Landscape Decisions Combining Uncertain Data and Models

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Decision Making on Future Landscapes

- Landscape decision making is complex

- It involves a lot of disciplines
  - Ecology
  - Economics
  - Climate Science
  - Social Science
  - …

- Each with their own models, data and expertise

- Don’t have time to deal with the detail and complexity
- Mathematician - abstract
- Single uncertain model
- We can do the the detail though

Decision making under Uncertainty

- We are making decisions about the unknown future using uncertain data with imperfect models

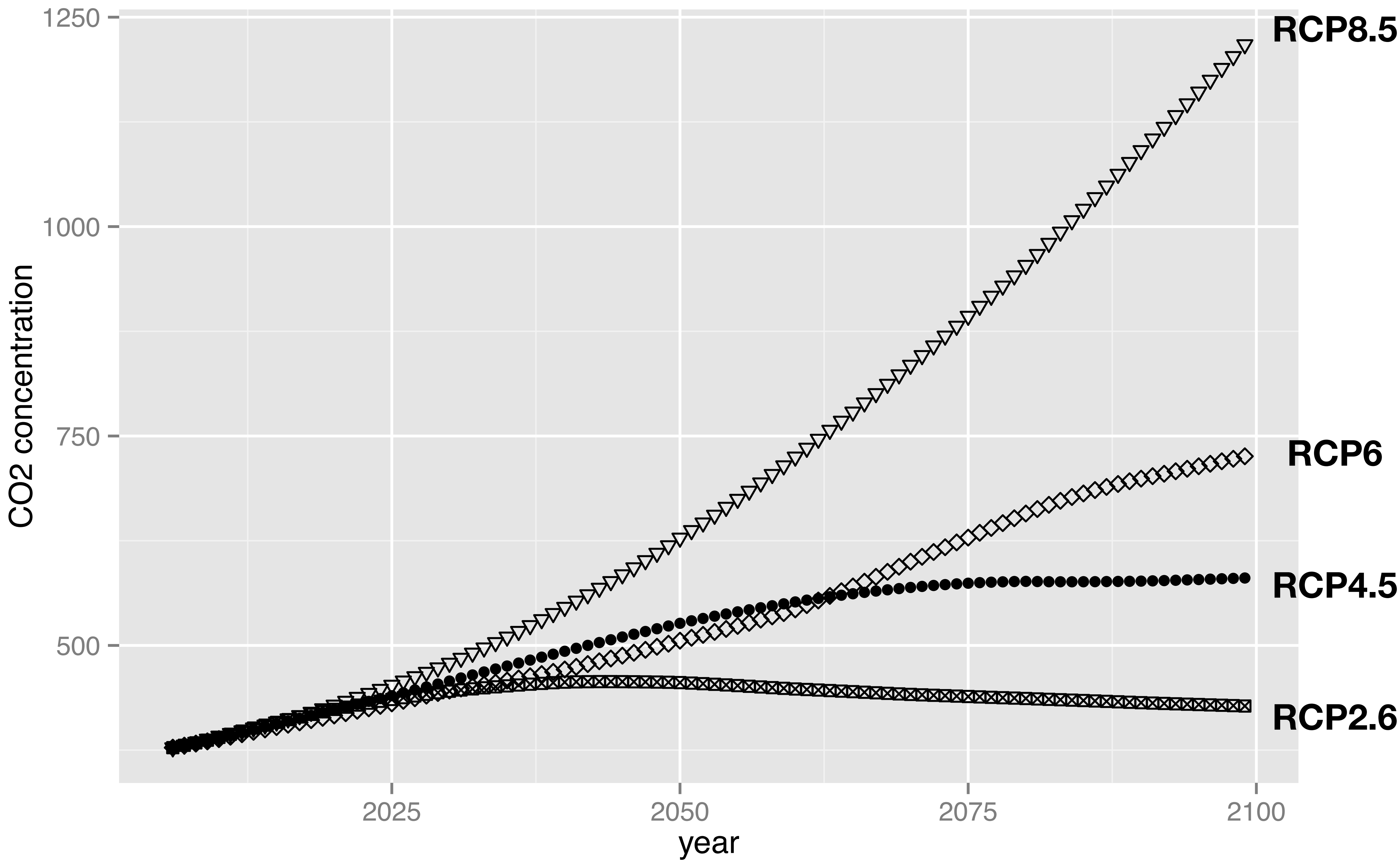
- What could possibly go wrong?

Model Discrepancy

- All models are wrong ...
- If we don’t take into account this fact we can generate very misleading results

Scenario Analysis

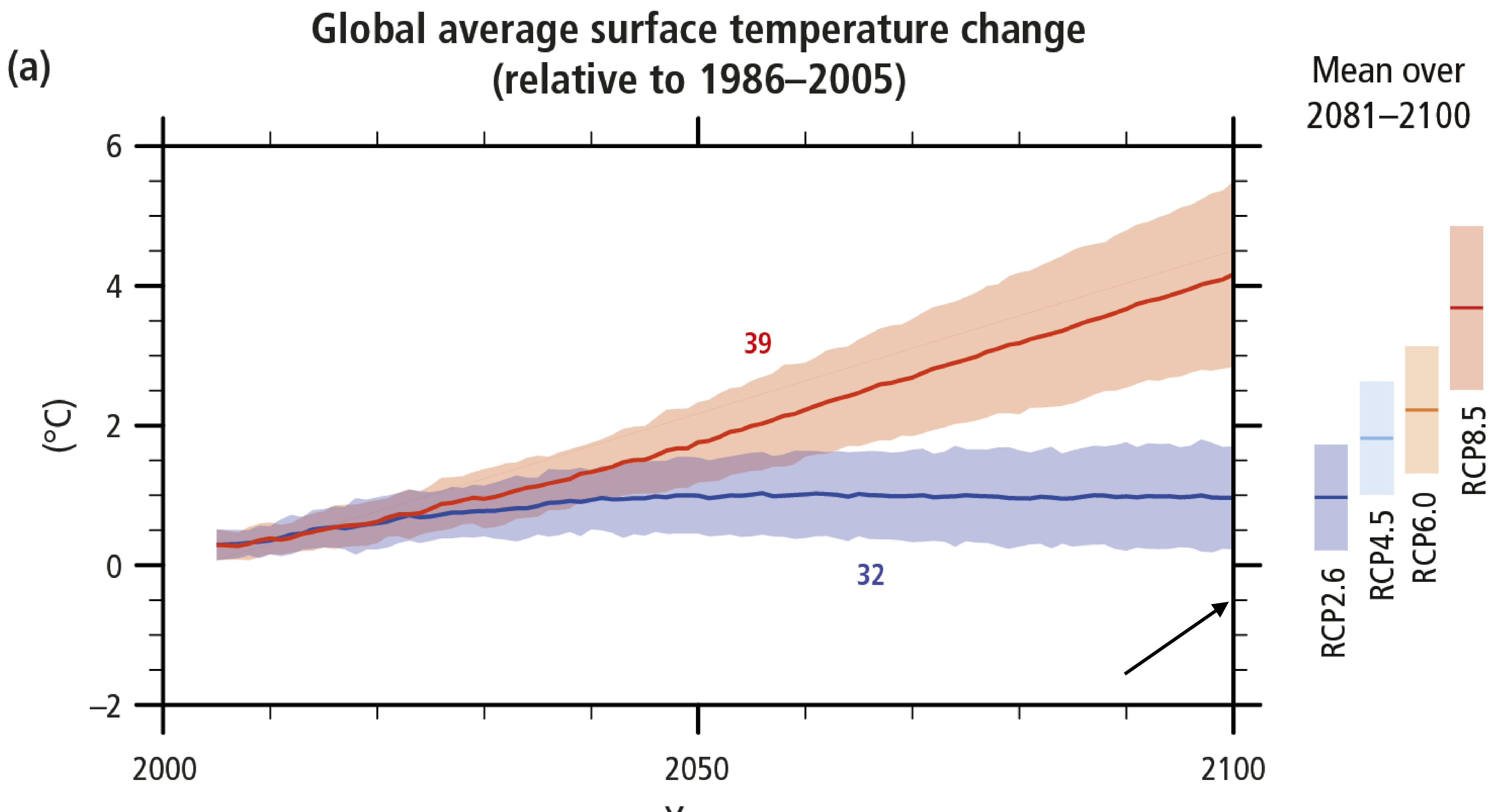
- Classic way of looking at this problem
- A number of ‘scenarios’ are explored
- Often in great detail
- A good example is the CMIP used by the IPCC



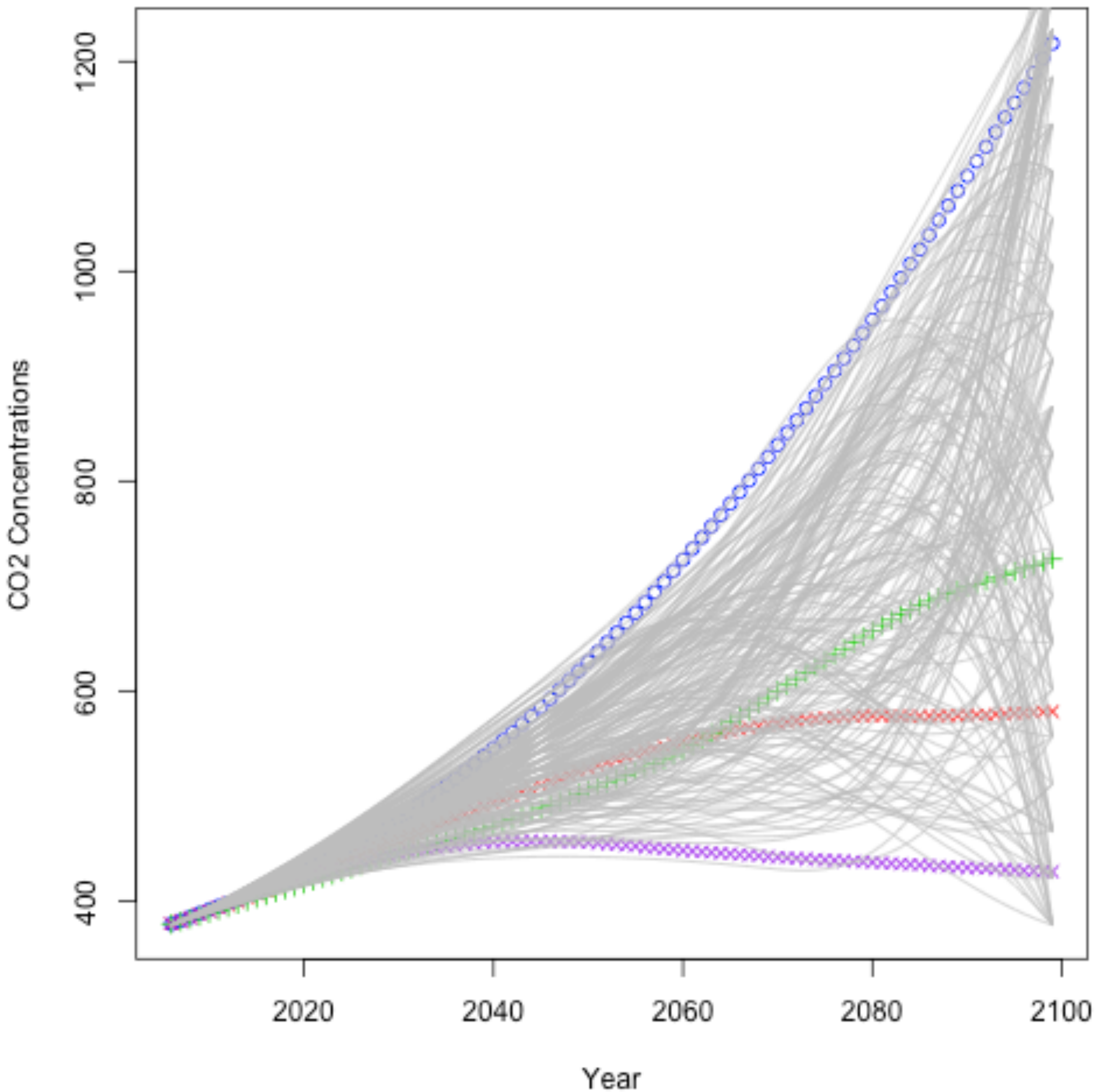
1250
1000
750
500
CO2 concentration
2025
2050
2075
2100
year
RCP8.5
RCP6
RCP4.5
RCP2.6

- Each of these curves is a scenario
- We can describe them with 5 numbers
- CMIP runs a variety of climate models for these scenarios
- One thing we can be certain of is that none of these scenarios will happen
- How could we get to a particular outcome in climate space

Climates Corresponding to the RCP Scenarios



- It can’t be done
- You could try to interpolate/extrapolate
- But this is frowned upon
- And would be very difficult



CO2 Concentrations
400
600
800
1000
1200
2020
2040
2060
2080
2100
Year

- So scenario analysis is pretty useless for decision support
- What are the alternatives?

Optimisation

- The usual alternative to scenarios is to optimise
- What model inputs optimise some output?
- Or what policy levers should I pull to get to the ‘best’ outcome?
- Can I find the ‘optimal’ 5 numbers to limit global mean temperature increase to 1.5°C

- This is much better for decision support than scenarios
- It concentrates on the decision
- But
  - Optimisation is a hard problem
  - Optimisation under uncertainty is even harder
  - Assumes there is only a single ‘best’ set of inputs
  - This best set is likely to not be very robust
  - Leaves the decision maker no freedom
  - It is difficult to include discrepancy in the optimisation framework

Inverse Modelling

- In both scenario modelling and optimisation we run the model in the forward direction
- $y = f(x)$
- But we can also, in theory, run the inverse of the model
- $x = f^{-1}(y)$
- Thus we can get the inputs given the outputs
- At least in principle

Post-Optimisation Decision Making

- Select what outcomes you want from the decision (not a single ‘best’ outcome but outcomes you could live with)
- Use the inverse model to map back to the inputs required
- So for the climate example we might specify global mean temperature rise to be $<1.5°C$ and find all the CO_2 pathways that get you there.

But I have to build the inverse of my model

- Building inverse models is non trivial
- Adjoints
- Automatic adjoint compilers
- Very messy business

Emulators and History Matching

- If the forward model is fast enough we can map out the inverse model with lots of run’s of the forward model
- Emulators are fast, surrogate models with estimators of their own uncertainty

- In History Matching we use a scaled distance between the data and the model to rule out regions of input space
- Implausible; too far from the data
- Refocus on the not ruled out (yet) region
- Iterate
- Refocusing at each wave

History Matching for Decision Making

- We can use ‘History Matching’ techniques to match to outcomes rather than data

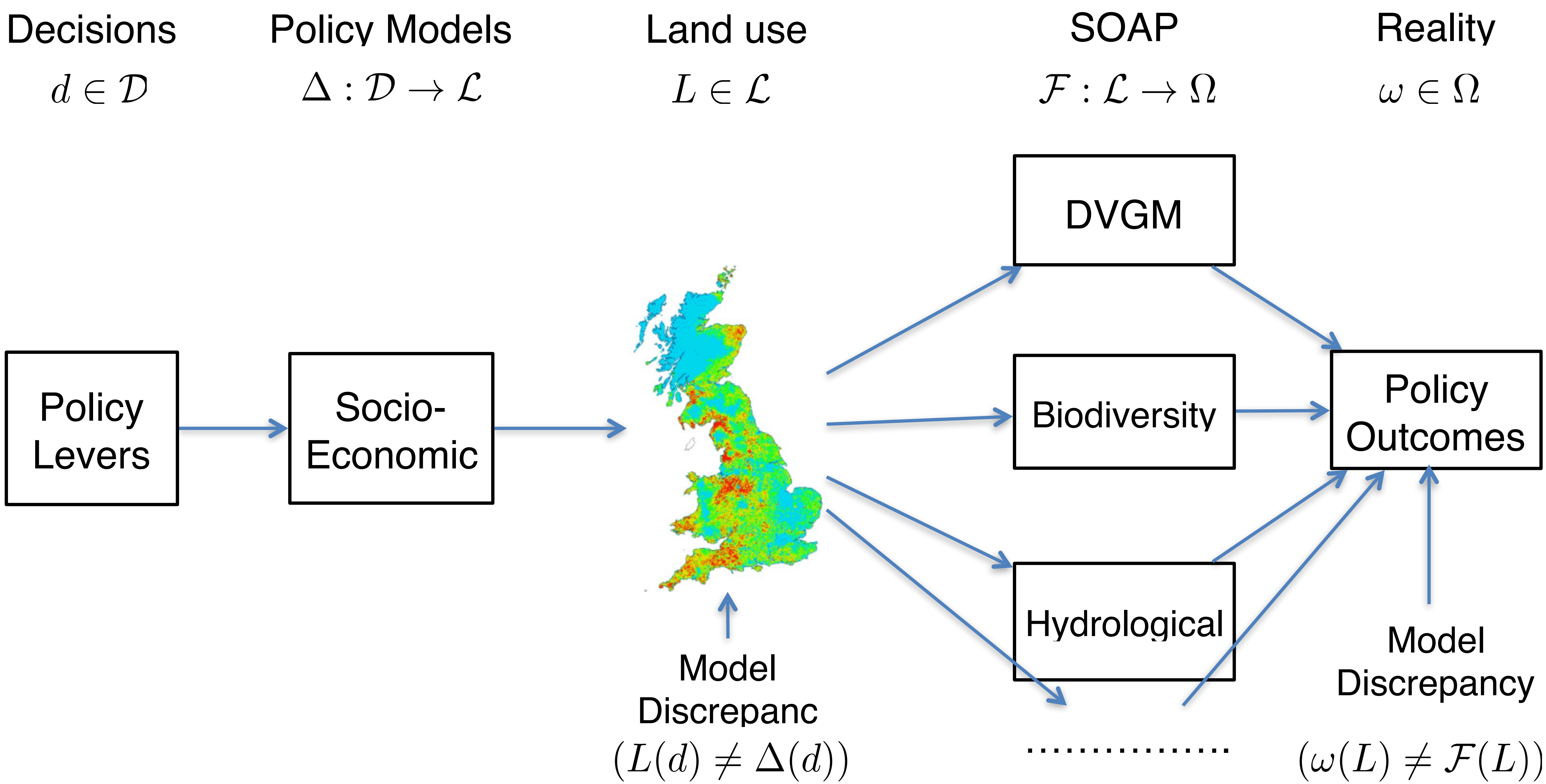
History Matching and Model Discrepancy

- Discrepancy is built into History Matching

What if we can’t get there

- History matching methods don’t guarantee to find a solution (unlike optimisation)
- There may be no inputs that correspond to our desired output
- No decision is ‘good’
- Rethink the problem

A Practical Application for Landscapes - Danny Williamson



For any subspace $\mathcal{G} \subset \Omega$ of 'good' policy outcomes this framework will:

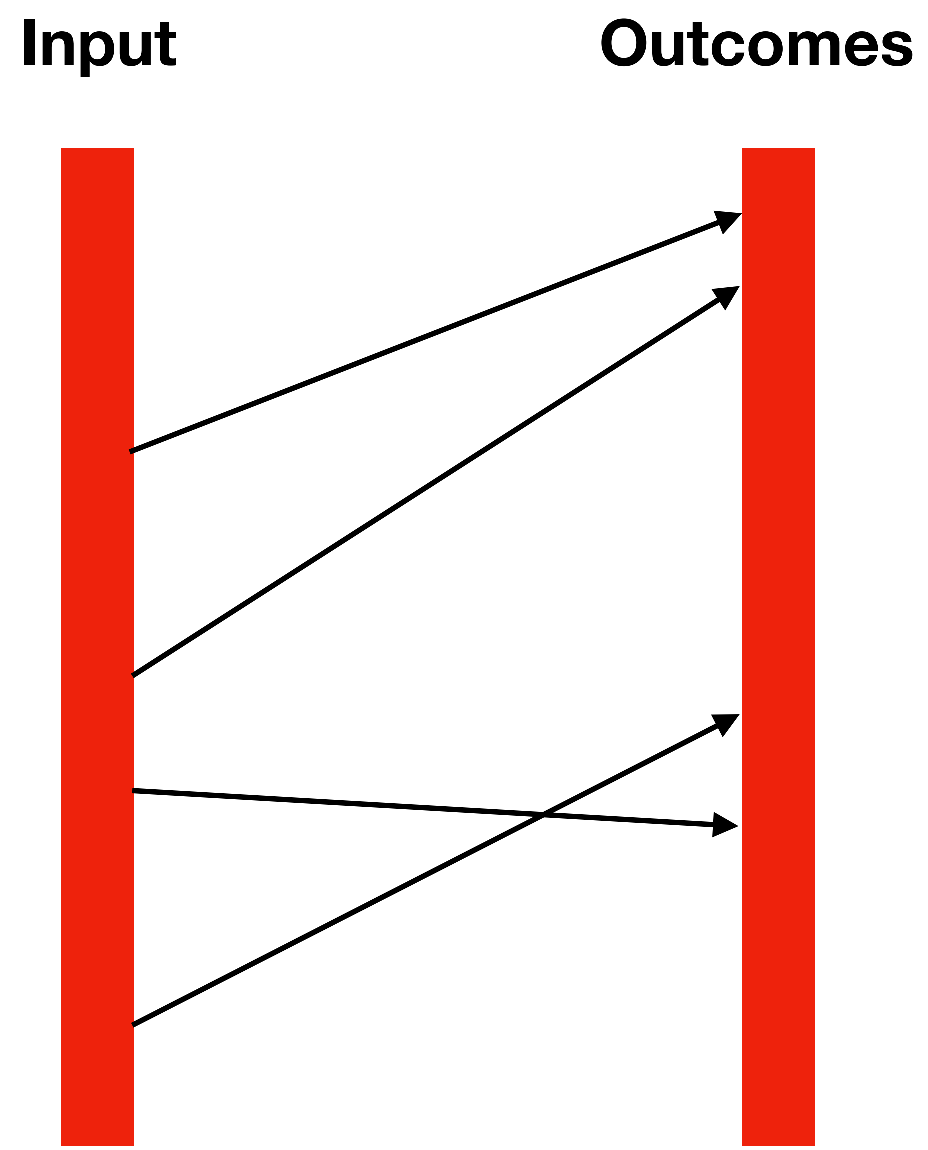
- Develop new Gaussian Process technology and novel multi-model based discrepancy assessment to find $\mathcal{L}_{\mathcal{G}} = \{L \in \mathcal{L} : \omega(L) \in \mathcal{G}\}$
- Develop spatial GPs for agent based models to find $\mathcal{D}_{\mathcal{G}} = \{d \in \mathcal{D} : L(d) \in \mathcal{L}_{\mathcal{G}}\}$.
- Go beyond optimisation by sampling level sets of $\mathcal{D}_{\mathcal{G}}$ to simultaneously show all decisions consistent with $\mathcal{G}$ as conditions on $\mathcal{G}$ are relaxed.

Summary

- Scenario analysis
- Optimisation
- Inverse Modelling

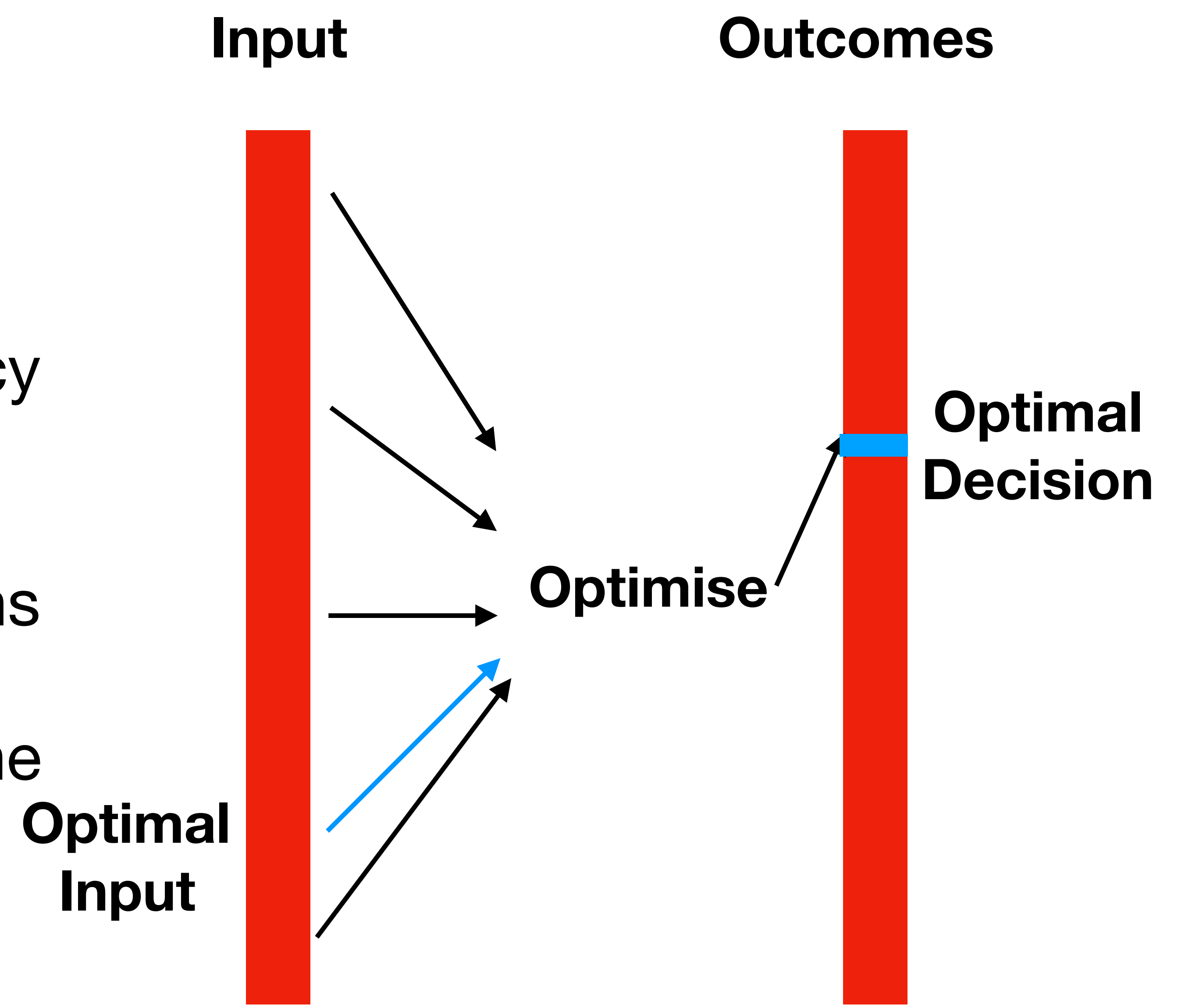
Scenario Analysis

- Limited number of forward model runs
- Not helpful for decision support
- No information away from scenarios



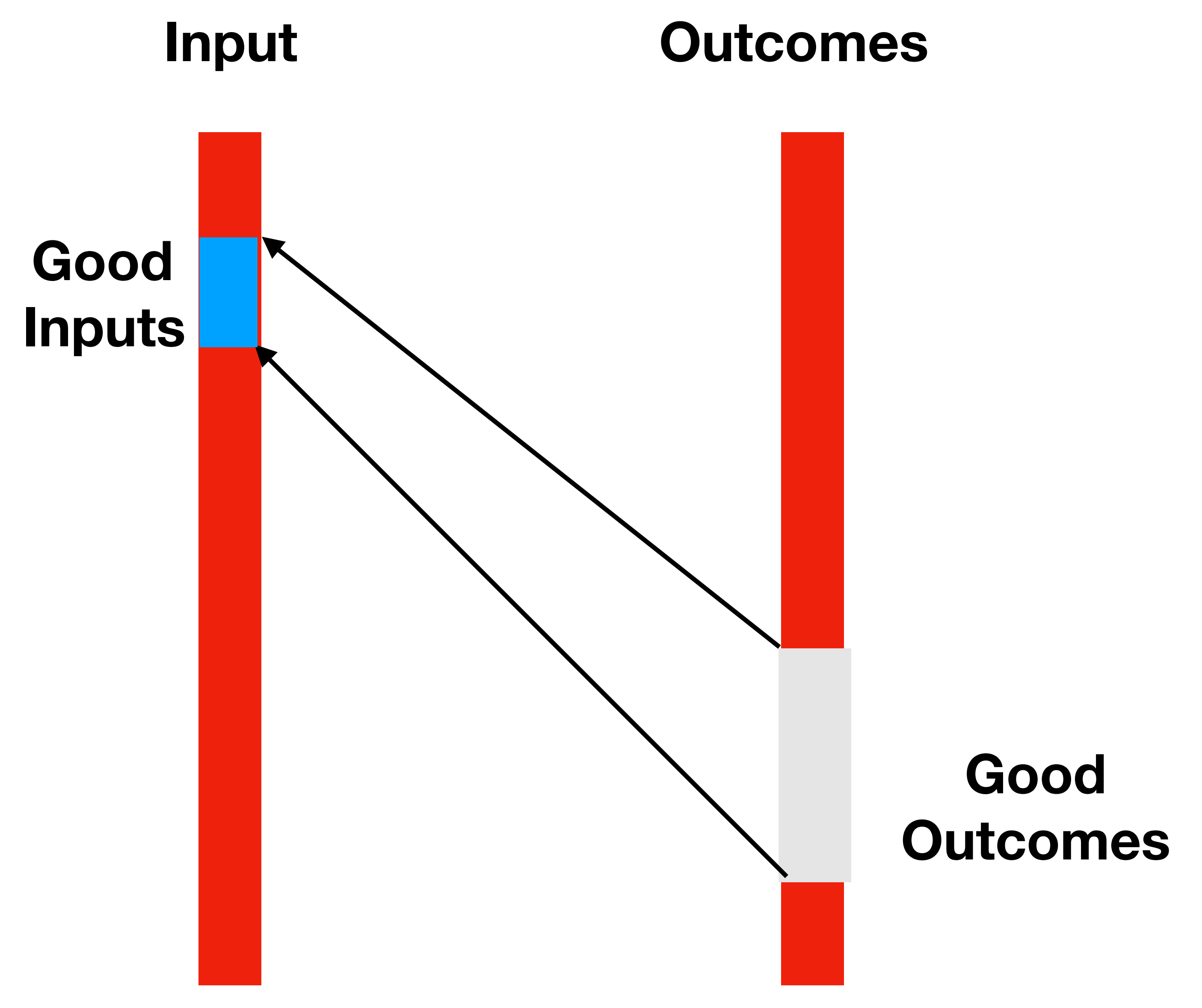
Optimisation

- Examines all options
- Optimisation is hard
- Difficult to include discrepancy and uncertainty
- Does not give range of options
- Almost certainly optimising the wrong problem



Inverse Modelling

- Requires fast models/ emulators
- Gives range of options (all of which give good outcomes)
- Allows decision maker to include immeasurable, externals.



Conclusions

- Proposed new method for using numerical models in decision support
- Based on inverse modelling
- Gives range of ‘good’ decisions
- Allows decision makers choice