From climate risk to action:
Analysing adaptation decision robustness under uncertainty

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Climate adaptation decision-making

How can we make robust climate adaptation decisions?

Uncertainty in climate risk:

- Climate projections
- Exposure and vulnerability

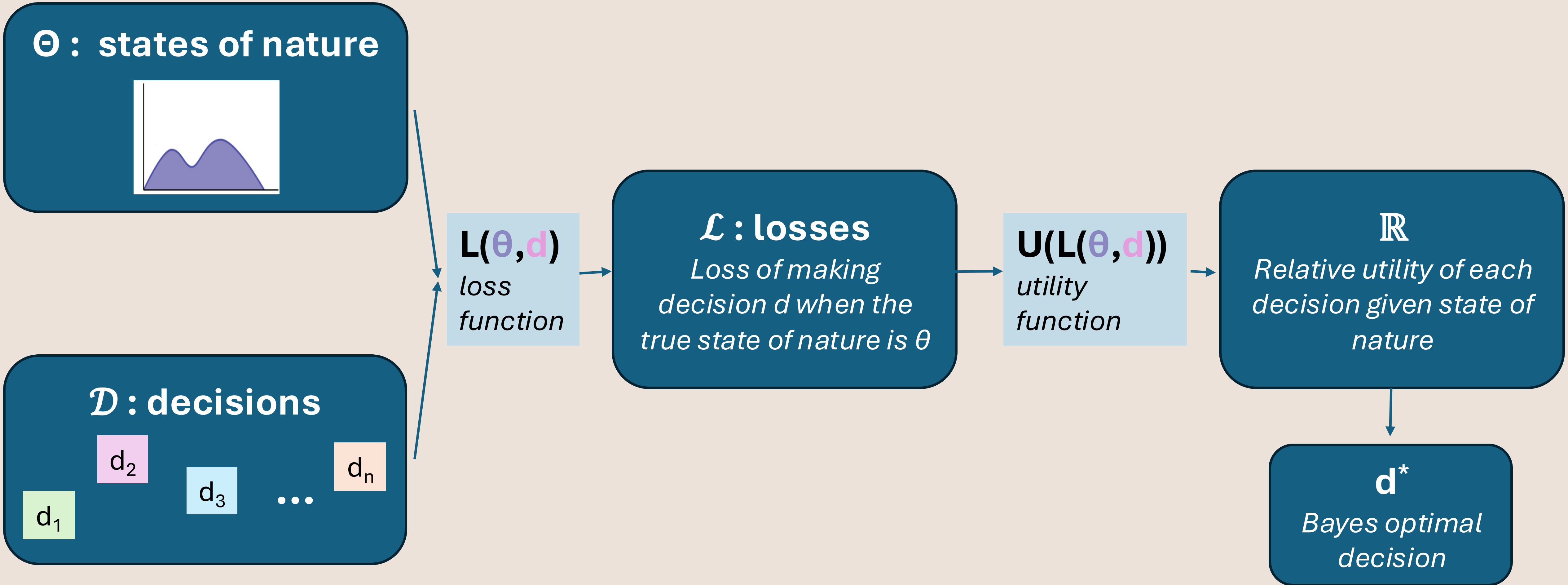
Uncertainty in characteristics of decision options:

- Financial costs
- Efficacies
- Characteristics of decision-makers

Bayesian Decision Analysis

Bayesian Decision Analysis

Framework for decision-making under an uncertain state of nature



Bayes optimal decision

- Select the decision that maximises expected utility:

Bayes decision under utility U

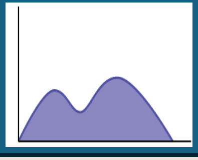
Select the decision d^* such that

$$d^* = \arg\max_d \sum_{\theta \in \Theta} U[L(\theta, d)]p(\theta) = \arg\max_d \bar{U}(d)$$

Example: Heat-stress in the UK

Our decision framework

Θ : expected annual days of work lost to heat stress



$\mathcal{D}$: decisions

- d_1 : do nothing
- d_2: modify working hours
- d_3: buy cooling equipment

L(θ,d)
loss function

$\mathcal{L}$: losses

- *Financial*
- *Non-financial*

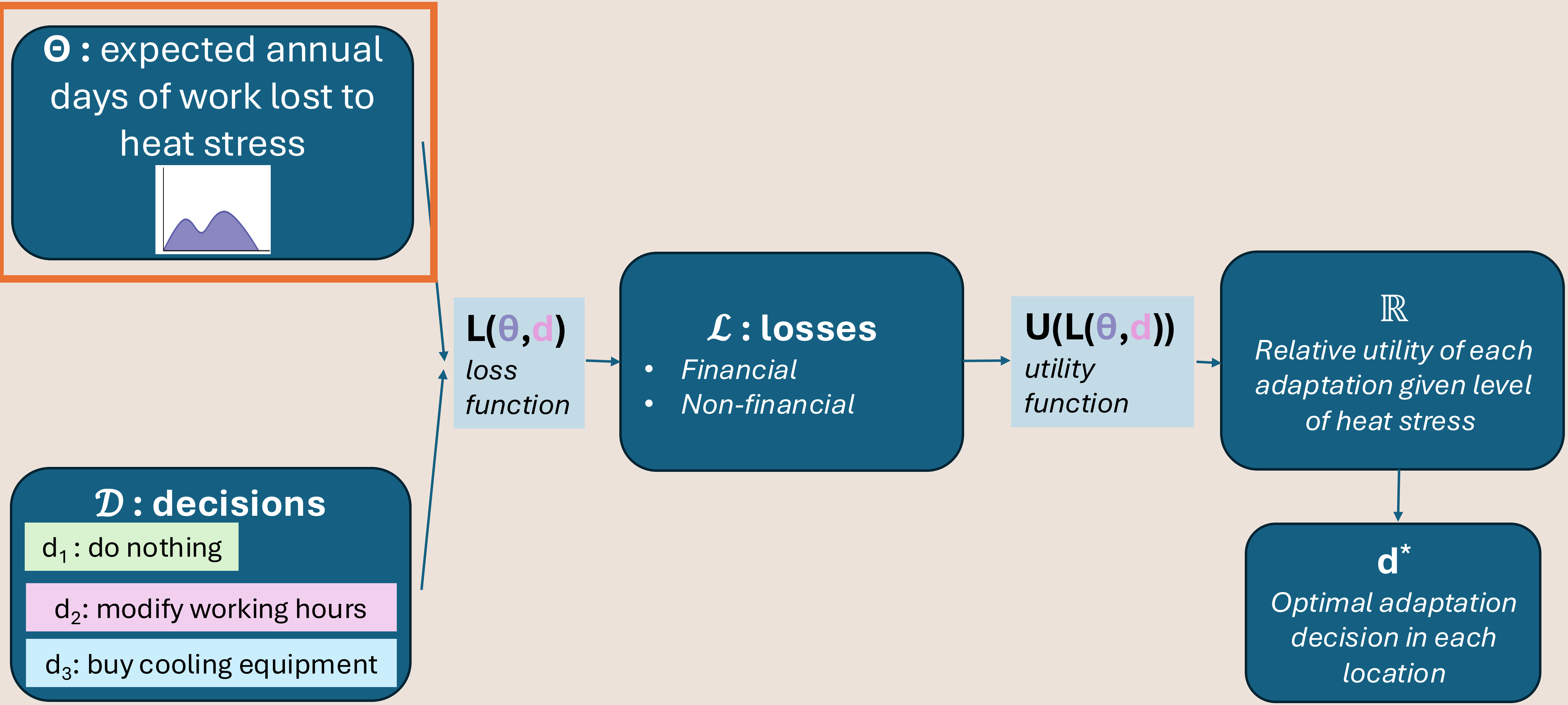
U(L(θ,d))
utility function

$\mathbb{R}$
Relative utility of each adaptation given level of heat stress

d^*
Optimal adaptation decision in each location

How robust are adaptation decisions to uncertainty in the inputs?

Uncertainty in risk



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loss function
𝓛 : losses
• Financial
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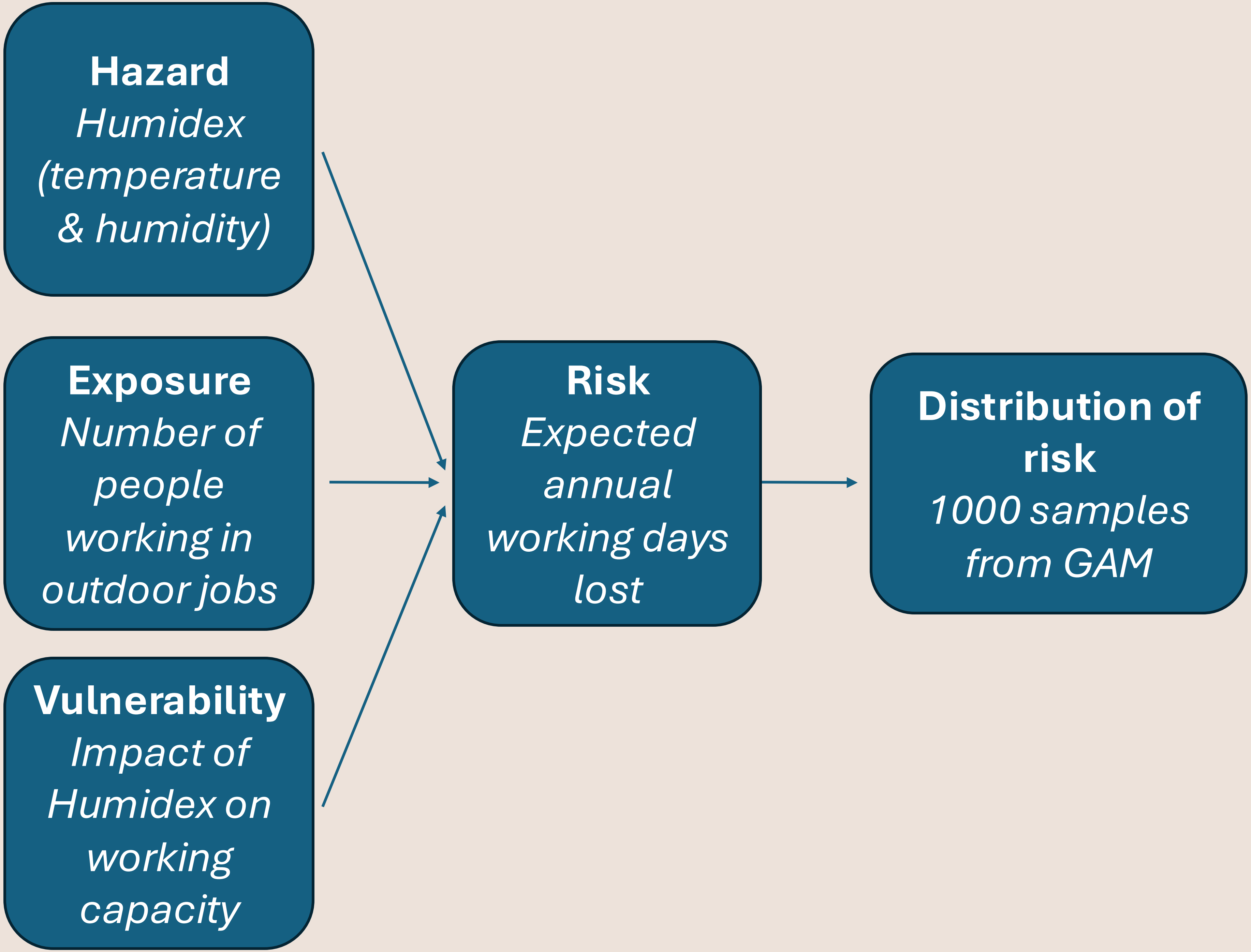
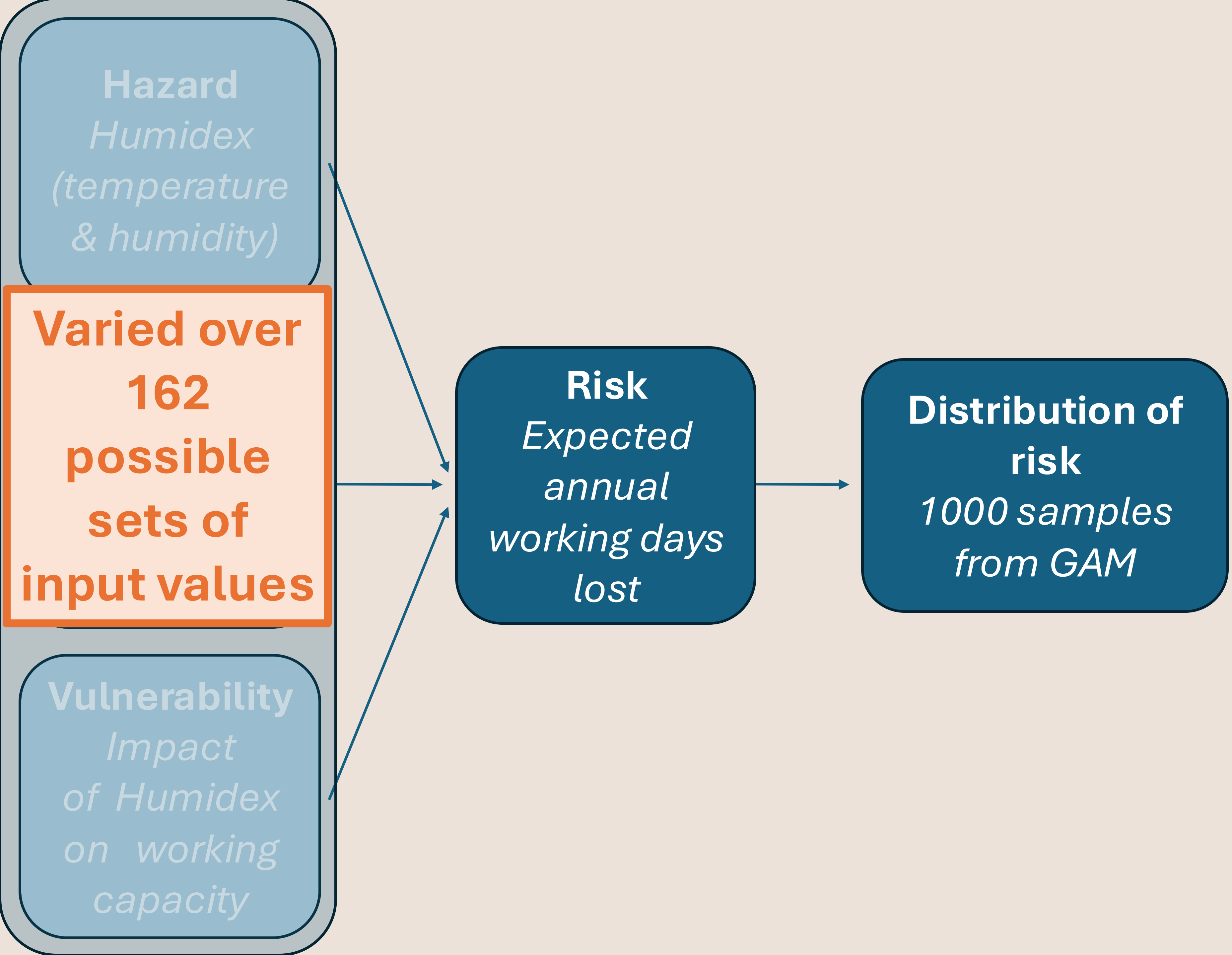


Quantifying uncertainty

Following Dawkins et al. 2023:

- Input hazard, exposure, and vulnerability data
- Apply a risk assessment model to each climate model ensemble member
- Generate 1000 samples of risk per location using Generalised Additive Models (GAMs)

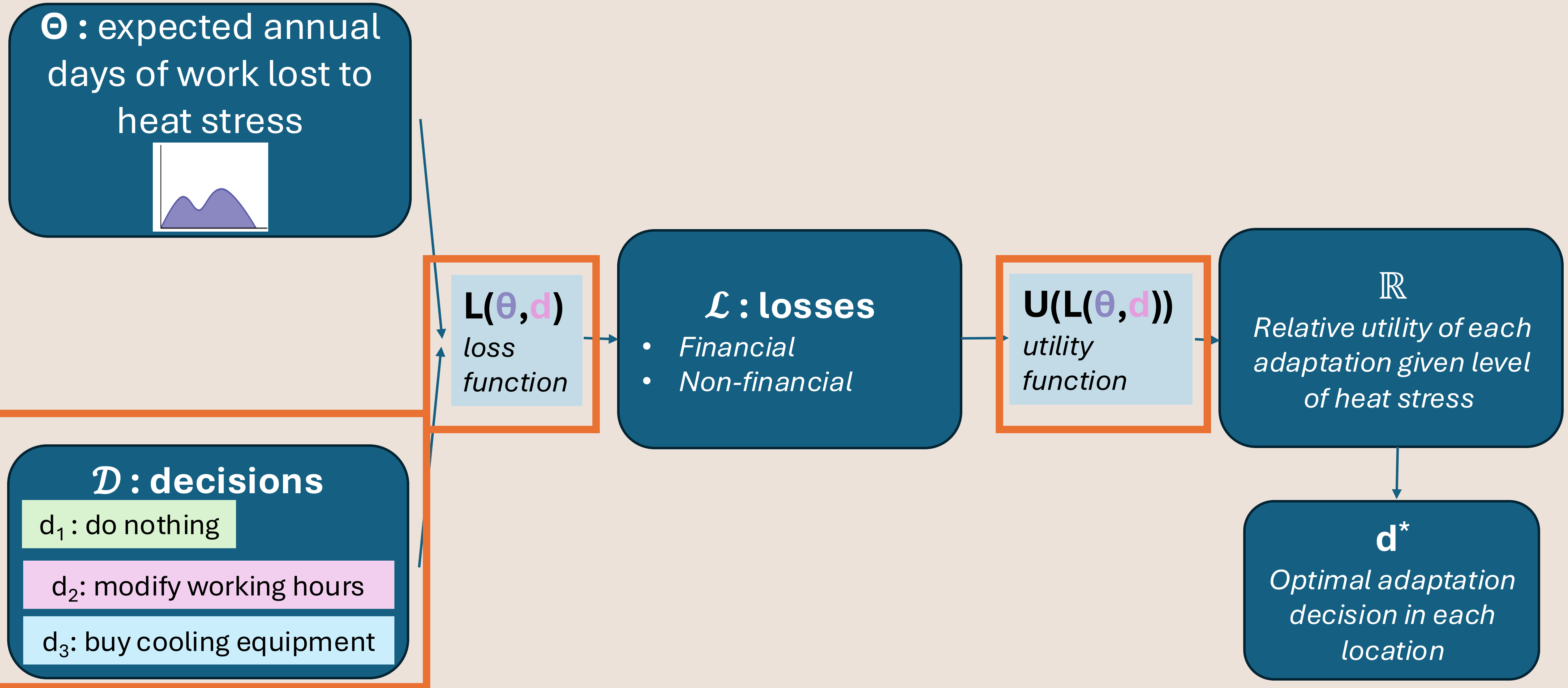
Uncertain risk-related inputs



Sample the risk for each combination of plausible values for 5 risk-related inputs:

- Hazard: calibration method, warming level
- Exposure: exposure model
- Vulnerability: function parameters

Uncertainty in decision attributes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Loss functions

$L(\theta,d)$: $\Theta \times \mathcal{D} \rightarrow \mathcal{L}$ is the loss of making decision *d* if the true state of nature is θ

For a location *j*, GAM sample *n*, and decision *i*:

Financial loss:

$L_1(\theta_{jn}, d_i)$ = (cost per person per year_i × number of people_j)

+ (cost per day of work × (1 – % effectiveness_i) × θ_{jn})

Non-financial loss:

$L_1(\theta_{jn}, d_i) = 10 - s_i$ where $0 \leq s_i \leq 10$

Utility function

U(L(θ,d)): $\mathcal{L} \rightarrow \mathbb{R}$ represents the relative value of each decision

For a location *j*, GAM sample *n*, and decision *i*:

Financial utility	Non-financial utility
$U_1(L_1(\theta_{jn}, d_i)) = 1 - \frac{L_1(\theta_{jn}, d_i)}{\max_{n',i'} L_1(\theta_{jn'}, d_{i'})}$	$U_2(L_2(\theta_{jn}, d_i)) = 1 - \frac{L_2(\theta_{jn}, d_i)}{10}$

Overall utility function:

$$U(\theta_{jn}, d_i) = k_1 U_1(L_1(\theta_{jn}, d_i)) + k_2 U_2(L_2(\theta_{jn}, d_i))$$

where $k_1, k_2 \geq 0$, $k_1 + k_2 = 1$

Uncertain decision-related inputs

Financial loss:

$L_1(\theta_{jn}, d_i) = (\text{cost per person per year}_i \times \text{number of people}_j)$
$+ (\text{cost per day of work} \times (1 - \%\ \text{effectiveness}_i) \times \theta_{jn})$

Non-financial loss:

$L_1(\theta_{jn}, d_i) = 10 - s_i$

Utility:

$$U(\theta_{jn}, d_i) = k_1 U_1(L_1(\theta_{jn}, d_i)) + k_2 U_2(L_2(\theta_{jn}, d_i))$$

Varied by taking 200 samples from a range of plausible values

Overall process

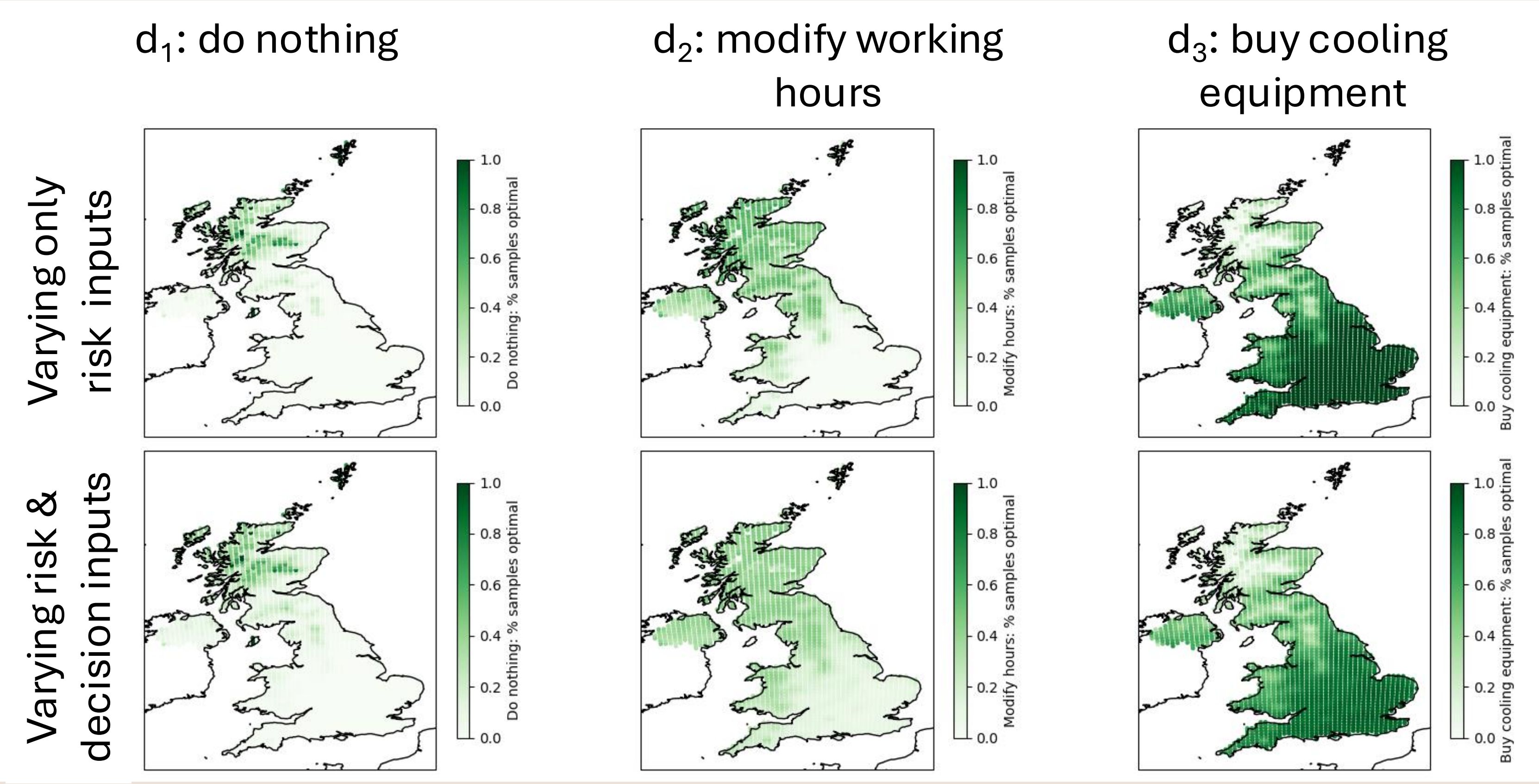
- Vary the risk-related inputs across a range of 162 combinations → record the optimal decision in each location
- Vary both risk-related and decision-related inputs across a range of 162 × 200 = 32,400 combinations → record the optimal decision in each location
- Characterise the uncertainty of the optimal decision & its sensitivity to each input

Results

Where are the different adaptation options most often optimal?

Optimal decision by location

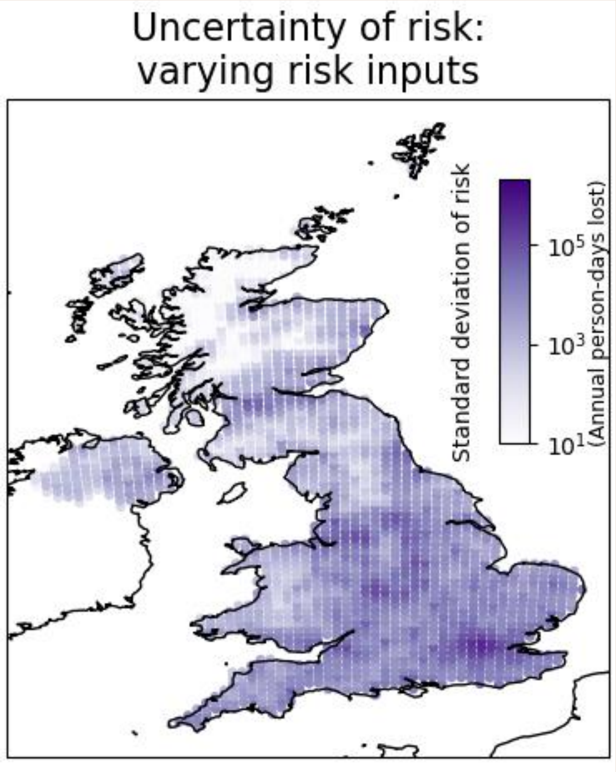
- **Spatial** distribution of where certain decisions are more often optimal
- We are less certain in the decision when varying risk **and** decision-related inputs

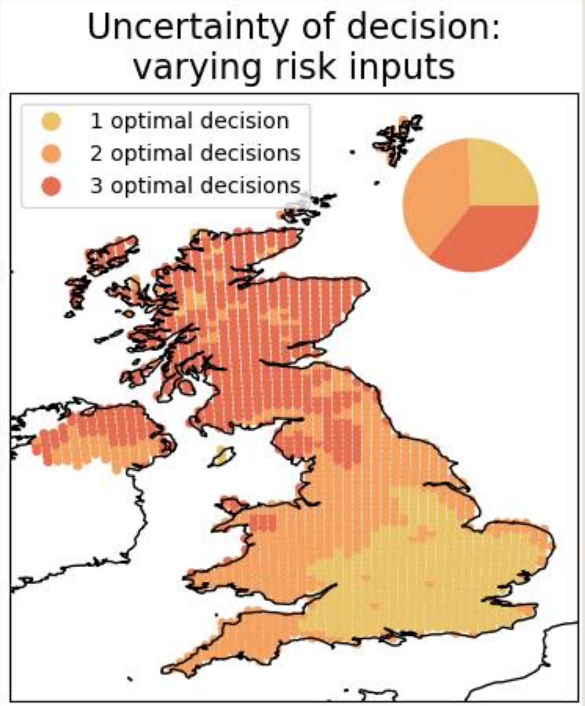


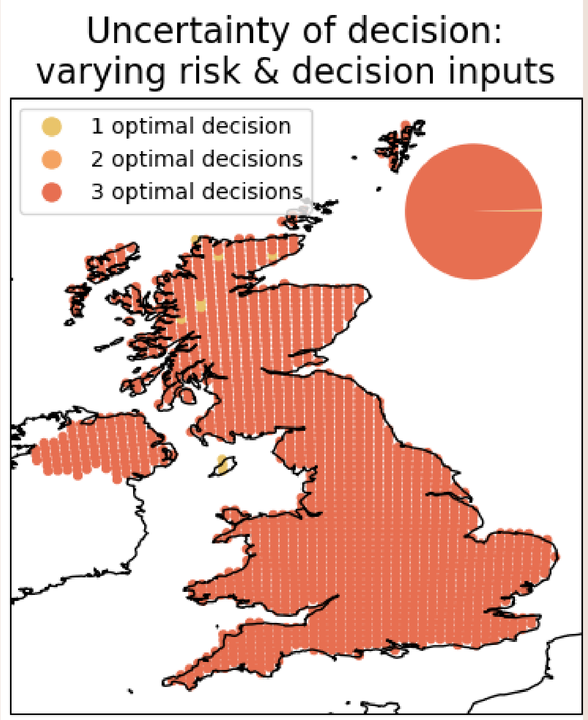
How uncertain is the optimal decision?

Decision uncertainty

- High uncertainty in climate risk **does not** necessarily translate into high uncertainty in decision
- When accounting for uncertainty in both risk and decision inputs, the decision becomes **far more uncertain**



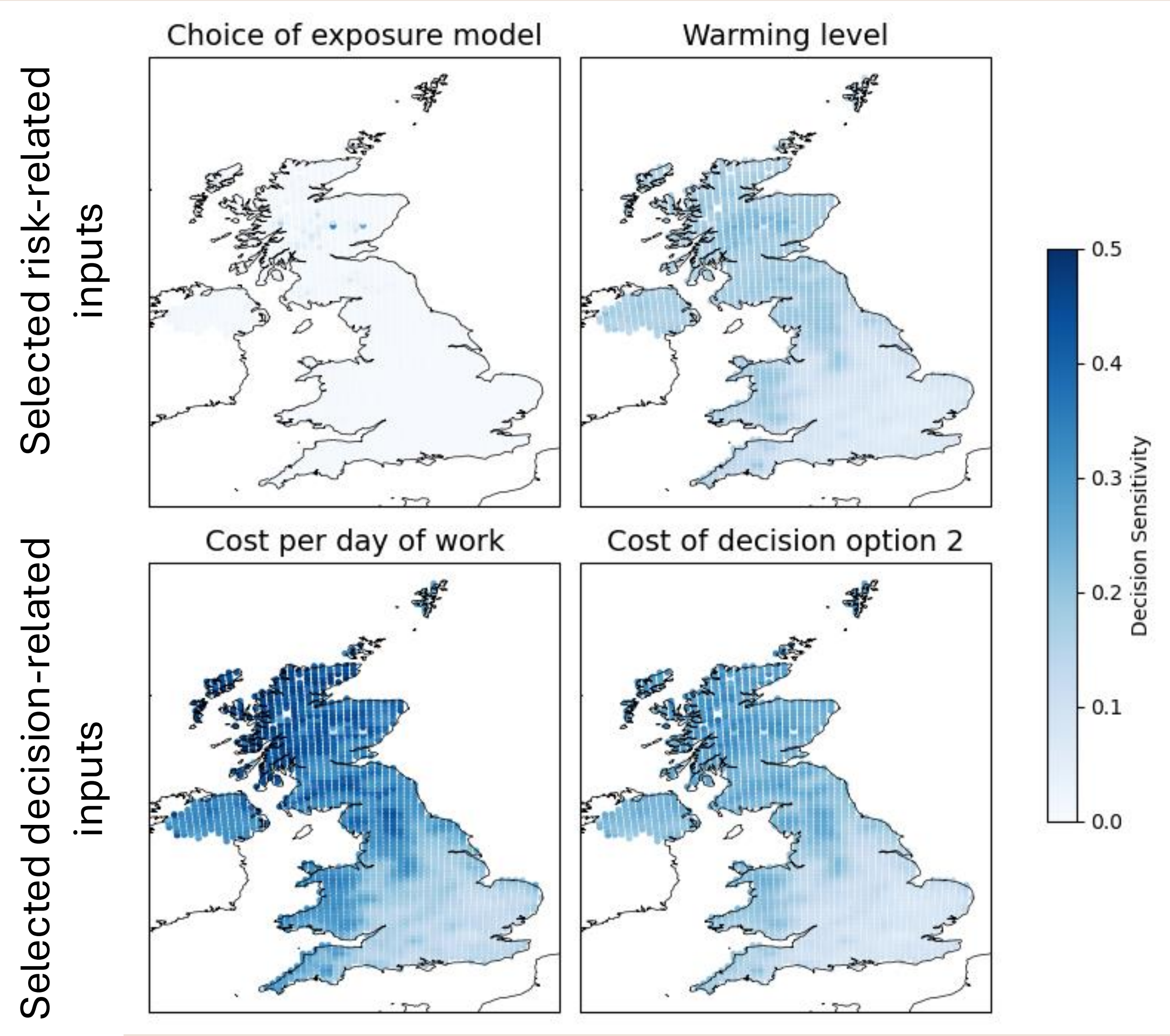




Which inputs is the optimal decision most sensitive to?

Decision sensitivity

- The decision is often more sensitive to **decision-related inputs** than to risk-related inputs
- Sensitivity to many inputs **varies regionally**



Conclusions

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- Uncertainty and sensitivity analysis should be performed on adaptation decisions, not only on climate risk
- Decisions can be less sensitive to risk-related inputs than they are to decision-related ones
- Uncertainty and sensitivity analyses should be performed on a local basis

What's next?

- Real-world application
- Extensions to decision theory/sensitivity analysis methods

Preprint: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5317909

Questions?