

# Bayesian Decision Analysis for climate decision-making

Sensitivity to decision attributes

#### **Cecina Babich Morrow**

COMPASS
Computational Statistics and Data Science
University of Bristol

#### **Overview**



- 1. Climate decision-making under uncertainty
- 2. Example: Heat-stress in the UK
- 3. Prior work: Uncertain risk
- 4. Current work: Uncertain decision attributes
- 5. Results
- 6. Conclusions

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## Climate decision-making under uncertainty

## **Climate decision-making**



Goal: Use our knowledge of climate risk to decide what to do:



But how can we make a decision when we are uncertain about pretty much everything?

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# Bayesian Decision Analysis for climate decision-making

Bayesian Decision Analysis (BDA) is a framework for decision-making under an uncertain state of nature.

How does uncertainty in decision-related attributes of the BDA framework lead to uncertainty in our decision?

- Uncertainty: How robust is our decision to variation in financial cost?
- Sensitivity: Which parameters is our decision most sensitive to?
- How does uncertainty and sensitivity vary spatially?

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# **Example: Heat-stress in the UK**

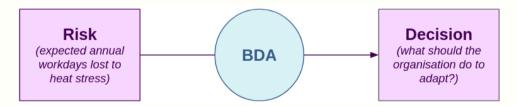
## An idealised example



# What should a UK organisation do to combat the effects of heat stress on their business?

We need to understand...

- Risk: How much is heat going to impact our workers?
- Optimal Decision: What action should we take given that risk level?



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### **Prior work: Uncertain risk**

## **Uncertainty in risk**



Following Dawkins et al. 2023<sup>a</sup>:

- Input hazard, exposure, and vulnerability data
- Apply the CLIMADA risk assessment platform<sup>b</sup> to each climate model ensemble member
- Use generalised additive models to generate 1000 samples of risk in each location across the UK

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Hazard (Humidex) Exposure Rick Distribution (Number of people CLIMADA GAMS (e.g. expected of risk working in outdoor annual impact) Vulnerability (Impact of Humidex on working capability)

<sup>&</sup>lt;sup>a</sup>Dawkins, Laura C. et al. (2023). Climate Risk Management.

<sup>&</sup>lt;sup>b</sup>Aznar-Siguan, G. and Bresch, D. N. (2019). *Geoscientific Model Development*.



#### **Current work: Uncertain decision attributes**

## **Bayesian Decision Analysis: Our framework**



#### **D** decisions

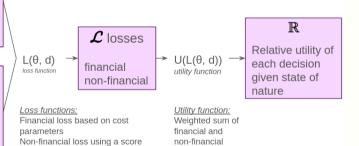
d: do nothing

d<sub>2</sub>: modify working hours

d<sub>3</sub>: buy cooling equipment

#### states of nature

1000 samples from the GAM for each location



utility functions

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s. representing alignment

with organisational values

### **Bayes optimal decision**



Pick the decision that maximises expected utility:

#### Bayes decision under utility U

Select the decision  $d^*$  such that

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

In our case.

$$d^* = \arg\max_{d} \frac{1}{1000} \sum_{n=1}^{1000} U(\theta_n, d)$$

## **Varying financial costs**



Took 1000 Latin hypercube samples of combinations of financial cost parameters for  $d_2$  and  $d_3$  from ranges of values:

Action	Cost per person	Added cost per day of use	Reduced cost per day	Si
$d_1$	£0	£0	£0	5
$d_2$	[£80, £120]	[£20, £60]	[£40, £60]	7
$d_3$	[£350, £800]	[£1.50, £2.50]	[£60, £90]	4

Table: Loss function parameters for each decision

Calculated the Bayes optimal decision  $d^*$  in each location for every sample.

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#### **Results**

### **Uncertainty**



How robust is our decision to variation in the financial cost parameters?

In the majority of cells, any of the three decisions could be optimal depending on the combination of financial cost parameters.

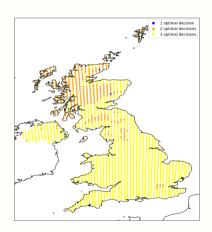


Figure: Number of optimal decisions per location across the 1000 combinations of financial cost parameters.  $_{10/15}$ 

## **Uncertainty**



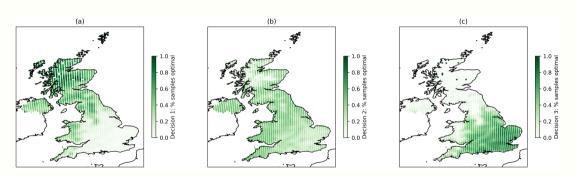


Figure: Proportion of Latin hypercube samples for which each decision was the optimal decision selected by BDA for (a)  $d_1$ : do nothing, (b)  $d_2$ : modify working hours, and (c)  $d_3$ : buy cooling equipment.

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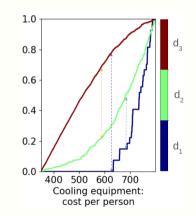
## **Sensitivity: Regional Sensitivity Analysis**



For a given financial cost parameter  $x_i$ , how different are the conditional CDFs of  $x_i$  given a particular optimal decision value?

Mean MVD is the average of the maximum vertical distances between the conditional CDFs  $F_{x_i|d_i}$ :

$$\begin{split} \mathsf{mean}_{j,k}[\mathit{MVD}(x_i)] &= \mathsf{mean}_{j,k}[\max_{x_i} \lvert F_{x_i \mid d_j}(x_i | \textit{d}^* = d_j) \\ &- F_{x_i \mid d_k}(x_i | \textit{d}^* = d_k) \rvert] \end{split}$$



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## **Sensitivity**





Figure: Mean MVD for each financial attribute of  $d_2$  and  $d_3$ .



#### **Conclusions**

#### **Conclusions**



#### So far...

- The optimal decision is not very robust to variation in financial cost parameters
- Decision sensitivity to the various financial cost parameters varies quite a bit
- The optimal decision may be more sensitive to variations in the decision attributes than to variations in risk

#### What's next?

- What happens when we vary other decision attributes? Both risk and decision attributes? Utility function?
- How can we use this information to improve how we make climate-related decisions?

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# **Questions?**

#### **Cecina Babich Morrow**

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