University of BRISTOL

Sensitivity of Bayesian Decision Analysis to decision attributes:

a tool for robust climate adaptation decision making

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Overview

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

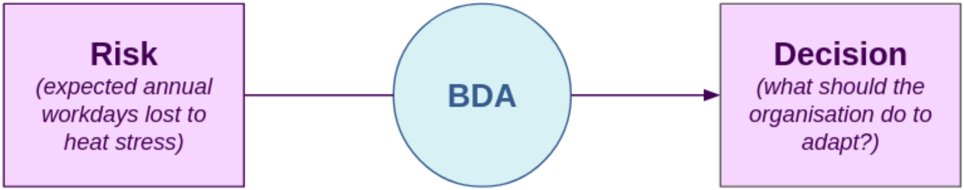
Example: Heat-stress in the UK

An idealised example

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

Using Bayesian Decision Analysis (BDA):

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



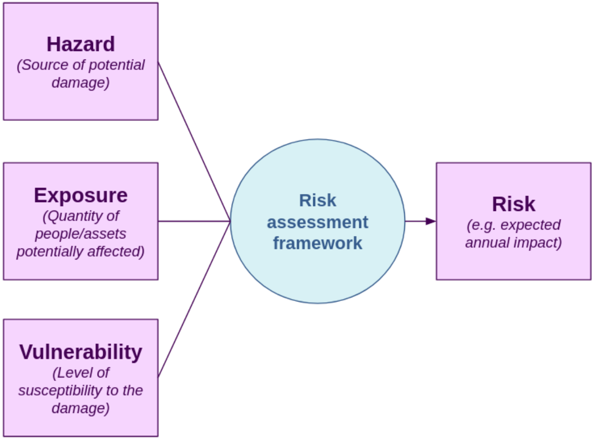
Goals

How does variation in decision-related attributes of the BDA framework affect the decision output?

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

Prior work: Uncertain risk

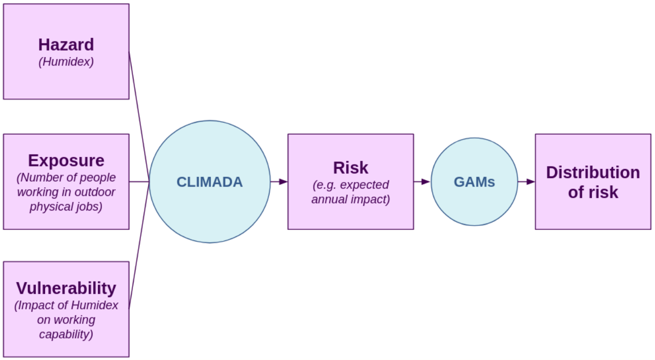
Risk


Hazard
(Source of potential damage)
Exposure
(Quantity of people/assets potentially affected)
Vulnerability
(Level of susceptibility to the damage)
Risk assessment framework
Risk
(e.g. expected annual impact)

Uncertainty in risk

Following Dawkins et al. 2023[a]:

1. Input hazard, exposure, and vulnerability[b]
2. Apply CLIMADA[c] to each climate model ensemble member
3. Generate 1000 samples of risk per location using GAMs



[a] Dawkins, Laura C. et al. (2023). *Climate Risk Management*.

[b] Reisinger, A. et al. (2020).

[c] Aznar-Siguan, G. and Bresch, D. N. (2019). *Geoscientific Model Development*.

Generalised Additive Models

- We only have $n = 12$ ensemble members for UKCP18
- We can use GAMs to come up with a more complete representation of uncertainty in risk[1]

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

m is the climate ensemble member, s is spatial location:

$$\log_{10}(\text{Risk}(m, s)) \sim N(\mu(m, s), \omega^2)$$
$$\mu(m, s) = f(lon(s), lat(s), orog(s), pop(s)) + \xi_m$$
$$\xi_m \sim N(0, \lambda^2)$$

[1] Dawkins, Laura C. et al. (2023). *Climate Risk Management*.

Generalised Additive Models

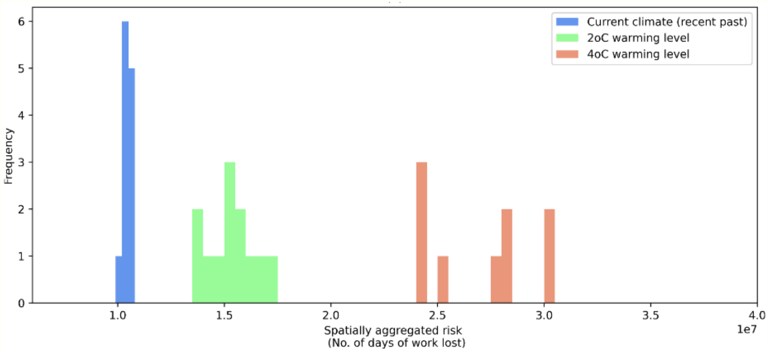


Figure: Distribution of spatially aggregated risk across the 12 UKCP18 ensemble members for each warming level (Reproduced from Dawkins et al. 2023 Fig. 4c).

Generalised Additive Models

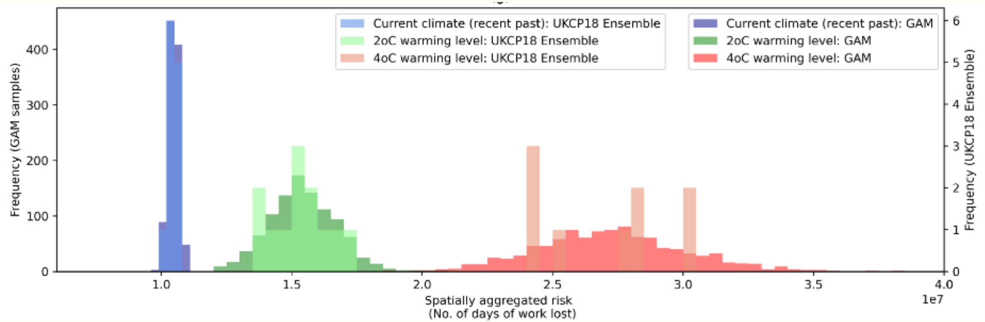
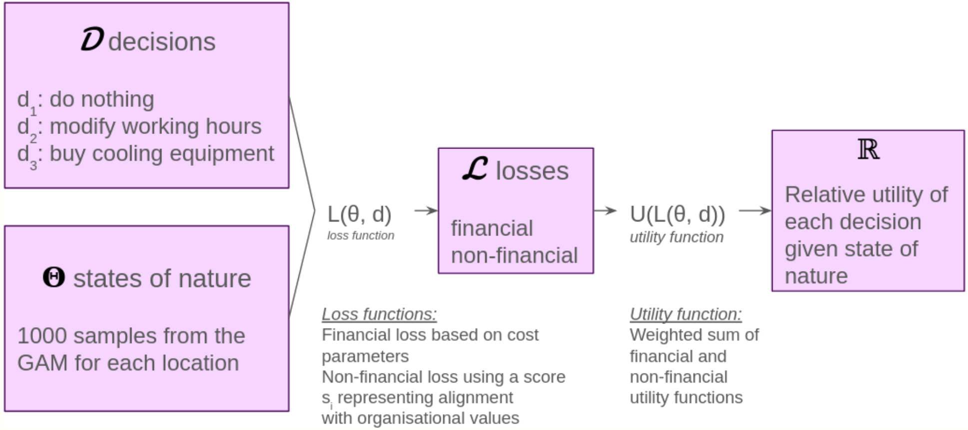


Figure: Distribution of spatially aggregated risk across the 1000 GAM samples for each warming level (Reproduced from Dawkins et al. 2023 Fig. 6g).

Current work: Uncertain decision attributes

Bayesian Decision Analysis: Our framework

Framework for decision-making under an uncertain state of nature



BDA: Loss functions

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

Financial loss:

$$\begin{aligned} L_1(\theta_n, d_i) = & \ (\text{cost per person}_i \times \text{number of people}_n) \\ & + (\text{added cost per day}_i \times \theta_n) \\ & + \text{cost per day of work} \times (1 - \text{reduced cost per day}_i/100) \times \theta_n \end{aligned}$$

Non-financial loss:

$$L_2(\theta_n, d_i) = 10 - s_i$$

where $0 \leq s_i \leq 10$ is a score representing how much d_i aligns with organisational values.

BDA: Utility functions

$U(L(\theta, d)) : \mathcal{L} \rightarrow [0, 1]$: utility function representing the relative value of each decision

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

Overall utility function:

$$U(\theta_n, d_i) = k_1 U_1(L_1(\theta_n, d_i)) + k_2 U_2(L_2(\theta_n, d_i))$$

where $k_1, k_2 \geq 0, k_1 + k_2 = 1$ represent the relative importance of financial and non-financial utility.

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	s_i
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 in each location for each Latin hypercube sample.

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.

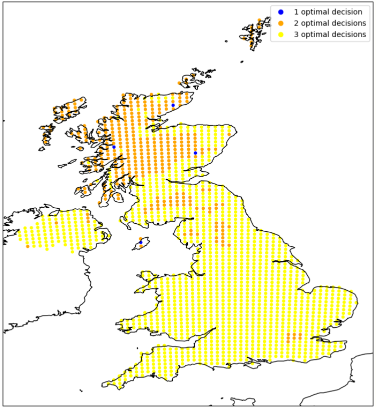


Figure: Number of optimal decisions per location across the 1000 combinations of financial cost parameters.

Uncertainty

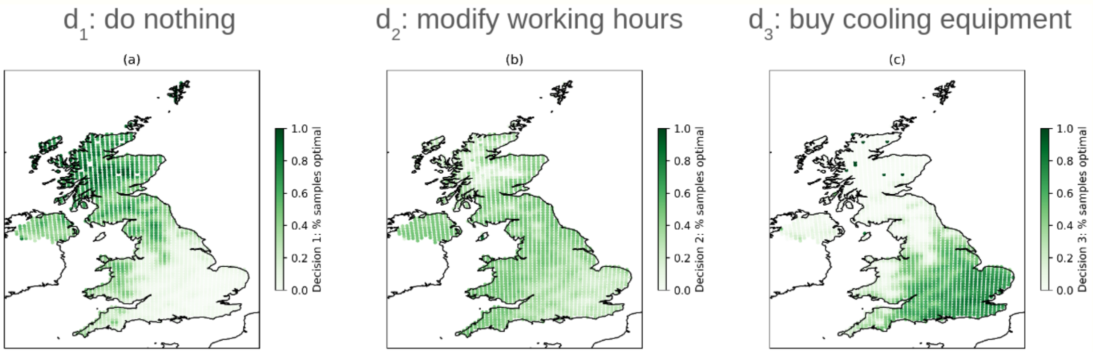


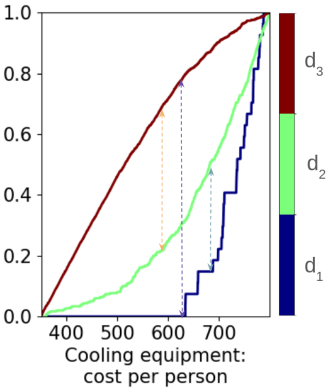
Figure: Proportion of Latin hypercube samples for which each decision was the optimal decision selected by BDA for (a) d_1: do nothing, (b) d_2: modify working hours, and (c) d_3: buy cooling equipment.

Sensitivity: Regional Sensitivity Analysis

RSA: Method for a discrete output variable[a]
For a given financial cost parameter x_i, how different are the conditional CDFs of x_i given a particular optimal decision value d_j?

Take the average Kolmogorov-Smirnov (KS) statistic between each conditional CDF $F_{x_i|d_j}$:

$$\text{mean}_{j,k}[KS(x_i)] = \text{mean}_{j,k}[\max_{x_i}|F_{x_i|d_j}(x_i|d^* = d_j) - F_{x_i|d_k}(x_i|d^* = d_k)|]$$



[a] Pianosi, Francesca et al. (2016). *Environmental Modelling & Software*.

Sensitivity

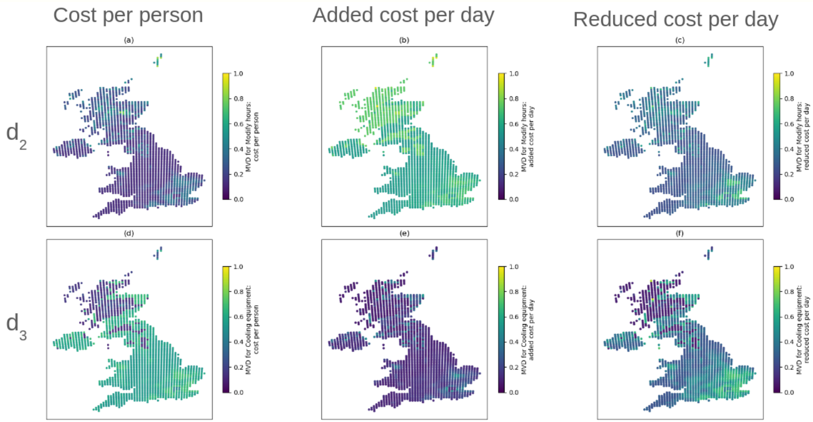


Figure: Mean KS statistic for each financial attribute of d_2 and d_3.

Conclusions

Conclusions

- BDA yields plausible optimal decisions by region given what we know about heat risk in the UK
- The optimal decision is not very robust to variation in financial cost parameters
- Decision sensitivity to the various financial cost parameters varies both spatially and by parameter
- The optimal decision *may* be more sensitive to variations in the decision attributes than to variations in risk[2]

[2] Dawkins, Laura C. et al. (2023).

Next steps

For the idealised example:

- 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?

And beyond:

Can we find some real-world application(s) to apply BDA to climate adaptation decisions?

Contact

I’m at the Met Office today through Wednesday – if you have more questions/comments/want to chat further, please send me an email!

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Questions?
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What's going on in Scotland?

In general, locations further north almost never have d_3 buy cooling equipment as the optimal decision.

But 8 cells in Scotland have d_3 as the optimal decision in $> 95\%$ of the samples.

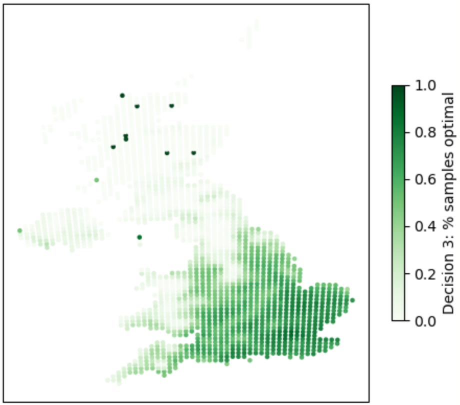

Figure: Proportion of Latin hypercube samples for which d_3: buy cooling equipment was the optimal decision.

Zero exposure

Exposure according to SSP2 in 2041[3] was 0 in 11 cells:

- The 8 "problem" cells in Scotland
- The 3 cells in the Isle of Man

When exposure is 0, financial loss becomes:

$$L_1(\theta_n, d_i) = (\text{added cost per day}_i + \$100 - \text{reduced cost per day}_i) \times \text{EAI}_n$$

$\Rightarrow$ d_1: For decisions 2 and 3, the reduced cost per day almost always outweighs the added cost per day, so d_1 is never optimal

[3] The year corresponding to warming level 2C.

Negative risk

$$L_1(\theta_n, d_i) = (\text{added cost per day}_i + \$100 - \text{reduced cost per day}_i) \times \text{EAI}_n$$

EAI > 0 and number of people $= 0$ $\implies$ optimal decision where (added cost per day $-$ reduced cost per day) is smallest

EAI < 0 and number of people $= 0$ $\implies$ optimal decision where (added cost per day $-$ reduced cost per day) is largest

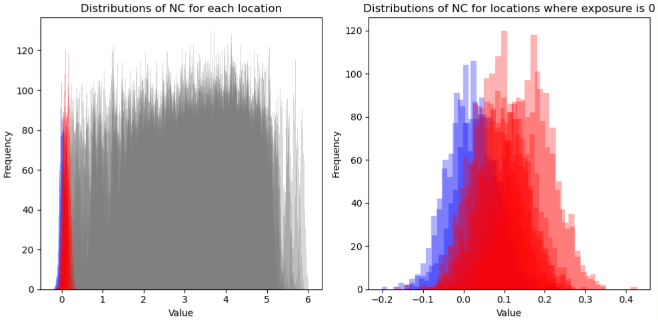

Figure: Histograms of GAM samples for each location. Scotland outlier locations are in red, and Isle of Man locations are in blue.

Uncertain components of risk

All of the components of risk are uncertain:

1. **Hazard:** heat stress based on temperature and relative humidity (Humidex[4])
    - Climate models have multiple ensemble members to represent uncertainty
    - There are multiple potential future warming levels
2. **Exposure:** number of people in a given location working in physical outdoor jobs
    - Shared socio-economic pathways (SSPs) model this variable across potential future scenarios[5]
3. **Vulnerability:** function calculating impact of heat stress on physical working capacity[6]
    - Our vulnerability function has two (uncertain) parameters

[4] Masterton, J.M. et al. (1979).

[5] O'Neill, Brian C. et al. (2014). *Climatic Change*.

[6] Foster, Josh et al. (2021). *International Journal of Biometeorology*.