Interactive comment on “Risk-based flood protection planning under climate change and modelling uncertainty: a pre-alpine case study” by Beatrice Dittes et al.

Author comment on the comment of anonymous referee #2

The authors would like to thank the referee for the thoughtful comments. Much of the reviewers notes were positive. We respond to suggestions for improvement in the following, with referee comments highlighted in *blue*.

1) *“The methods (Bayesian analysis and backwards induction optimization) are summarized very briefly with not enough information for the nonexpert to fully understand them. While references are given, it is suggested that more detail be provided.” / “[…] it is not clear how flexibility was considered.”*

We recognise that this was a weak point in the initial manuscript and have extended our description of the methods:

“Flood protection is a dynamic process, as illustrated in Fig. 2: A flood protection system is implemented initially and later revised, based on data (e.g., discharge observations) that becomes available in the future. These future discharge observations are not yet known, hence for planning purposes they have to be simulated probabilistically, as described in the next paragraph. The damages caused by discharges in the future depend on the protection system that will then be in place. The risk is defined as the expected damages, i.e. the sum of the damages associated with each future scenario, weighted by the probability of that scenario. Ultimately, the sum of the two monetary quantities, risks and costs, is to be minimized over the measure life-time following Eq. (2). If the demand has changed based on the new observations, it may be necessary or desirable to adjust the protection capacity. The cost for both the initial implementation of the protection system and for adjustments depends on the system flexibility: a more flexible system decreases adjustment costs, but this saving must be balanced with potentially higher costs of implementing a flexible system initially. When there is large uncertainty, it becomes more likely that a design has to be adjusted later on, as more information becomes available. To take these aspects into account, we have developed a quantitative decision framework that considers planning as a sequential process. It accounts for the system flexibility and the future learning process through Bayesian updating of the initial PDF of parameters, $f_{\boldsymbol{\Theta}|Q}(\boldsymbol{\theta}|\boldsymbol{q})$ (Sect. 2.1.), with new information in the future (Dittes et al., 2017). *It evaluates, which flood protection system is recommendable based on the uncertainty in extreme discharge, described by $f_{\boldsymbol{\Theta}|Q}(\boldsymbol{\theta}|\boldsymbol{q})$, and the flexibility of the considered*

flood protection systems. As will be shown in Sect. 3.5, the flexibility is intrinsic in the measure costs in this case study.

The PDF $f_{\boldsymbol{\Theta}|Q}(\boldsymbol{\theta}|\boldsymbol{q})$ *contains the information from the currently available data: discharge projections as well as their uncertainty (through Eq. (4)). Future discharges are randomly generated from this PDF, creating a multitude of 'possible futures'. At a first revision point (e.g. 30 years into the measure life time), for each 'possible future' the PDF is updated with the discharges that were simulated to have been observed by then and a decision is made on whether the protection has to be adjusted. This process is repeated for several revision steps, leading to a decision tree with alternating adjustment decisions and observation periods (see Fig. 3). To find the optimal initial protection decision based on this tree – that is, the protection decision which minimizes the sum of life-time risks and costs – we use the technique of Backwards Induction Optimization (Raiffa and Schlaifer, 1961). The technique works by first determining the system that should be installed at the last adjustment, depending on the existing protection and observations (data) available by then. This is a deterministic problem, since at the last adjustment all the data has been collected. The evaluation is done for all possible futures and they are weighted by their probability based on the PDF. The obtained recommendation for the last adjustment is then used to find the system that should be installed at the second to last adjustment and so forth until arriving at a recommendation for the system that should be installed initially."*

2) *"One challenge is that a major source of uncertainty is ignored – the emission scenario. Here they only assumed one – how can method be used if planning done more realistically under multiple emission scenarios ?"*

There appears to be a misunderstanding: the uncertainty on the emission scenario (which we call forcing scenario) is part of the analysis, via the 'hidden uncertainty'. We have added a sentence to clarify this: " *[…] when only one model was used at a certain step in the modeling sequence (e.g. only one forcing scenario was used), the potential for greater model spread if more models had been used is included via an estimate of the so-called 'hidden uncertainty'."*

3) *"The authors determined the effectiveness of each strategy and then evaluated their performance under the uncertainties of damages and discharges. It is not clear to me why just enumeration and evaluation of all the possible sets of strategies without the optimization model would also have been effective as small number of options. Thus would have been useful to understand the value of the optimization model. Also, the discussion of the results almost seem similar to results of conventional scenario analysis – what strategy works most reasonably over all the scenarios. Perhaps this was just a check of the results."*

We hope that we interpret the referee's point correctly as asking about the distinction between a scenario-based approach versus our optimization. As such, it points back to 1) (better description of the optimization model). The key point is that our optimization takes into account the uncertainty in discharge (including climate projections on a continuous rather than scenario-based uncertainty spectrum, future updating, measure flexibility etc., as described in

1) and (Dittes et al., 2017)) but it does not account for the uncertainty in damage model or measure building cost. This is because we focussed on irreducible uncertainties (in particular, climate) when developing our methods, whereas local building costs and damage potential are informations which can be known. Because they turned out to be not so well known after all at the case study site, we made the pragmatic decision to perform our optimization for a number of damage models and building costs. We realize that the description of the results could have been clearer, which may have contributed to the confusion of the referee. Therefore we have completely rewritten it, as well as condensed the results into one table only (see below): *"The expected sum of life-time costs and risks is given in Tab. 9, with the expected life-time costs individually stated in brackets. The life-time risks are calculated using Eq. (5). They are independent of measure building costs yet dependent on the system that is initially implemented. Let us first look at the damage model SDAM (which best fitted the damages of the 2013 flood, see Sect. 3.5.4) used with the reference building costs (the 'buest guess' for the building costs, see Sect. 3.6). The light blue coloring indicates that S4 is recommended for initial implementation. Thus, the expected life-time cost is the same as the initial building cost, 25.0 M €, since no adjustments are possible. The sum of life-time costs and risks is 42.6 M €. The table also shows results for the two other damage models (RAM ATKIS and RAM CLC) as well as the four other scenarios of initial building cost. When S3 is recommended for initial implementation (darker blue), the expected cost comprises the initial building cost and the expected cost of adjustment to S4 (probability of needing to adjust to S4 × cost of adjusting to S4). For SDAM, the probability of needing to adjust from S3 to S4 at a later point, if S3 was chosen initially, is 58%. For RAM using the ATKIS land cover, this probability is just 3% due to the very low damage estimates – probably a strong underestimation, as discussed in Sect. 3.5.4. When S1 is implemented initially, our computations show a residual risk of €124 M for SDAM. Thus, it is clearly better to follow the recommendation of implementing S4."*

Table 9. Life-time costs + risks (in brackets: life-time costs only) [M €] associated with the optimal protection strategy

Build costs \ Damage model	*SDAM*	*RAM ATKIS*	*RAM CLC*
Reference	*42.6 (25.0)*	*27.8 (25.0)*	*47.8 (25.0)*
Higher polder costs	*55.6 (38.0)*	*32.0 (8.8)*	*60.8 (38.0)*
Very high polder costs	*70.2 (40.1)*	*32.7 (9.5)*	*85.8 (63.0)*
Higher costs 1m initially	*46.6 (29.0)*	*31.8 (29.0)*	*51.8 (29.0)*
Very high costs 1m initially	*49.6 (32.0)*	*34.8 (32.0)*	*54.8 (32.0)*

4) *"In Figure 10, the low period discharges in many years seem higher than the high period discharged."*

This was a mixup in the description, the sentence should read *"[…]a set of relatively low discharges (blue dots) or a set of relatively high discharges (orange dots)."* (rather than *"blue"* and *"orange"* the other way round).

5) *“What are the x-axis units in Table 6”*

Table 6 shows protection strategies. Thus one could label the x-axis with “Strategy 1, Strategy 2, …” but we feel that the existing table header *“Potential protection strategies for Rosenheim”* may be sufficiently explanatory.

6) *“[…] the term ‘flexibility parameter” is used but not defined.”*

Yes, while flexibility was introduced in some detail, the ‘flexibility parameter’ was not. We adapt the sentece as follows: *“The decision to heighten dikes and walls by 1 m would correspond to a flexibility parameter of 0.7 following (Dittes et al., 2017), where 1 corresponds to full flexibility and 0 to no flexibility.”*

7) *“I suggest that it may be useful to compare this method to other methods of DMUUC such as Robust Decision Making, Decision Scaling, Dynamic Adaptation Pathways and Policies.”*

We briefly answer to the methods mentioned by the referee, but would like to point to (Dittes et al., 2017) for a fuller discussion of the utilized optimization framework with respect to other DMUUC methods, which we feel does not fit into the scope of the presented paper. The consideration of system performance under a broad range of possible future developments is inherent (and quantitative) in the proposed framework, as such, it leads to robust decisions. Decision Scaling and Dynamic Adaptation Pathways and Policies also lead to robust decisions, but they do so in a discrete, (semi-)qualitative way. We take a quantiative, probabilistic approach to Engineering problems and for that reason developed our optimization framework accordingly.

References

Dittes, B., Špačková, O. and Straub, D.: Managing uncertainty in design flood magnitude: Flexible protection strategies vs. safety factors, Journal of Flood Risk Management, submitted [online] Available from: https://www.era.bgu.tum.de/fileadmin/w00bkd/www/Papers/2017_Dittes_managing_uncertainty.pdf, 2017.

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