From climate risk to action:

Analysing adaptation decision robustness under uncertainty

Cecina Babich Morrow

Supervisors: Laura Dawkins, Dan Bernie, Dennis Prangle

Met Office Science Profession Seminar

10 February 2026

NEWS

Atmospheric carbon dioxide rise to remain too fast to track global climate targets in 2026

Author: Press Office
10:59 (UTC) on Thu 5 Feb 2026

WEATHER

Home | Weather Warnings | Flood Warnings | Monthly Outlook | Coast and Sea | Help

Double record-breaking year for UK as 2025 confirmed as warmest and sunniest on record

England enters fourth heatwave as temperatures reach 33.4C

EEA report 01/2026

Overheated and underprepared: Europeans' experience of living with climate change

Report (PDF) | Published 04 Feb 2026

"Every fraction of a degree of warming will cause more hospital admissions and heat deaths, putting more strain on the NHS."

Professor Antonio Gasparrini
Lead of the EHM Lab, LSHTM

CLIMATE ACTION AND WASTE REDUCTION

What is climate change adaptation and why is it a priority at COP27?

Oct 28, 2022

11 December 2025

UK social homes are unprepared for rising heat as policy fails to keep pace, new research warns

Women and Extreme Heat: Simple Adaptations Make a Big Difference

CEO of World Neighbours Dr. Kate Schecter explains how extreme heat undermines women's livelihoods and what can be done to adapt

by **Kate Schecter - CEO of World Neighbors** — December 23, 2025 in **Climate Change**, **Health**, **Society**

Europe, Physical Risk, UK July 14, 2025

Employers told to invest in climate adaptations as workers feel the heat

By Florence Jones

Comment | Published: 29 January 2026

Climate change adaptation must consider older people

Liming Yao, Shiqi Tan, Chengwei Lv, Nan Wang, Yoshikuni Yoshida & Yin Long

Nature Human Behaviour (2026) | Cite this article

Older adults face higher risks from climate change. We propose an age-sensitive climate adaptation framework, which emphasizes non-digital communication, financial assistance and community-based strategies for older populations.

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

Our questions

Where are different adaptation options most often optimal?

How **uncertain** is the optimal decision?

How does decision uncertainty relate to climate risk uncertainty?

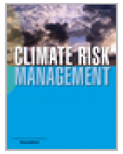
Which inputs is the optimal decision **most sensitive** to?

How does the sensitivity of the optimal decision vary spatially?

Paper: https://www.sciencedirect.com/science/article/pii/S2212096325000658

ELSEVIER

Climate Risk Management
Volume 50, 2025, 100751



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

Cecina Babich Morrow [a], Laura Dawkins [b], Francesca Pianosi [c], Dennis Prangle [a], Dan Bernie [b d]





Example:
Heat-stress in the UK

An idealised example

What should a UK company do to combat the effects of heat stress?

- **Risk:** How much is heat going to impact our workers?
- **Adaptation options:** What are the characteristics of our potential adaptations?

Optimal decision: What action should we take, given what we know about the risk level and the adaptations?

Example: Heat-stress risk

Heat stress risk

Risk: Expected annual total number of days of physical work lost due to heat stress

Calculated based on:

- **Hazard:** Humidex
- **Vulnerability:** Impact = f_{vuln}(hazard intensity)
- **Exposure:** number of people working in outdoor physical jobs (now and in the future)

Heat stress risk

Risk: Expected annual total number of days of physical work lost due to heat stress

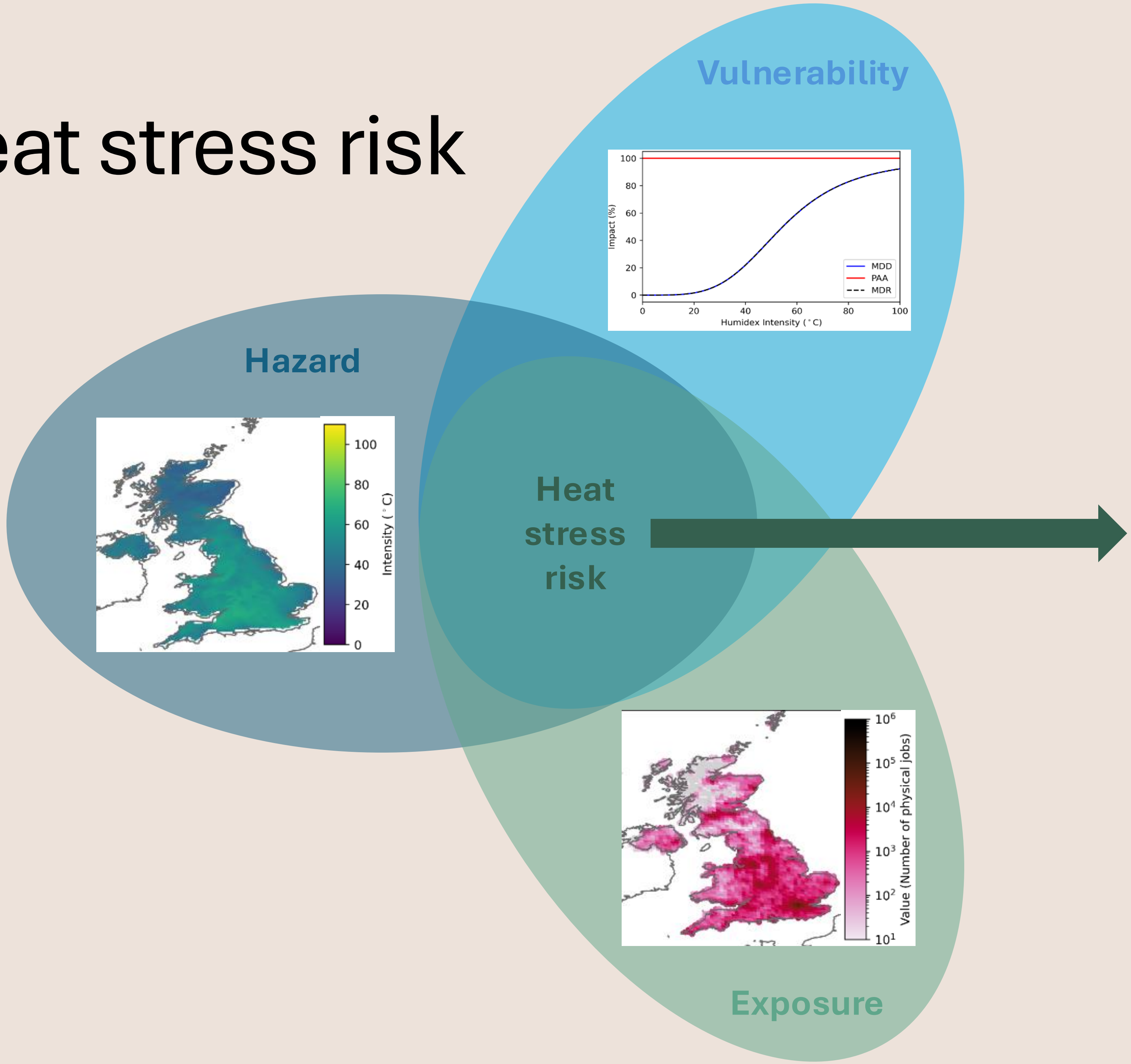
Calculated based on:

- **Hazard:** Humidex
- **Vulnerability:** Impact = f_{vuln}(hazard intensity)
- **Exposure:** number of people working in outdoor physical jobs (now and in the future)

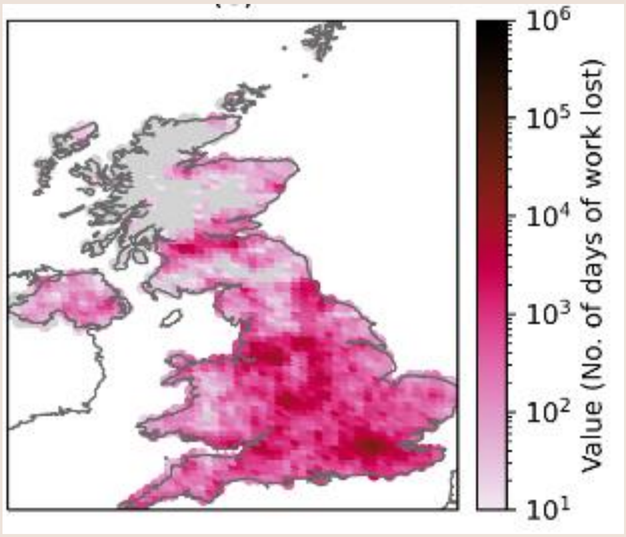
Severity = Exposure × f_{vuln}(hazard intensity)

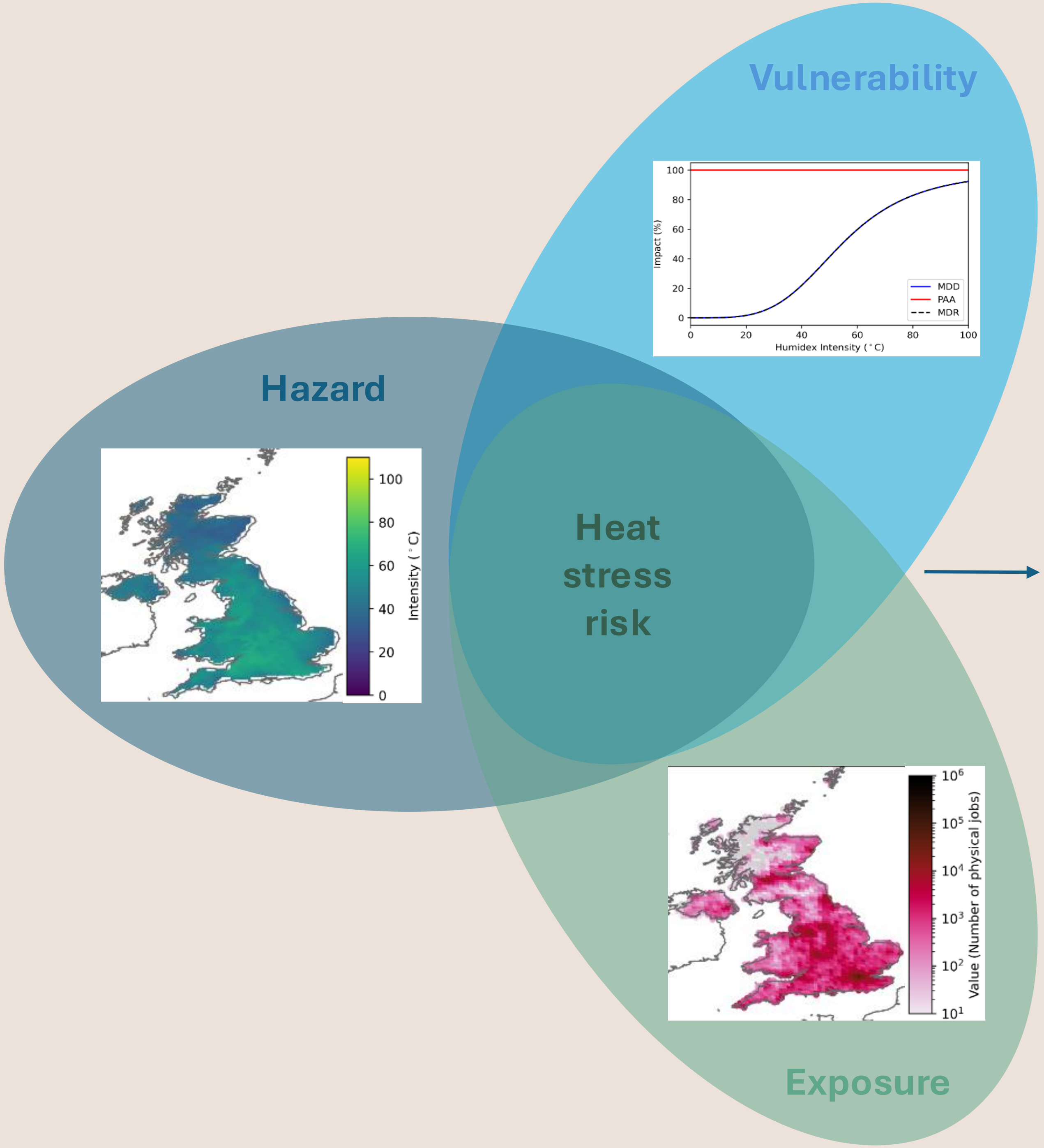
Risk = Probability × Severity

Heat stress risk



Risk from 1 ensemble member





Distribution of risk

1000 samples from GAM

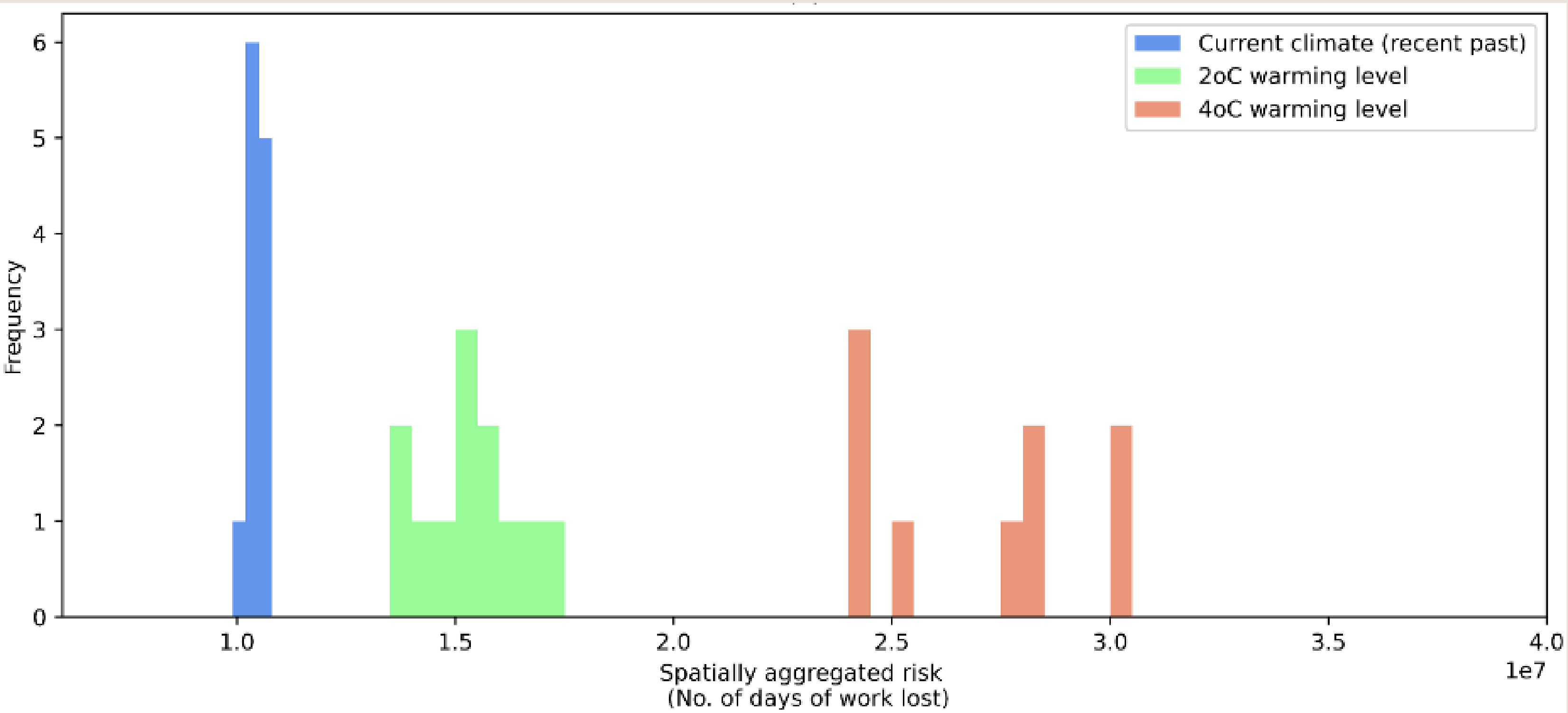
Quantifying uncertainty

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)

Why use GAMs?

We only have *n* = 12 ensemble members for UKCP18.



Distribution of spatially aggregated risk across the 12 UKCP18 ensemble members for each warming level. *(Reproduced from Dawkins et al. 2023.)*

Generalised Additive Models

Generalised Additive Model (GAM): models response variable using a sum of smooth functions

For climate ensemble member m and spatial location s:

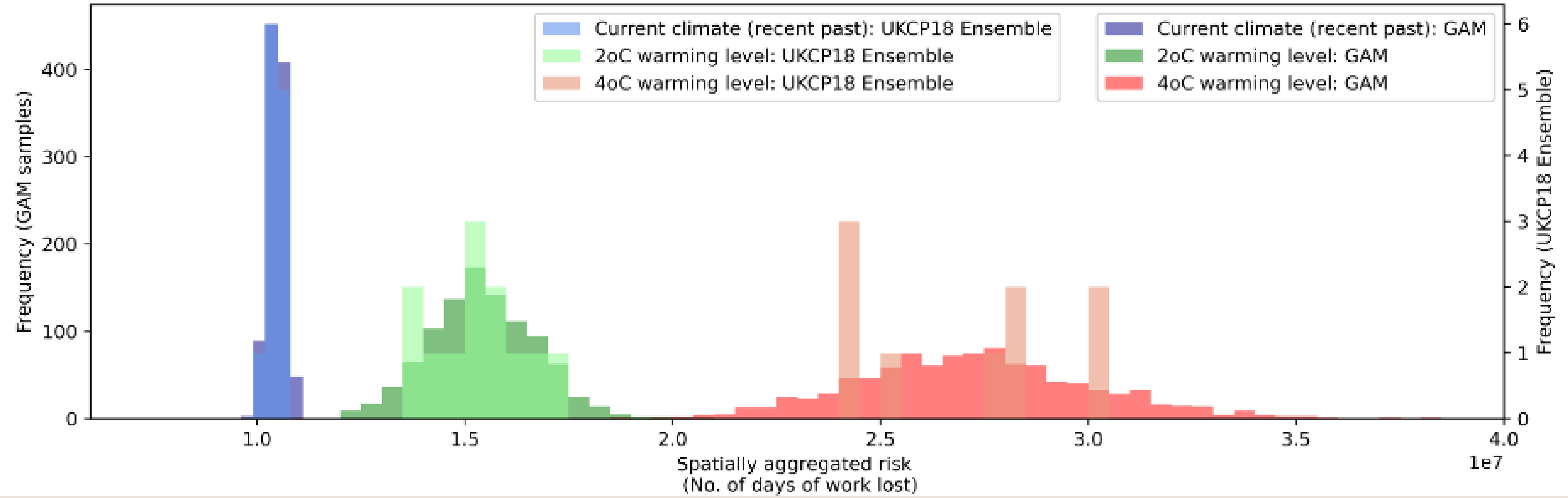
$$\log_{10}(\text{Risk}(m, s)) \sim N(\mu(m, s), \omega^2)$$

$$\mu(m, s) = f(\text{lon}(s), \text{lat}(s), \text{orog}(s), \text{pop}(s)) + \xi_m$$

$$\xi_m \sim N(0, \lambda^2)$$

Generalised Additive Models

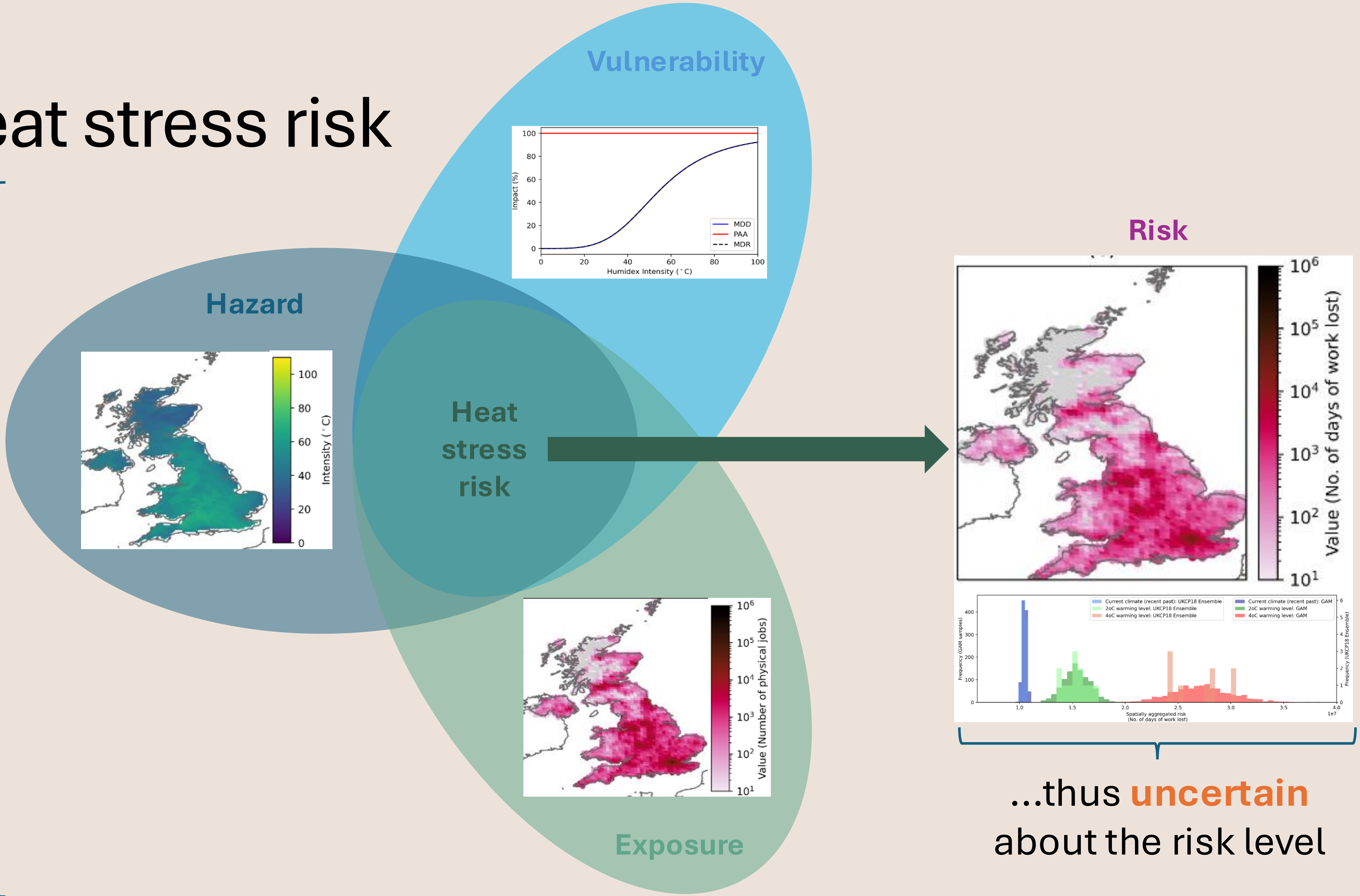
Now we have *n* = 1000 representations of risk for each warming level.



Distribution of spatially aggregated risk across the 1000 GAM samples for each warming level.
(Reproduced from Dawkins et al. 2023.)

Heat stress risk

Uncertain about characteristics of hazard, vulnerability, and exposure



...thus **uncertain** about the risk level

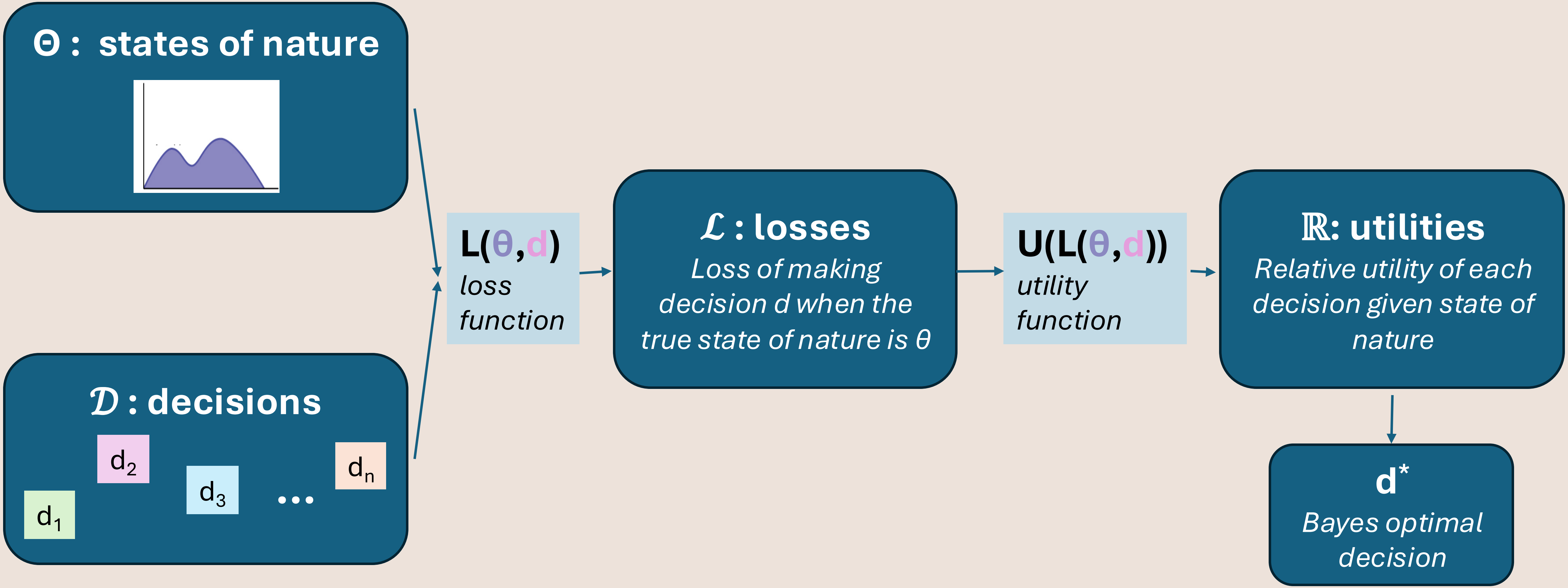
Example: Adaptation decision-making

Potential adaptations

Action	Relative annual cost per person	Relative effectiveness	Alignment with organisational objectives
d_1: Do nothing	No cost	No efficacy	Neutral
d_2: Modify working hours	Lower cost	Moderate efficacy	Fairly well-aligned
d_3: Buy cooling equipment	Highest cost	Highest efficacy	Not aligned with net zero

Bayesian Decision Analysis

Framework for decision-making under an uncertain state of nature



Bayes optimal decision

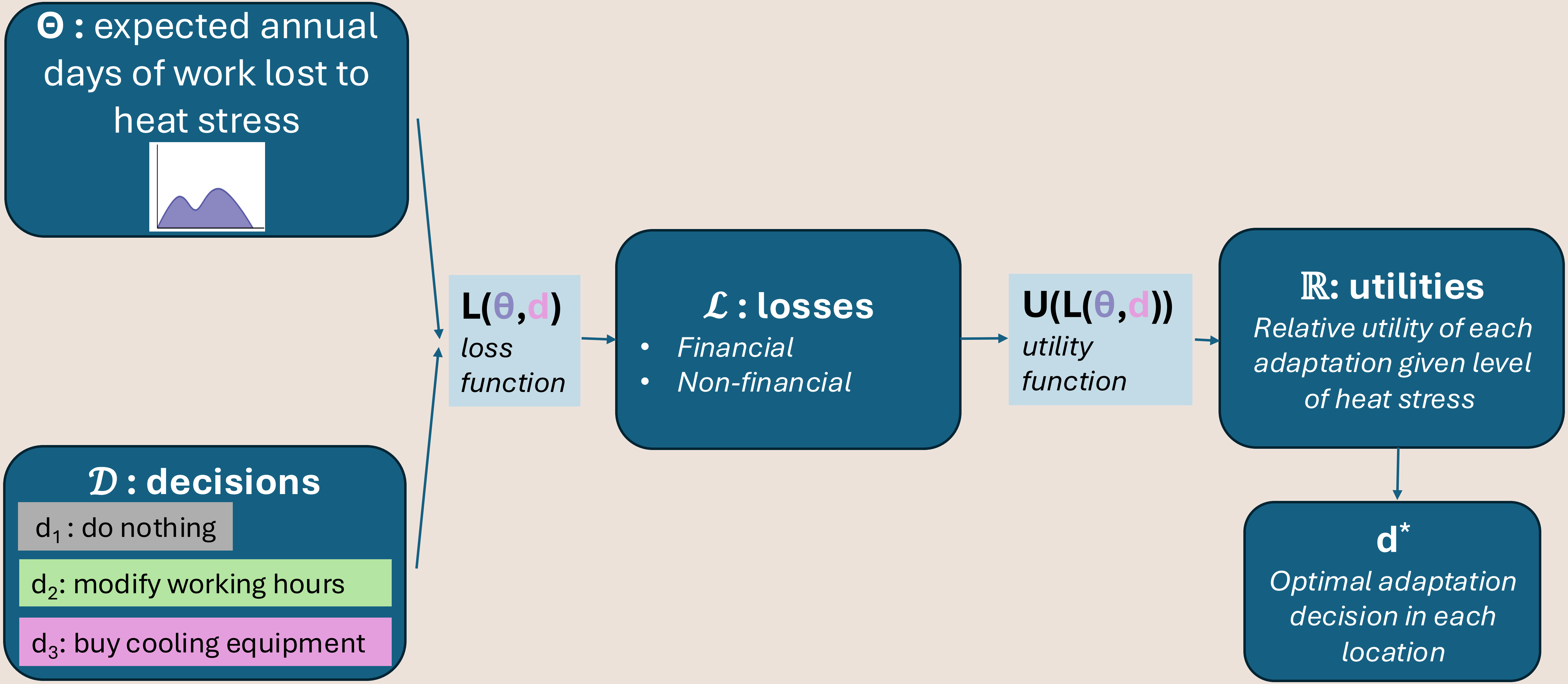
Select the decision that maximises expected utility:

Bayes decision under utility U

Select the decision d^* such that

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

Our decision framework



Loss functions

$L(\theta,d)$: 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:

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

where θ is the annual number of working days lost to heat stress

Non-financial loss:

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

Utility function

U(L(θ,d)): represents the relative value of each decision

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

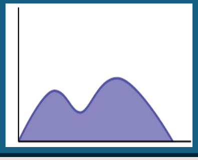
Financial utility	**Non-financial utility**
$U_1(L_1(\theta_{jn}, d_i)) = 1 - \frac{L_1(\theta_{jn}, d_i)}{\max_{n',i'} L_1(\theta_{jn'}, d_{i'})}$	$U_2(L_2(\theta_{jn}, d_i)) = 1 - \frac{L_2(\theta_{jn}, d_i)}{10}$

Overall utility function:

$$\boxed{U(\theta_{jn}, d_i) = k_1 U_1(L_1(\theta_{jn}, d_i)) + k_2 U_2(L_2(\theta_{jn}, d_i))}$$ where $k_1, k_2 \geq 0$, $k_1 + k_2 = 1$

Example: optimal decision in Exeter

$\mathbf{\Theta}$: 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

$\mathcal{L}$: **losses**

- *Financial*
- *Non-financial*

$\mathbb{R}$: **utilities**

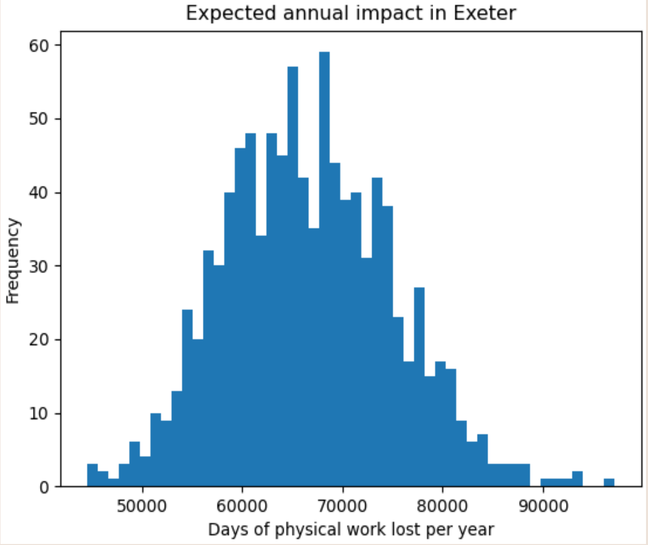
Relative utility of each adaptation given level of heat stress

$\mathbf{d}^*$

Optimal adaptation decision in each location

Example: optimal decision in Exeter

Risk



$\mathcal{D}$: decisions

d_1 : do nothing

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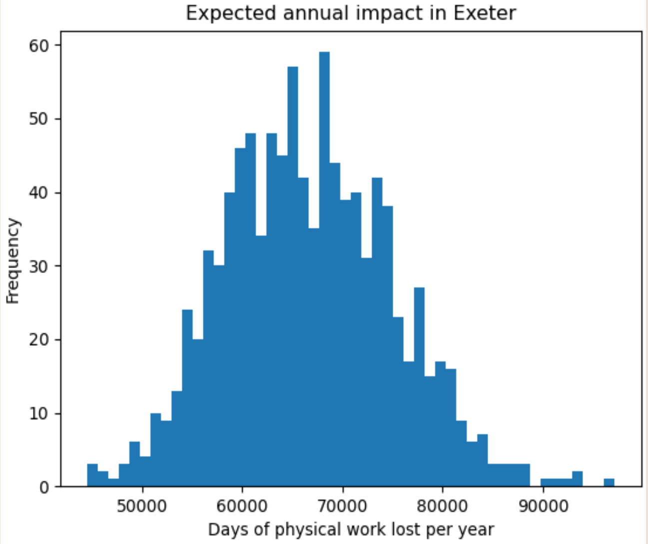
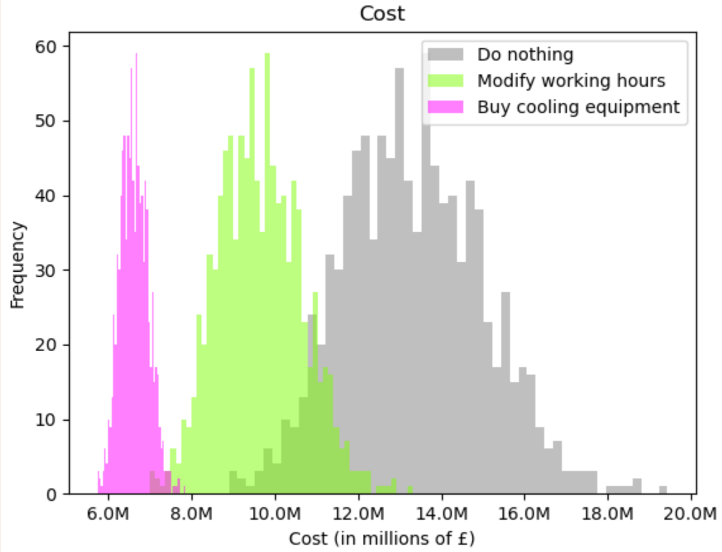
Example: optimal decision in Exeter

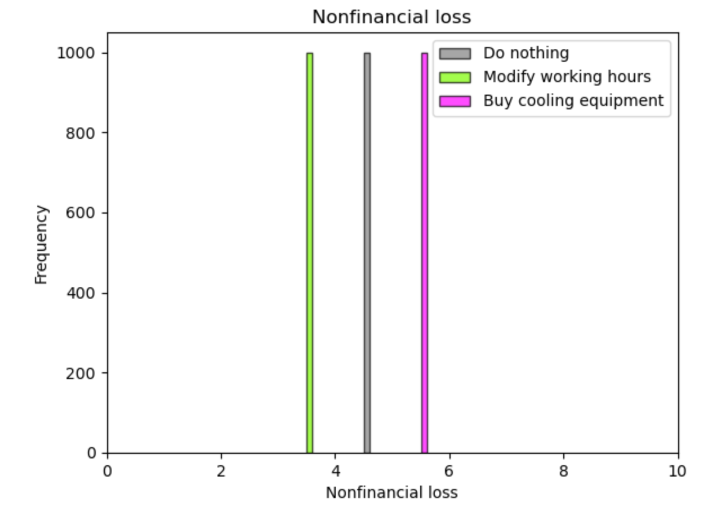
Risk



Financial loss



Non-financial loss



$\mathcal{D}$: decisions

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d_2: modify working hours

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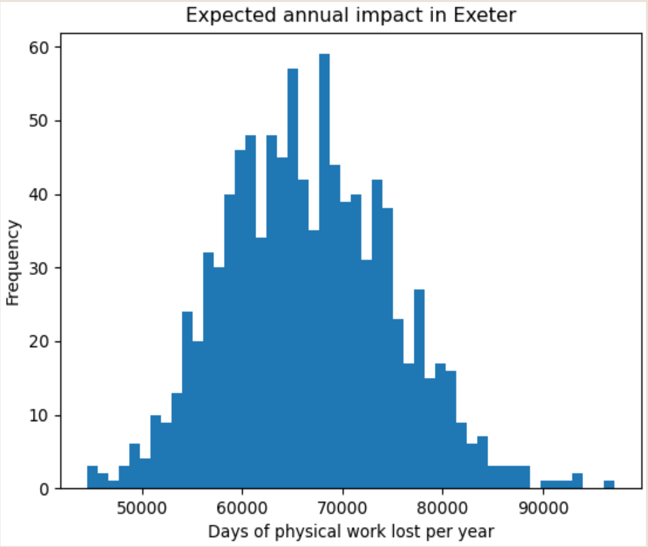
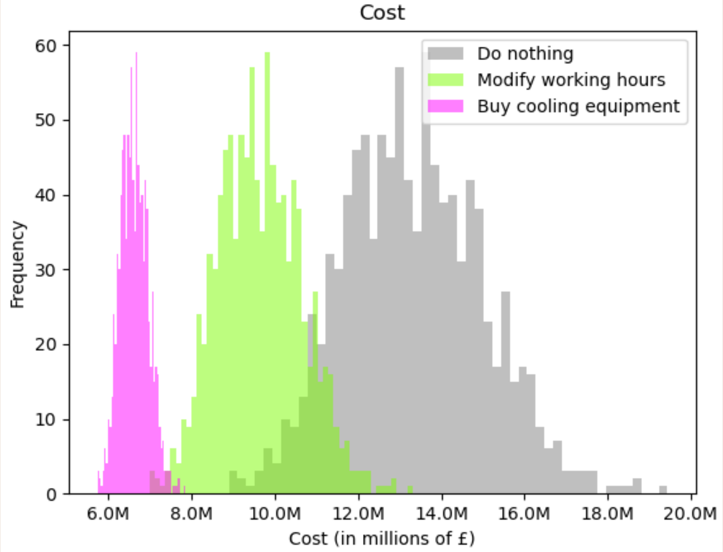
Example: optimal decision in Exeter

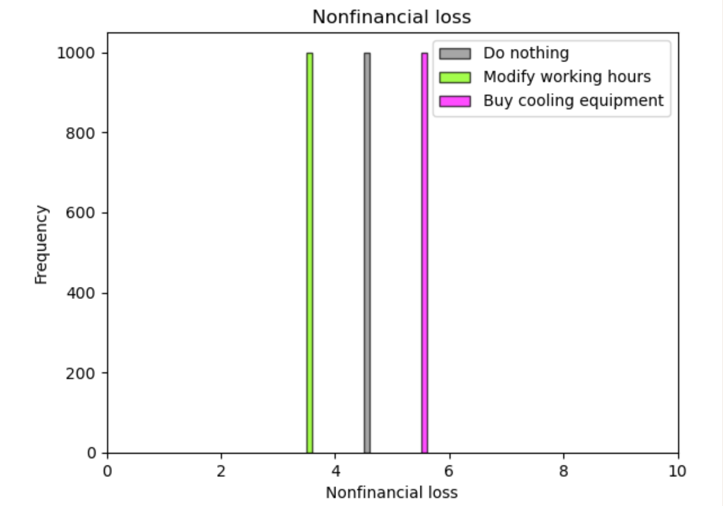
Risk



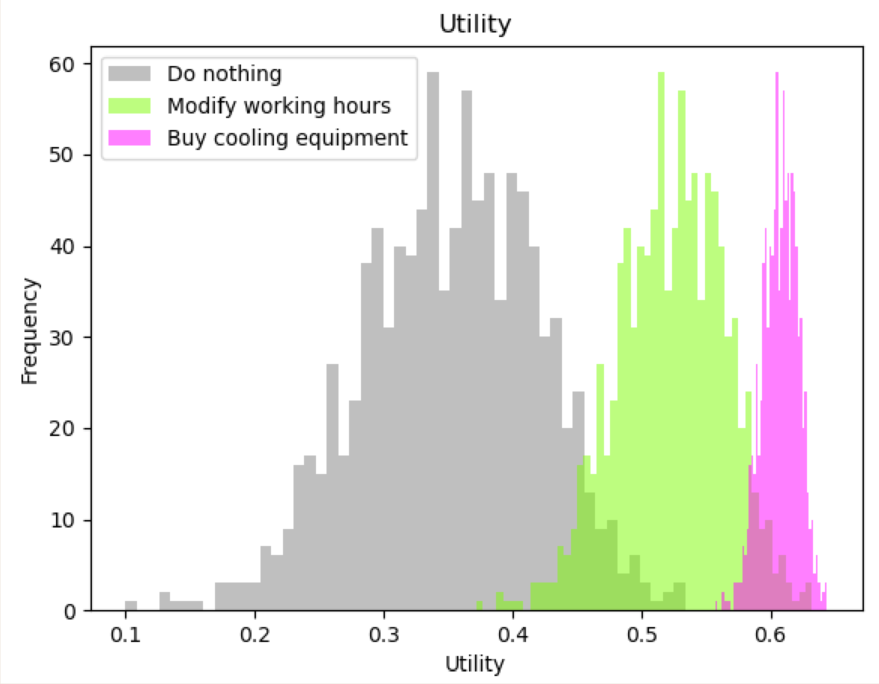
Financial loss



Non-financial loss



Utility



$\mathcal{D}$: decisions

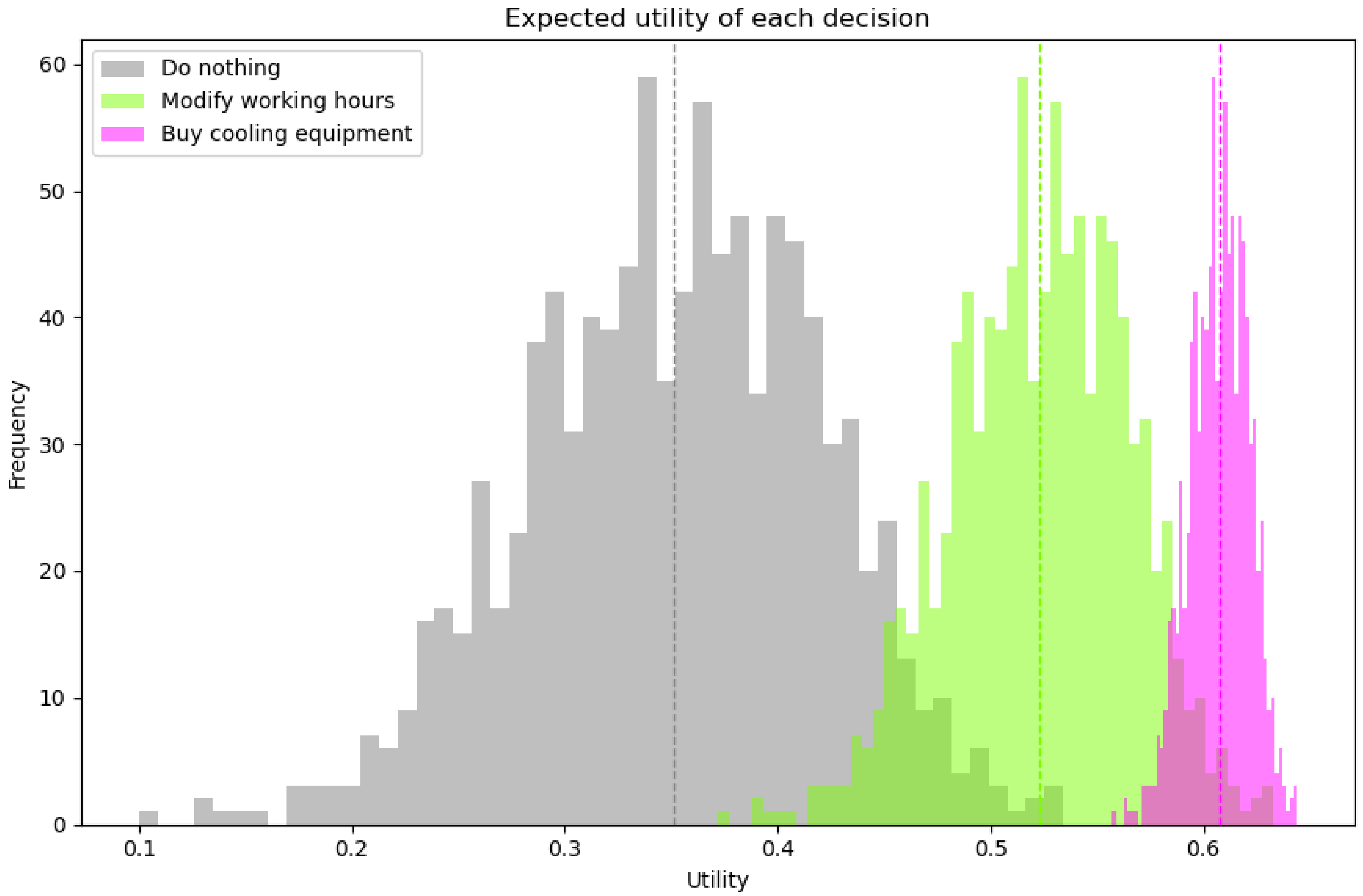
d_1 : do nothing

d_2: modify working hours

d_3: buy cooling equipment

Optimal decision in Exeter

Utility



d*

Optimal adaptation decision:

Buy cooling equipment

Potential adaptations

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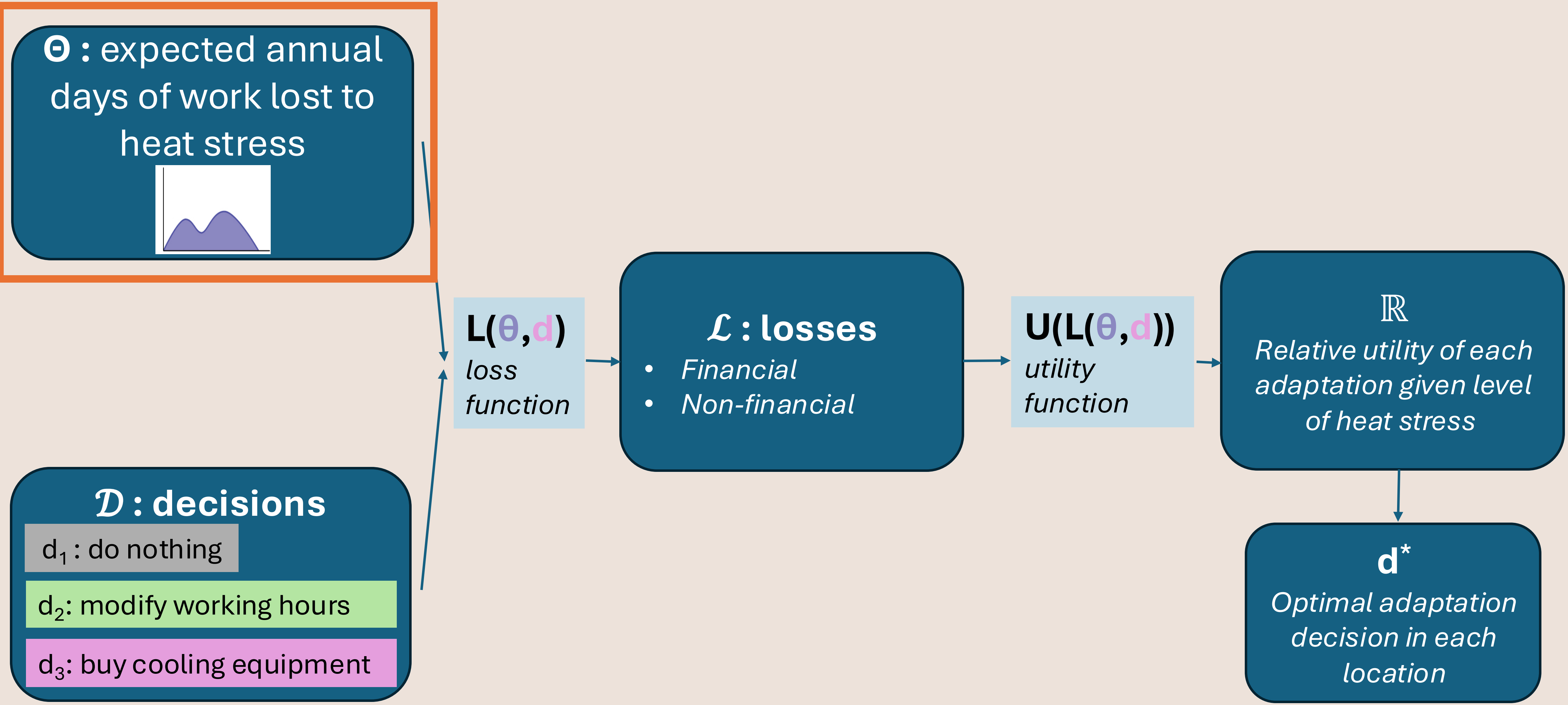
Uncertain about these values and their relative importance to the decision-maker

Accounting for uncertainty

Uncertainty in risk


Θ : expected annual days of work lost to heat stress
𝒟 : decisions
d_1 : do nothing
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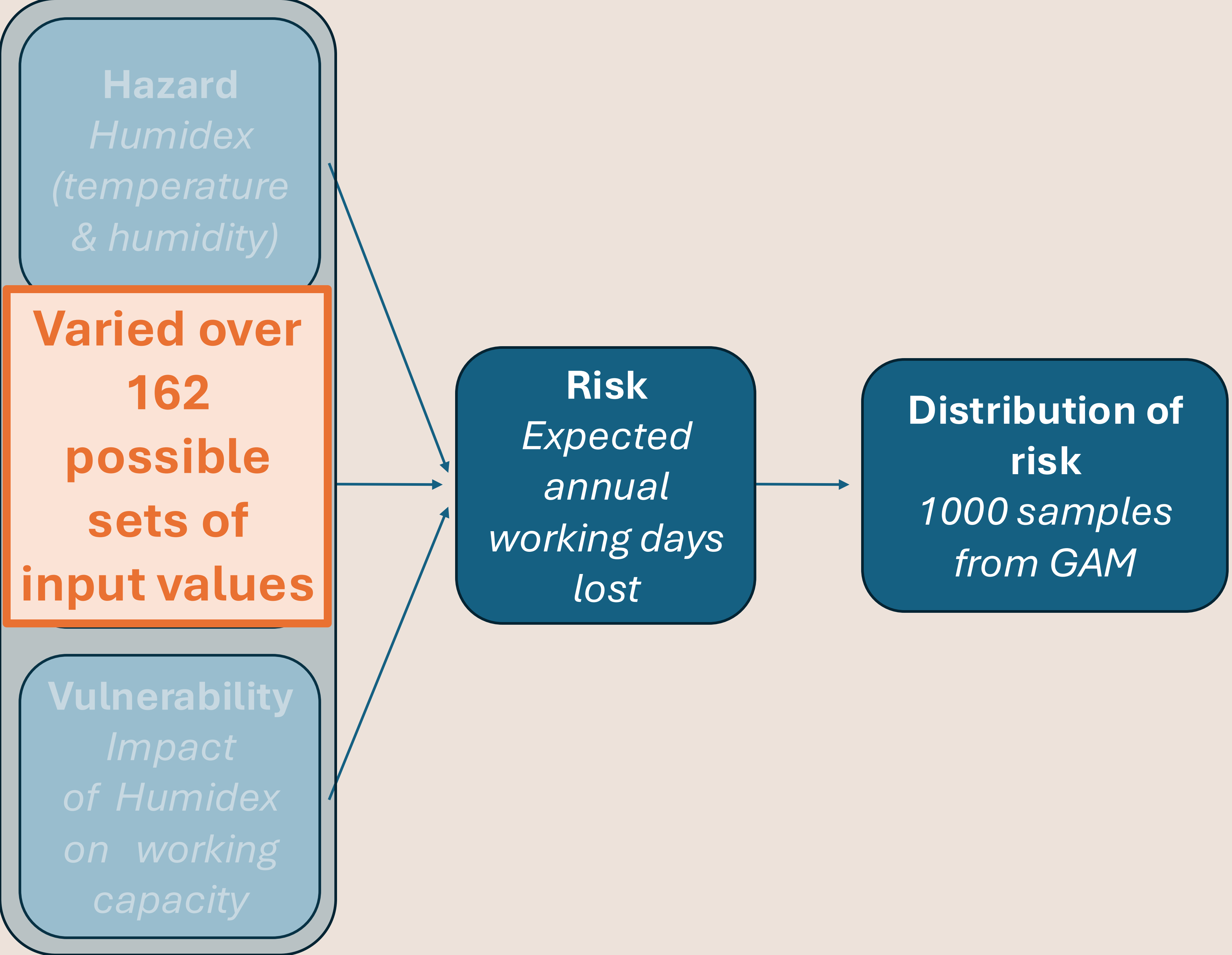
L(θ,d)
loss function
ℒ : losses
• Financial
• Non-financial
U(L(θ,d))
utility function
ℝ
Relative utility of each adaptation given level of heat stress
d*
Optimal adaptation decision in each location

Uncertain risk-related inputs

Used GAMs to quantify the uncertainty in risk for a specific set of hazard, exposure, and vulnerability inputs

But we are still uncertain about our choices for those inputs

Risk-related input	Possible values
Calibration method	Uncalibrated, Bias corrected, Change factor
Warming level	+2 °C above pre-industrial, +4 °C above pre-industrial
Socio-economic pathway	SSP1 (sustainability), SSP2 (middle of the road), SSP5 (fossil-fuelled development)
Vulnerability function parameter 1	Lower bound (53.78 °C), Mean value (54.5 °C), Upper bound (55.79 °C)
Vulnerability function parameter 2	Lower bound (−4.597%/°C), Mean value (−4.1%/°C), Upper bound (−3.804%/°C)

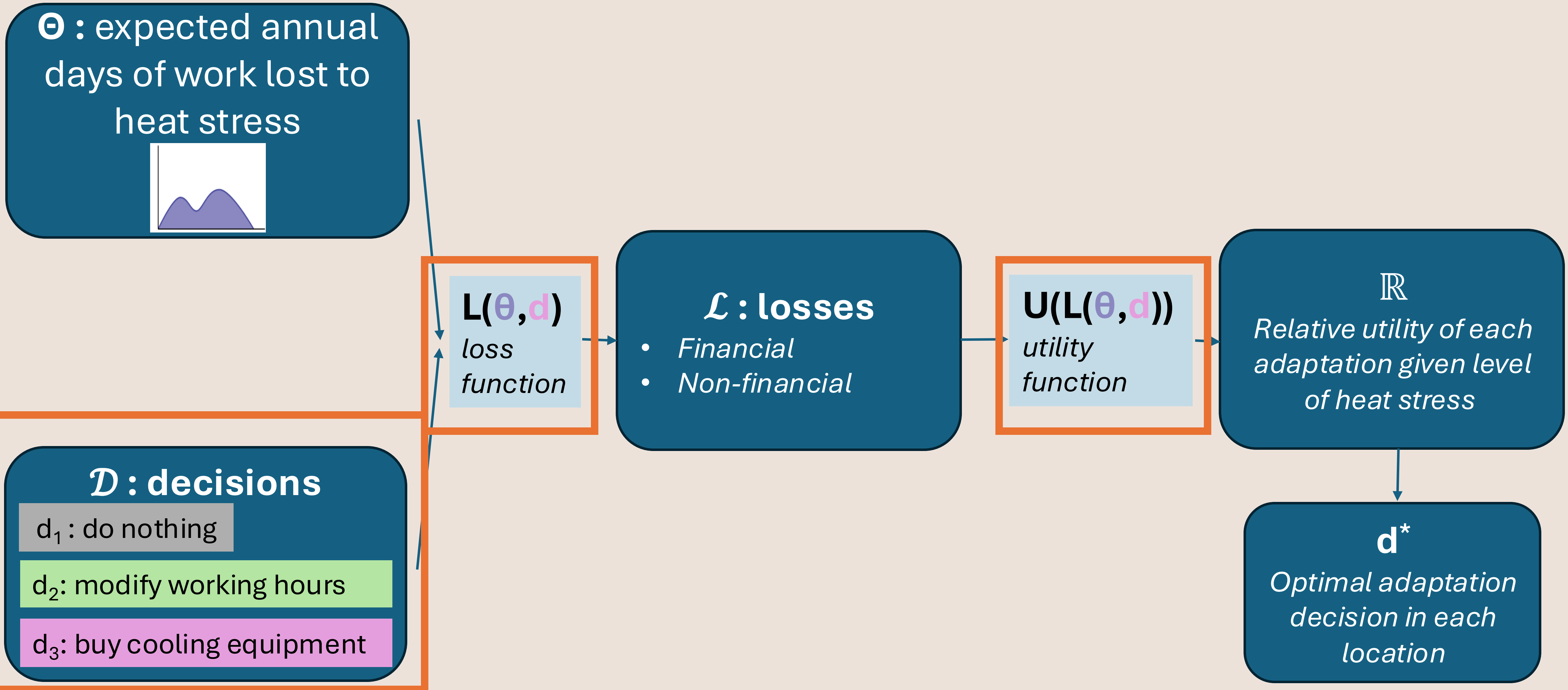


Uncertain risk-related inputs

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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Uncertain decision-related inputs

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$+ (\boxed{\text{cost per day of work}} \times (1 - \boxed{\%\ \text{effectiveness}_i}) \times \theta_{jn})$

Non-financial loss:

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

Utility:

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

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

Uncertainty & sensitivity analysis

Quantifying uncertainty

Discrete approach:

- Find the number of adaptation options that are optimal for ***at least one*** combination of input parameters

Continuous approach:

- Determine the ***percentage*** of combinations for which each of the three decisions was optimal

Quantifying sensitivity

PAWN method for a continuous output:

- ***Global*** sensitivity analysis method
- For a model of the form $y = f(\mathbf{x})$ and a particular input variable x_i:
    - Distance between unconditional CDF and conditional CDF:

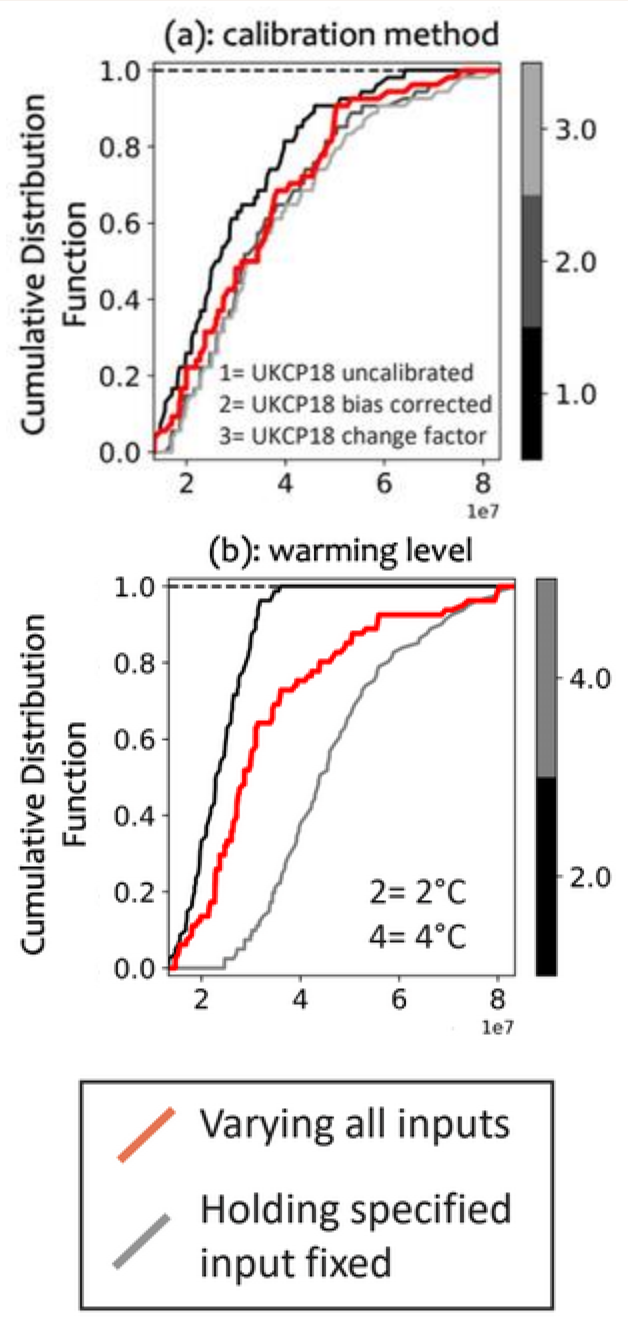
$$\boxed{KS(x_i) = \max_{y} \left| F_y(y) - F_{y|x_i}(y) \right|}$$

Maximum distance between unconditional (red) and one conditional (grey) distribution

    - PAWN sensitivity index:

$$\boxed{S_i = \underset{x_i}{\mathrm{stat}} \left[KS(x_i) \right]}$$

Average of the maximum distances across all grey distributions



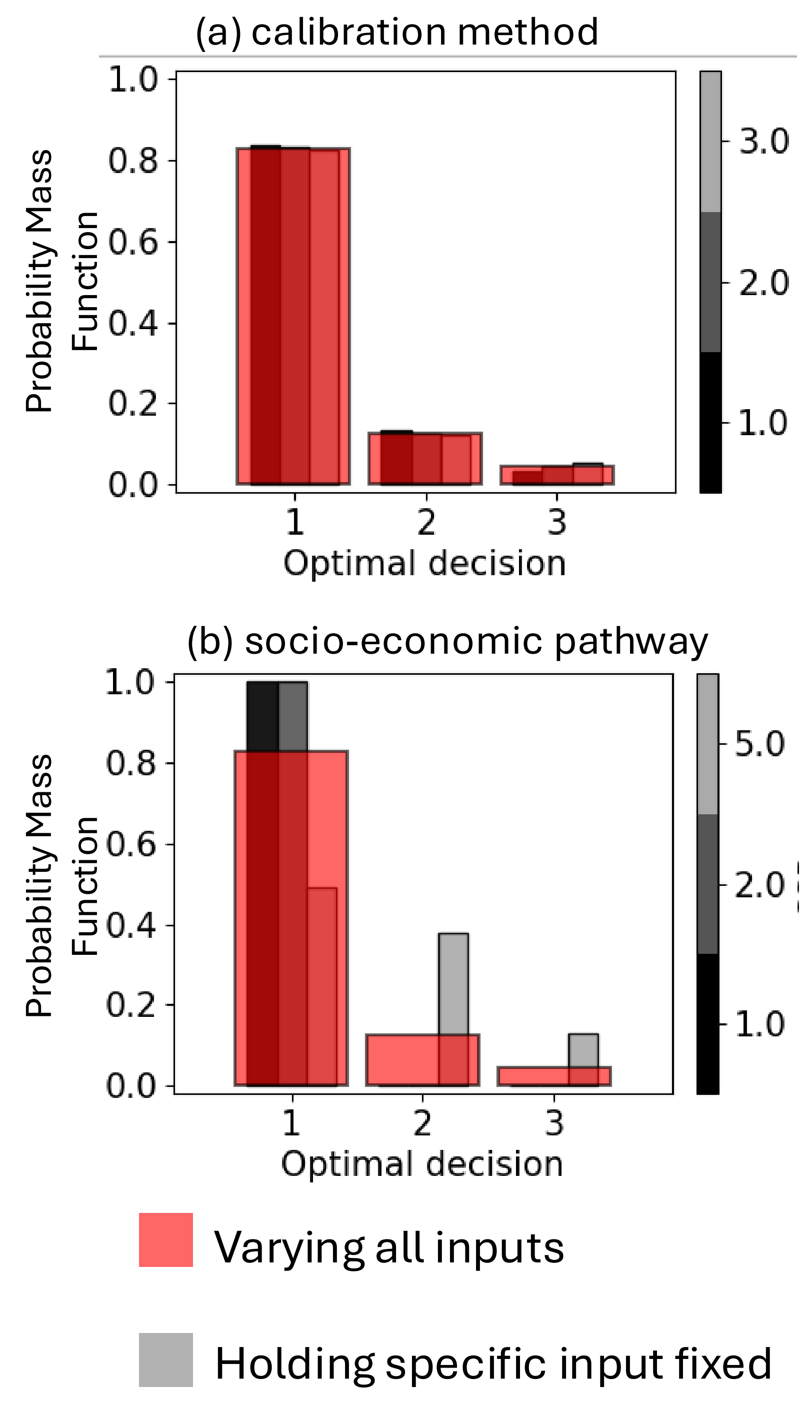
Quantifying sensitivity

Modified PAWN method for a discrete output:

- For a model of the form $y = f(\mathbf{x})$ and a particular input variable x_i:
  - Modified PAWN sensitivity index:

$$S_i = \underset{x_i}{\text{stat}} \left[\max_y \left| f_y(y) - f_{y|x_i}(y) \right| \right]$$

Average of the maximum distance between the red bar and the grey bars

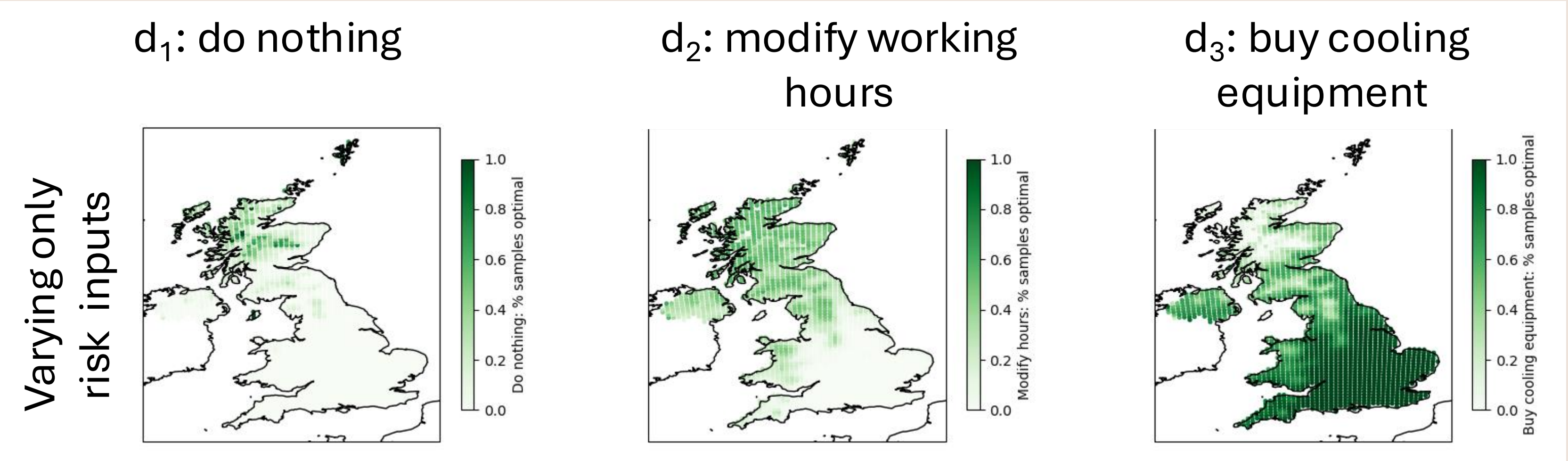


Results

Where are the different adaptation options most often optimal?

Optimal decision by location

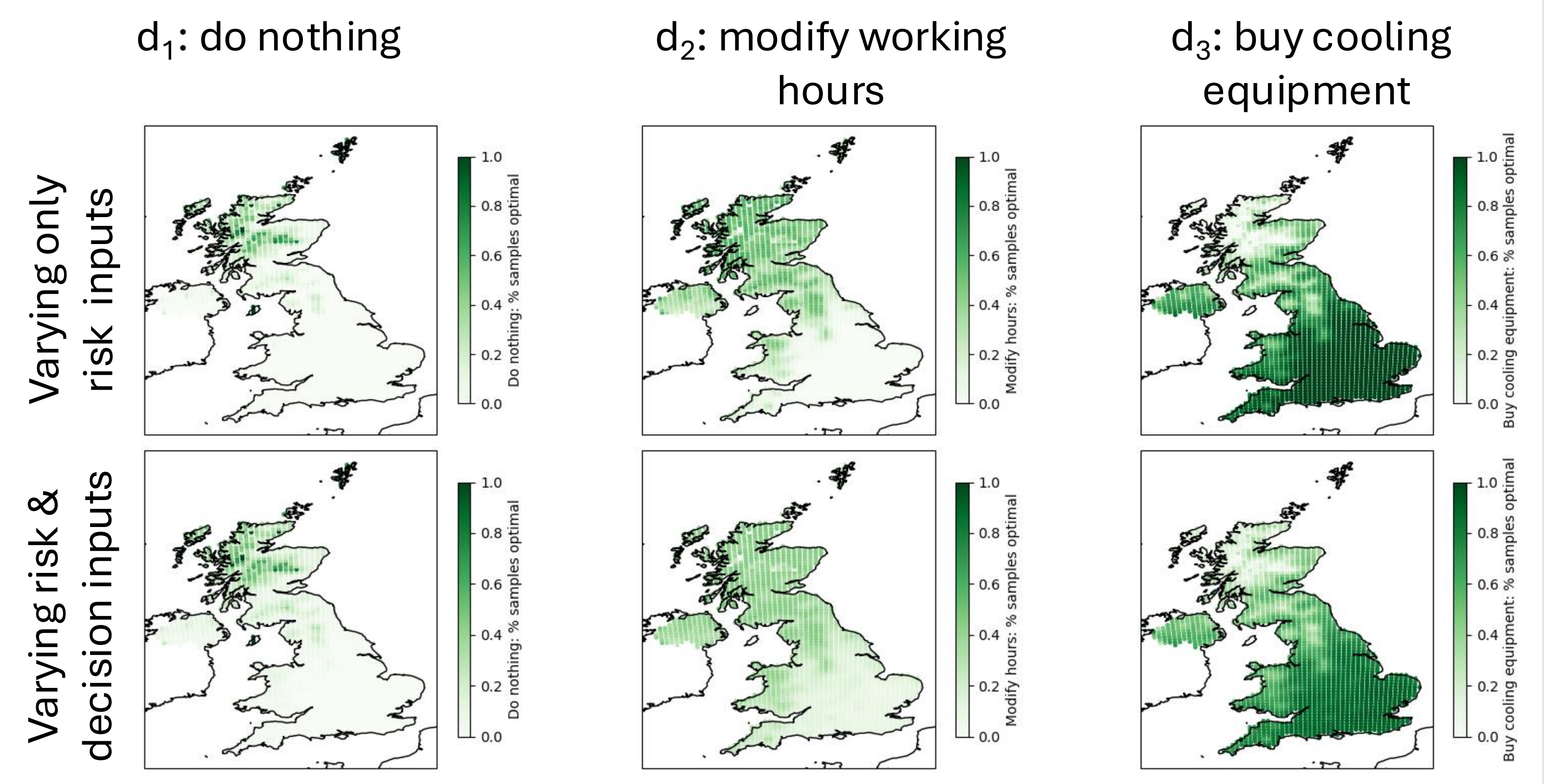
- **Spatial** distribution of where certain decisions are more often optimal



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

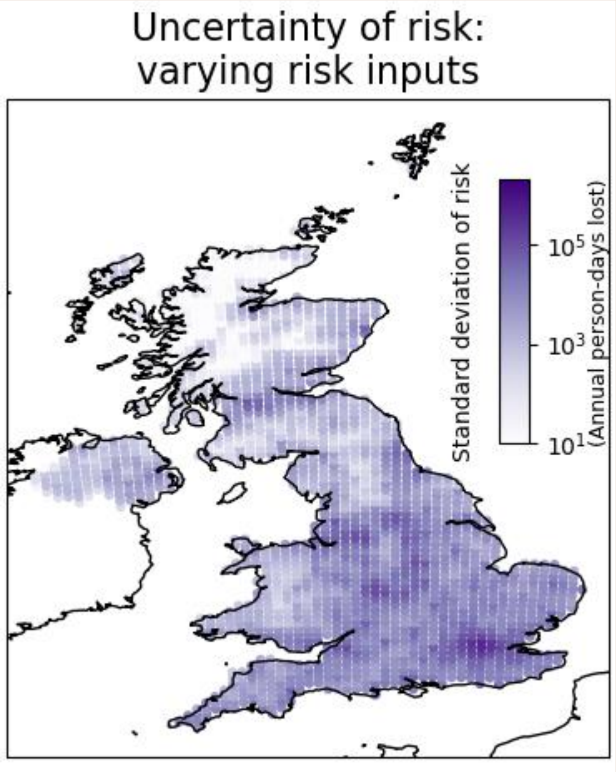
BDA provides logical adaptation decisions across the country.

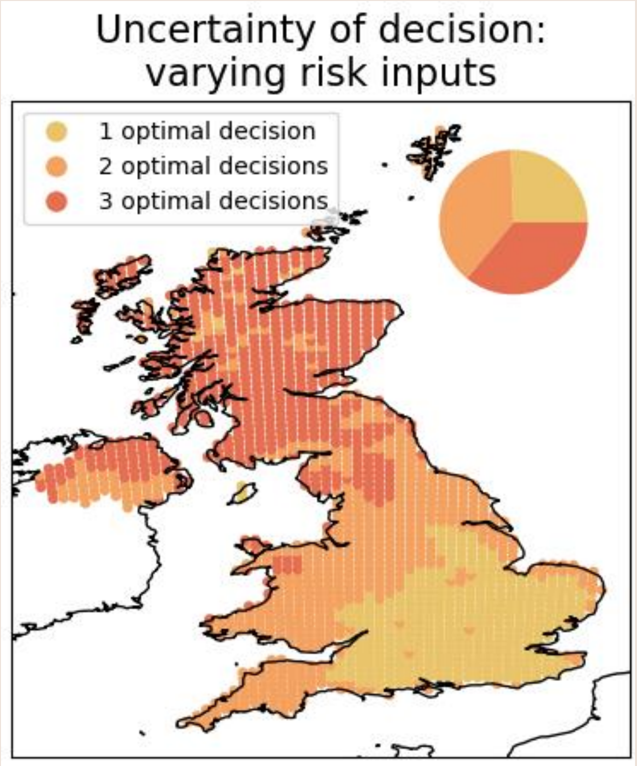


How **uncertain** is the optimal decision?

Decision uncertainty

- High uncertainty in climate risk **does not** necessarily translate into high uncertainty in decision

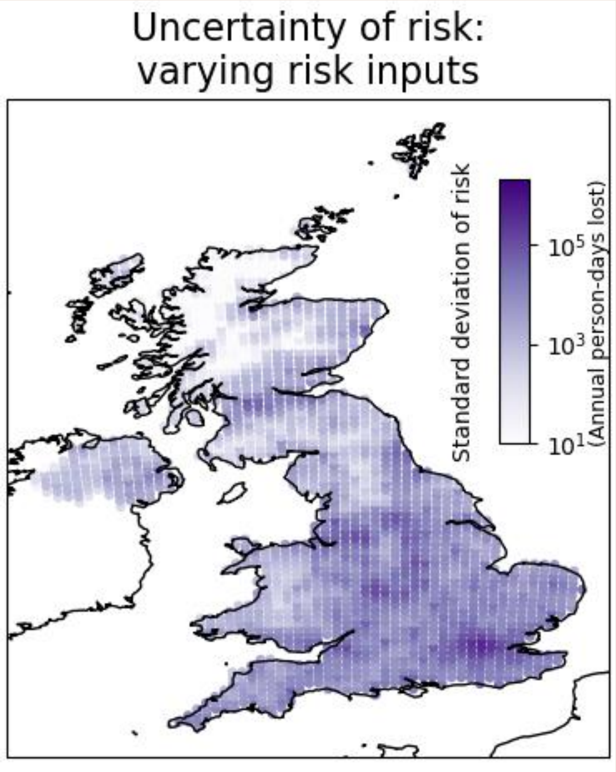


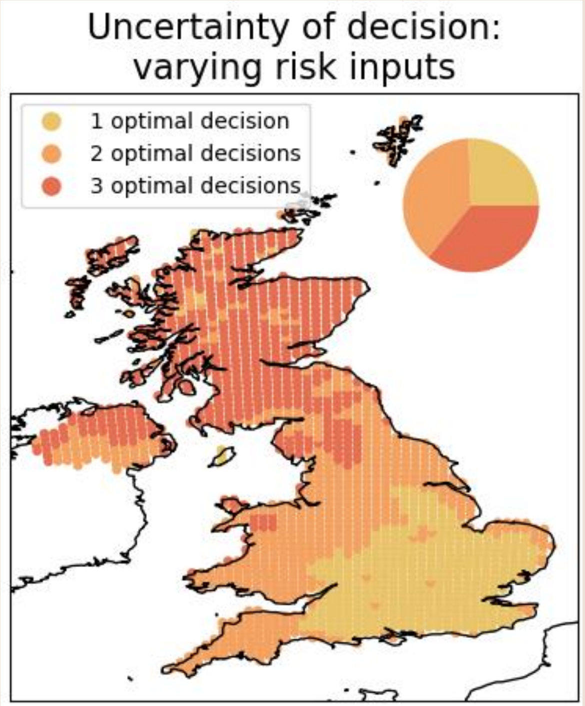


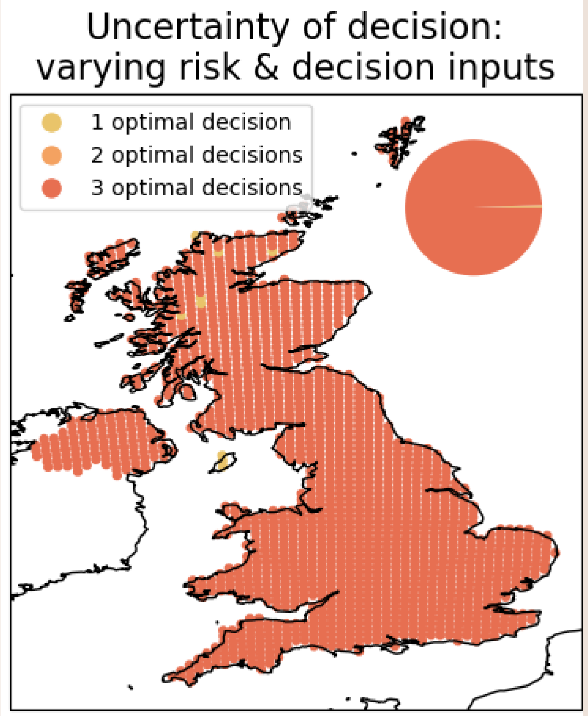
Decision uncertainty

- 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**

Uncertainty analysis must be performed on the adaptation decision, not on climate risk alone.





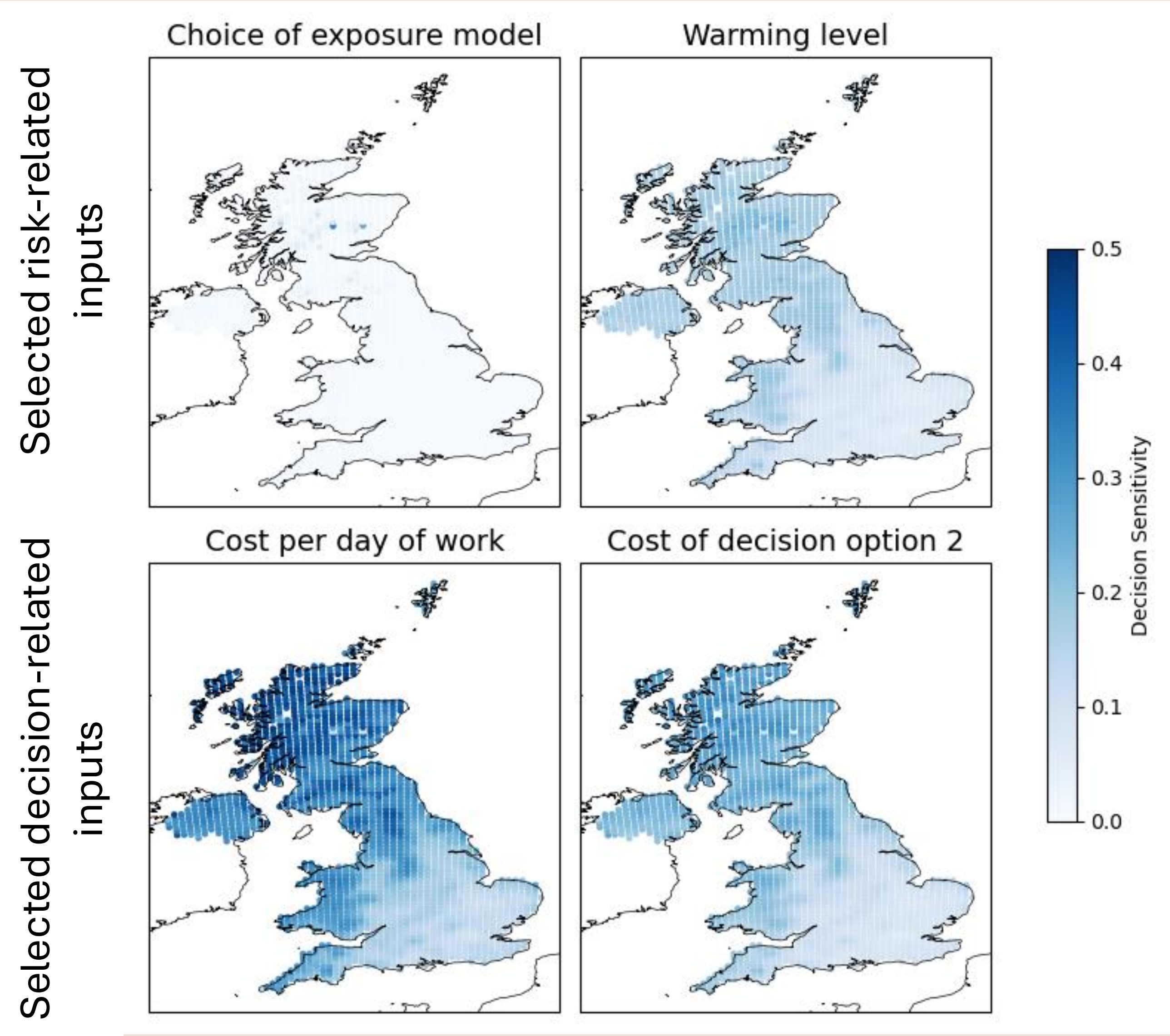


Which inputs is the optimal decision **most sensitive** to?

Decision sensitivity

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

Local sensitivity analysis can be used to prioritise data-gathering efforts for decision-makers.



Conclusions

Conclusions

- We can use BDA to find reasonable adaptation decisions **across space**.
- 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
    - Case study with an electricity distribution network operator
- Extensions to decision theory/sensitivity analysis methods
    - Value of Information: what is the value to the decision-maker of learning more about a particular input?
    - Decision-making across time, as well as space
    - Comparison to other decision-making methods

Paper: https://www.sciencedirect.com/science/article/pii/S2212096325000658

Questions?

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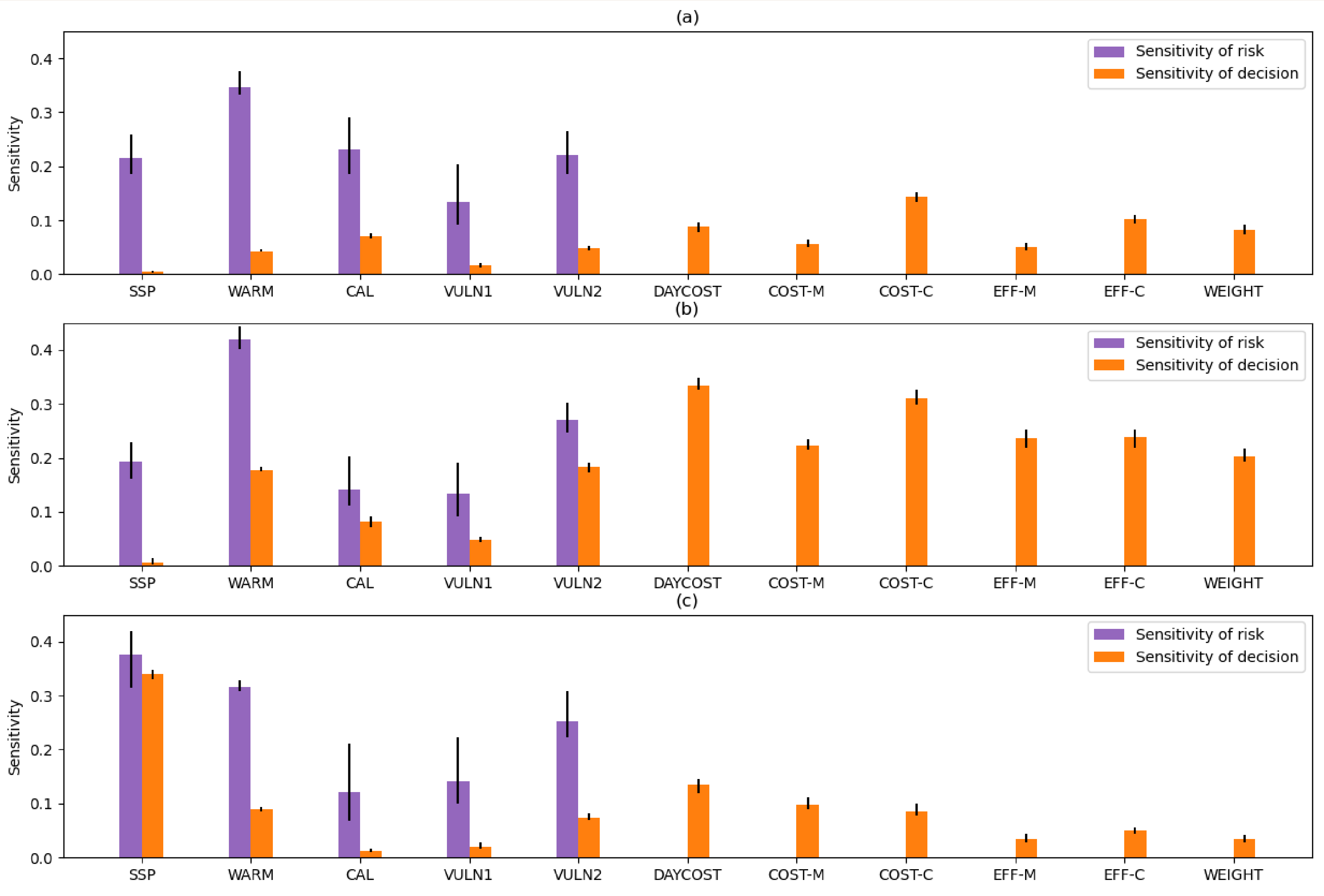

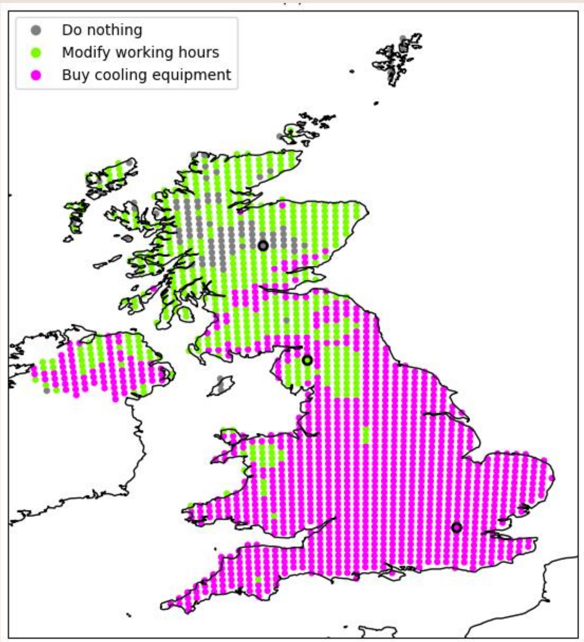

Sensitivity of risk (purple) and of the optimal decision (orange) to the eleven uncertain input factors for three locations.