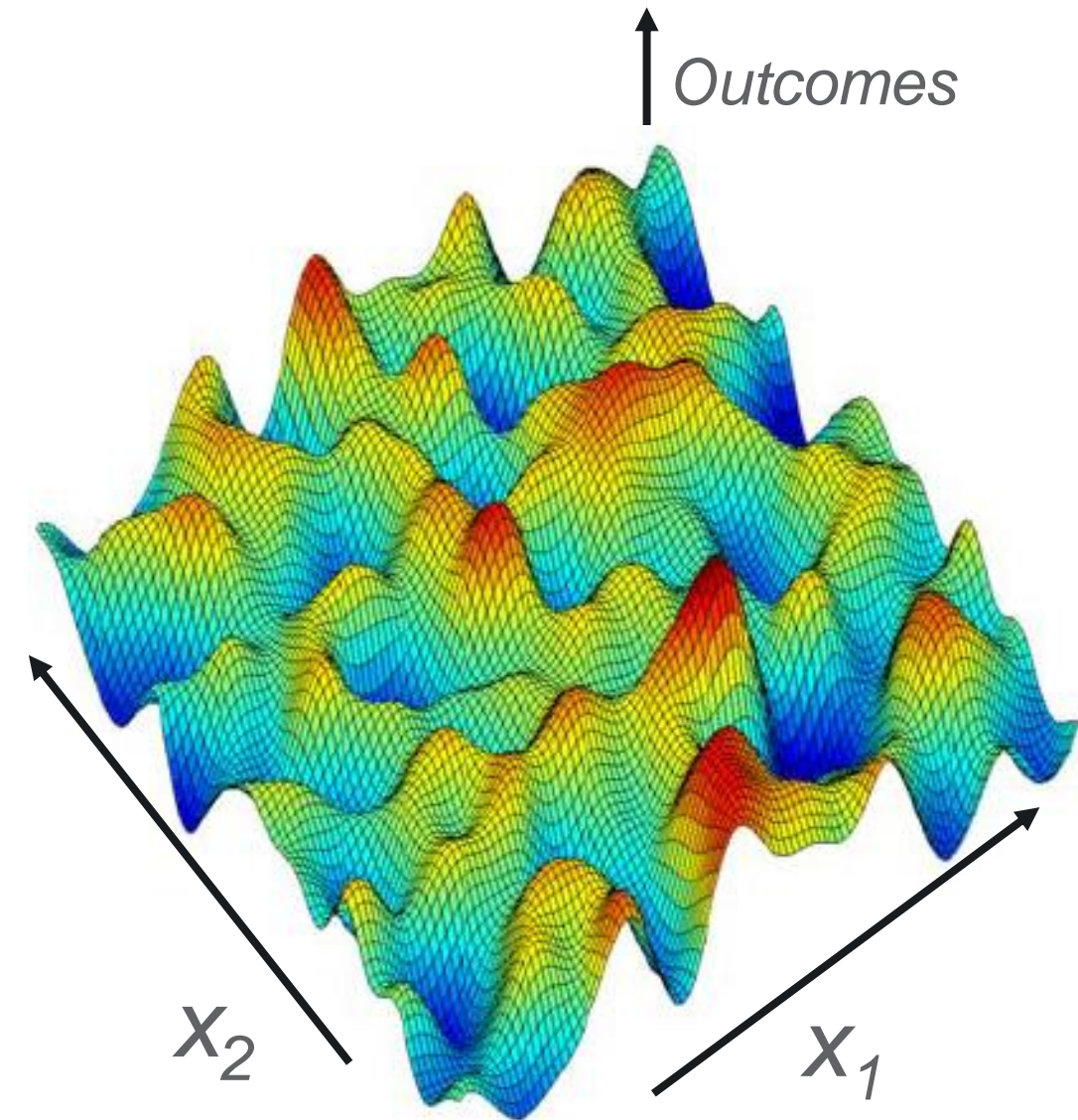
Kasprzyk et al. 2013 *Env. Mod. Soft.*

Scenario Discovery usually uses ML for classification.

- Factorial recombination of categorical inputs (Dolan et al 2021 *Nature Comm* Water Scarcity, Dolan et al 2022 *Earth's Future* Land availability, Woodard et al 2023 *EF* Energy system makeup)
- Or sampling continuous inputs in some dimension (Kanyako et al 2023 *EF* GDP and Population compounding uncertainties, Birnbaum et al 2024 *ERL* Hydrological uncertainty)

## Are we missing outcomes because of our sampling?

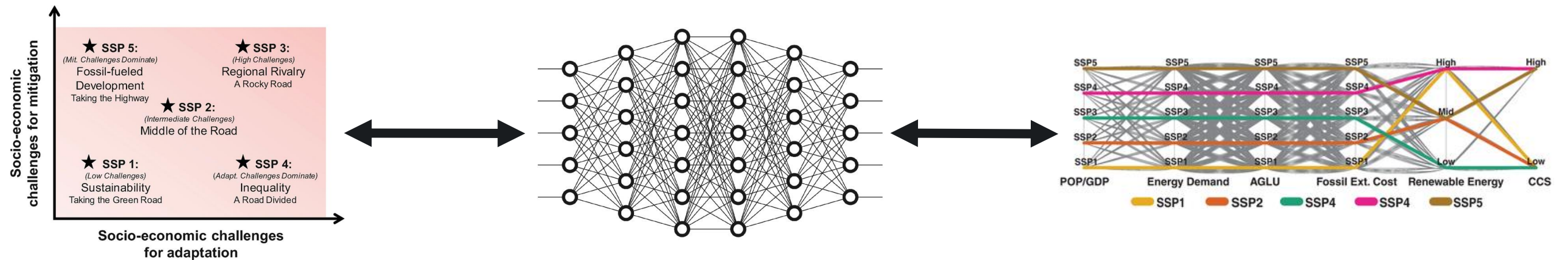
- A lot of Scenario Discovery has been focused on identifying hi/lo of some metric of interest
- How many local optima are there? Are we missing anything?
- But what is the rate of change of GCAM's different outputs with respect to its inputs?
- Being able to identify that would give us greater insight to which inputs drive GCAM's variability
- And let us know which inputs are most beneficial to run greater or fewer ensemble members on: **Targeted searches and targeted GCAM ensembles**



Dellago and Bolhuis 2008,  
**illustrative purposes only.**  
 GCAM is much higher dimensional than this



# Deep-Learning Aided Scenario Discovery



**SSPs:** Targeted scenarios based on expert opinion.

**DL-SD:** Targeted ensemble search to identify critical drivers

**Scenario Discovery:** Expansive search to identify critical drivers.

Previous approaches are computational book-ends to scenario development.

DL-SD can leverage large-ensembles to provide targeted scenarios, efficiently.

**Potentially:** Next evolution of our work in scenario discovery

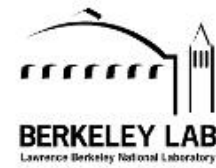


# Thank you!

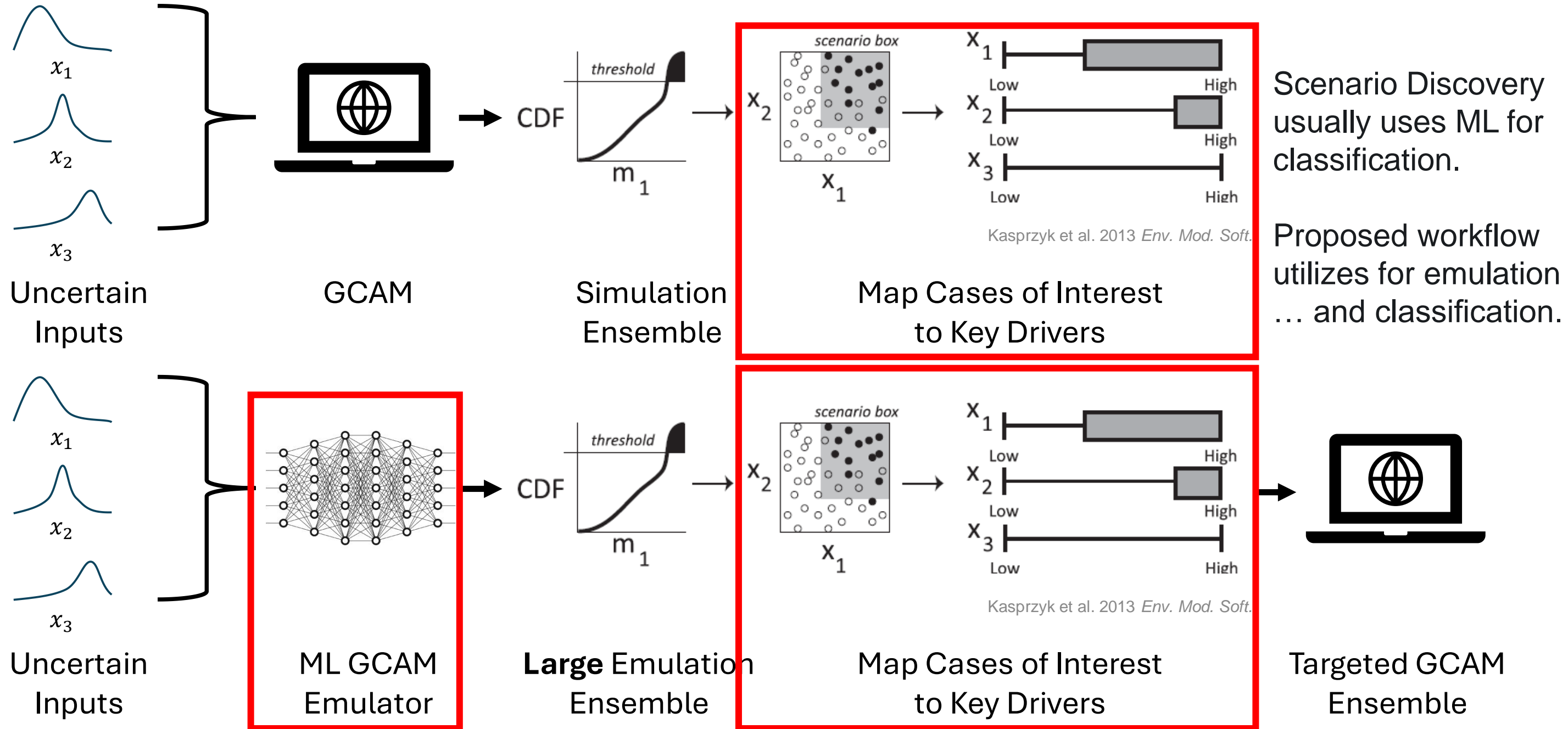
This research was supported by the U.S. Department of Energy, Office of Science, as part of research in MultiSector Dynamics, Earth and Environmental System Modeling Program. The Pacific Northwest National Laboratory is operated for DOE by Battelle Memorial Institute under contract DE-AC05-76RL01830. The views and opinions expressed in this paper are those of the authors alone.

And a very special thanks to our Western Washington University team, led by **Prof Brian Hutchinson**:

- Andrew Holmes
- Matt Jensen
- Sarah Coffland
- Hidemi Mitani
- Logan Sizemore
- Seth Bassetti
- Brenn Nieva



# Deep-Learning Aided Scenario Discovery



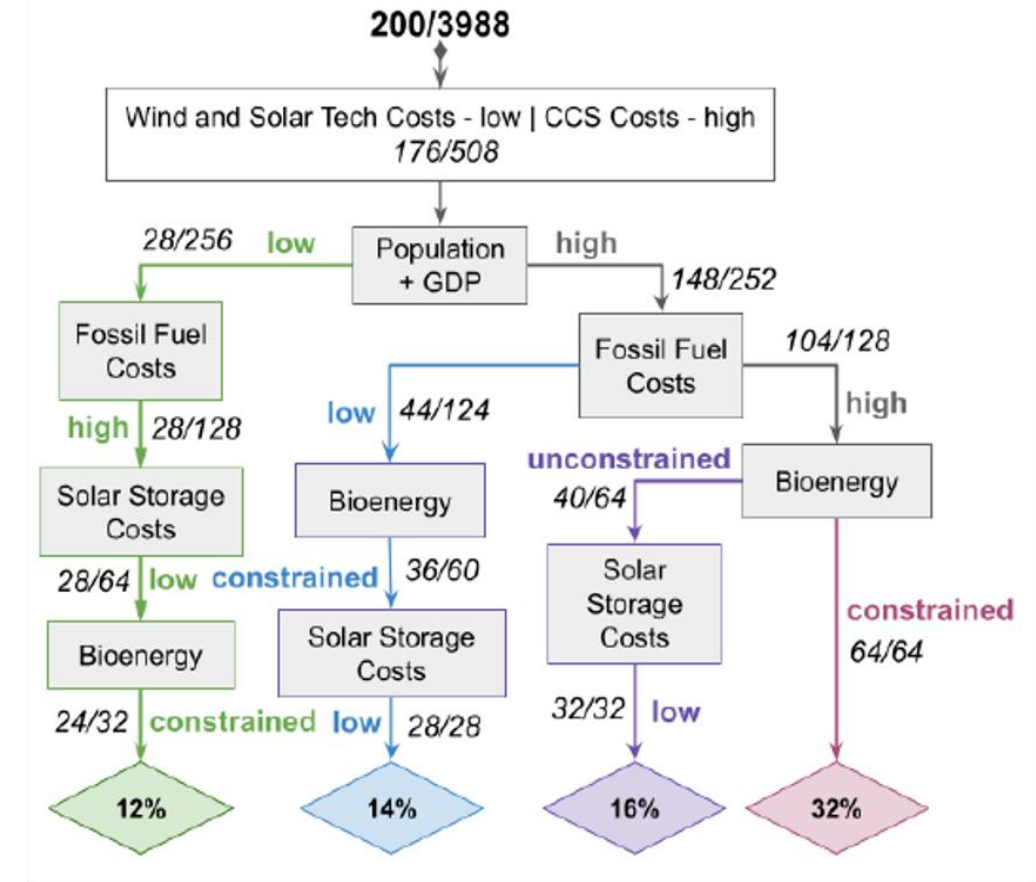


### Scenario Discovery Analysis of Drivers of Solar and Wind Energy Transitions Through 2050

Dawn L. Woodard , Abigail Snyder, Jonathan R. Lamontagne, Claudia Tebaldi, Jennifer Morris, Katherine V. Calvin, Matthew Binsted, Pralit Patel

Ranged over high and low values for 12 expert identified relevant drivers = **4096 GCAM runs**:

Input	Description
Backups	Systems needed to backup solar and wind
Bioenergy	Tax applied to bioenergy
Carbon Capture	Cost to store CO <sub>2</sub>
Electrification	Share of buildings, industries and transport using electricity
Emissions	CO <sub>2</sub> emission costs
Energy	Demand - GDP and population assumptions
Fossil Fuel	Costs of oil, natural gas and coal
Nuclear	Cost of nuclear energy
Solar Storage	Solar storage capacity
Solar Tech	Cost to install and use solar
Wind Storage	Wind storage capacity
Wind Tech	Cost to install and use wind

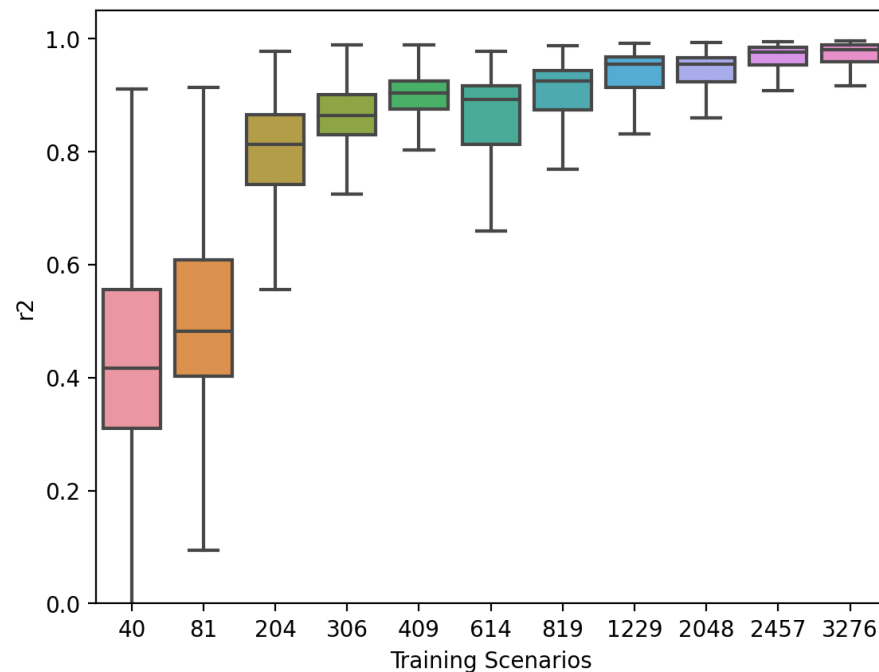
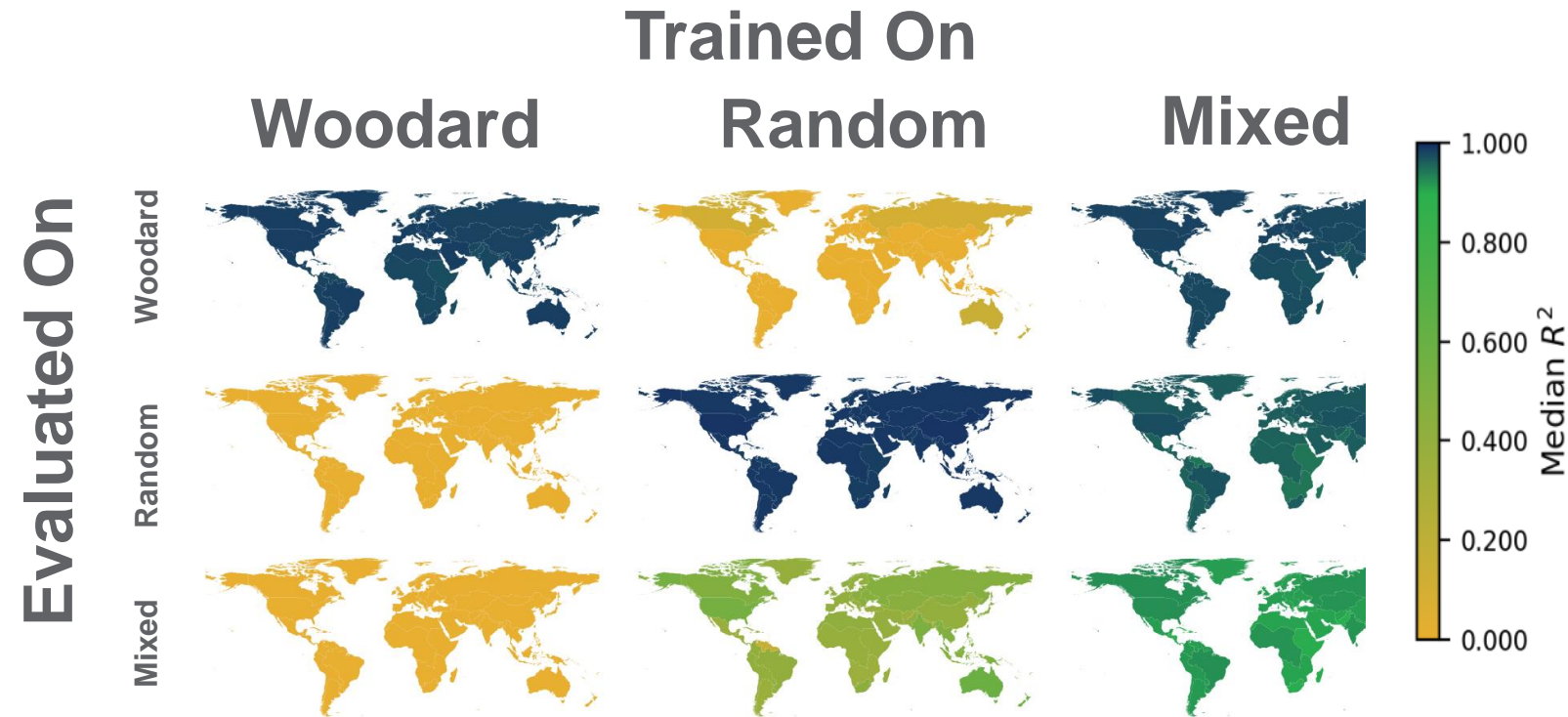


**Using SD, identified four paths to energy sectors with high wind & solar adoption globally. Each pathway has its own consequences for different sectors in different regions (bottom panel).**



## Using the Woodard et al ensemble of 4096 runs, training DNN over different subsets led to:

- Identify ideal sampling strategy for training ensembles (Mixed, explicitly including some hi/lo boundary values as in the Woodard experiment, as well as random sampling from the interior)
- Highlight that smaller ensemble size sufficient to train the emulator (800 instead of 4000)



- Do it for 23 outputs across 32 GCAM regions covering economic and physical quantities for energy, water, and land, out to 2100: *Outputs have more than 23k entries to inputs with 12.*
- The emulator features the same sensitivities as GCAM, meaning we can start thinking about derivative-based measures more broadly.**