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Value of information of combinations of proof loading and pore pressure monitoring for flood defences

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ABSTRACT

Spatial variability and limited measurements often result in low reliability estimates of geotechnical failure modes of dikes (i.e., earthen flood defences). Required dike reinforcements are usually not executed within a few years after inception, which enables efforts to improve reliability estimates by reducing uncertainty. Often decision makers are unclear on whether uncertainty reduction is worth investing, and which (combination of) methods yields the highest Value of Information (VoI). This paper presents a framework to assess the VoI of two uncertainty reduction methods (proof loading and pore pressure monitoring) for a case study of a typical river dike with an insufficiently stable inner slope, using a decision tree. In all cases, a positive VoI was found for at least one strategy consisting of a proof load test, monitoring or both. The optimal strategy of proof loading and monitoring has a VoI of 4.0 M€, being a reduction in total cost of 25% compared to a conventional dike reinforcement. It was also found that sometimes proof loading enhances the VoI of pore pressure monitoring, which demonstrates the benefits of jointly considering different methods in a single decision tree. The decision framework yields insight in total cost and VoI of risk reduction strategies, which enables decision makers to determine where proof loading and/or pore pressure monitoring are efficient, leading to more efficient flood defence asset management.

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1. Introduction

Dikes (i.e., earthen flood defences) are important structures to mitigate flood risks in deltas around the world. Asset managers continuously prioritise their sparse resources over many reinforcement projects that are to be carried out, weighing their potential costs and benefits. Benefits of flood defences are mainly reduction of risk, as expressed by various risk indicators, such as loss-of-life and economic damage (Jonkman et al., 2003). Based on such requirements for acceptable risk, optimal reliability targets can be derived based on the relation between investment cost and risk reduction (Vrijling, 2001), which are then taken as a starting point for decision analysis.

One major issue that often arises is that the reliability estimates for geotechnical failure modes such as inner slope instability and backward erosion piping are dominated by large uncertainty in load (effects) and soil properties. These are typically knowledge uncertainties that are the result of spatial variability, measurement uncertainty, and a limited amount of measurements (e.g. Phoon & Retief, (2016)). Reduction of these uncertainties can potentially lead to much more efficient flood risk management. The evaluation of the effects of uncertainty reduction on decisions is typically done using a Bayesian pre-posterior analysis (Raiffa & Schlaifer, 1961; Thöns, 2018), where based on the a priori information the expected benefits of various decisions or strategies compared to a reference are calculated. This is also called the Value of Information (Raiffa & Schlaifer, 1961).

For dikes, uncertainties can be reduced by a variety of methods, where for reducing uncertainties related to geotechnical failure modes, additional site investigation (Schweckendiek, 2014) and pore pressure monitoring (Klerk et al., 2019; Schweckendiek & Vrouwenvelder, 2013) have been considered in literature. Another method to demonstrate the safety of structures is proof loading, for example proof pile load tests to verify the reliability of foundations (Zhang, 2004). This paper considers two uncertainty reduction strategies for dikes: pore pressure monitoring and a proof loading.

Pore pressure monitoring is aimed at reducing uncertainty on the position of the phreatic line (Koelewijn et al., 2014), representing the response of pore water pressures in the dike body to hydraulic loads. Such responses are typically dependent on the hydraulic conductivity of the dike material, which is often heterogeneous hence uncertain due to the limited amount of measurements that are available. An important aspect of pore pressure monitoring is that the information obtained (resulting in uncertainty reduction) is dependent on the water levels observed during the monitoring period (Klerk et al., 2019; Schweckendiek, 2014). In some cases, for instance at locations with a large tidal range, frequently occurring situations are

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similar to design conditions, resulting in significant uncertainty reduction. At other locations, such as the river dikes regarded in this paper, conditions leading to large uncertainty reduction occur less often. Consequently, the longer the monitoring period, the higher the probability of obtaining useful information that can be used to reduce uncertainty, as was shown in Frangopol et al. (2008) and Klerk et al. (2019).

Proof loading involves imposing a design load in order to prove the resistance of a structure. Since a rise of the phreatic line in the dike is one of the main factors causing instability (as it leads to higher pore pressures and hence lower effective stress), it is considered to artificially impose a high phreatic line by means of infiltration on the dike crest as proof load in this paper. The observed performance, being survival information (i.e. a stable dike under de imposed loading condition), is used to improve the reliability estimate, using Bayesian Updating, see Zhang et al. (2011), Li et al. (2018), and Schweckendiek et al. (2014). Note that proof loading only reduces uncertainty in the (variables relating to the) overall resistance, conditional to the imposed proof load. It does not lead to additional knowledge about the actual response of the phreatic line to flood conditions. Thus, pore pressure monitoring and proof loading are complementary.

The decision whether, where, and which type of uncertainty reduction method to use is typically difficult for decision makers, as this can vary strongly per location, and this also depends on the context of their decision (Diamantidis et al., 2019; Sousa et al., 2019), e.g., within what time a dike reinforcement has to be carried out. It was identified by Klerk et al. (2016) that a short time horizon until a dike reinforcement is often unfavourable for pore pressure monitoring as the amount of information is time-dependent and the probability of not obtaining useful information is relatively large. In such cases, proof loading or additional site investigation might be more promising, as the information is time-independent for these methods.

The aim of this paper is to provide a framework to answer the question under what conditions to invest in uncertainty reduction for dikes (proof loading and/or pore pressure measurements), and which strategy (combination of proof loading and pore pressure monitoring) yields the highest Value of Information. This is illustrated by a case study of a typical river dike that currently does not meet the required reliability for the failure mode of slope instability. Any uncertainty reduction efforts have to be carried out before the reinforcement project will start (a period of 5 years is assumed in this paper).

Section 2 presents general methods for evaluating various strategies for proof loading and pore pressure monitoring. Section 3 presents approaches that are specific to the case study and a sensitivity analysis. Results are presented in Section 4, while sections 5 and 6 present a broader discussion on the practical meaning of the results as well as the main conclusions.

2. Method

2.1. Reliability of dikes

Dikes have multiple failure modes for which the safety is assessed: overflow, overtopping, slope stability, piping backward erosion, among others (Vrijling, 2001). For dikes on soft soil foundations (e.g. soft clay or organic soils such as in the Netherlands), slope instability is one of the most prominent failure modes contributing to the probability of flooding (Jongejan & Maaskant, 2015). This is mainly because of the large uncertainty of geotechnical properties due to spatial variability, sparse data and measurement errors.

Generally, the safety against slope stability is assessed using limit equilibrium methods, (e.g. Bishop, Spencer, Uplift-Van), which calculate the factor of safety against instability (F_s) considering driving forces (e.g. weight) and resisting forces (e.g. shear stress) acting on a slip plane. The probability of failure is defined as $P(F) = P(g < 0)$, where F is the failure event of instability, and g the performance function. It holds that $g = F_S(\mathbf{X}) - 1$ with F_S the factor of safety against instability with input variables $\mathbf{X}$, being the soil parameters, (hydraulic) loads and model uncertainty. For convenience, it is written $P(F) = P(g(\mathbf{X}) < 0)$.

This paper considers a dike which has insufficient safety against instability, i.e. the failure probability ($P(F)$) is larger than the (risk-based (see e.g., Vrijling (2001)) economically optimal target failure probability (P_T): $P(F) > P_T$. Or, in terms of reliability index: $\beta < \beta_T$, where $\beta = \Phi^{-1}(1 - P(F))$ and Φ^{-1} the inverse standard normal cumulative distribution function. This study considers only slope stability reliability in the flood risk analysis, as it is the most prominent failure mechanism. Although other failure modes also contribute to flood risk depending on the local conditions, here it is assumed these contributions are minor. Besides, extension of the approach with more failure modes is straightforward and especially useful if the reliability of other mechanisms is also mainly determined by reducible uncertainties.

Here, fragility curves are used to calculate the slope reliability of dikes, see Schweckendiek et al. (2017). Fragility curves describe the conditional failure probability given a (load) variable. Here the failure probability conditional to the water level h: $P(F|h) = P(g(\mathbf{X}, h) < 0|h)$ is considered, where $\mathbf{X}$ is the vector of random variables except for h. The annual probability of failure is obtained by combining $P(F|h)$ with the PDF of annual maxima of the load h as follows:

$$P(F) = \int P(F|h) f(h) dh. \quad (1)$$

Note that fragility curves can in principle be made for any (load) variable. This approach is described in Section 3.

2.2. Framework to support decision-making towards efficient utilization of proof loading and monitoring

Formulation of the framework

Insufficient safety against slope instability is typically remedied by decreasing the slope angle or by constructing a stability berm at the inner toe of the dike to increase the resisting weight at the passive side of the slip plane. When space is available, these measures are relatively cheap as the construction and material costs of soil are low. However, when space is scarce (e.g., in densely built areas like the

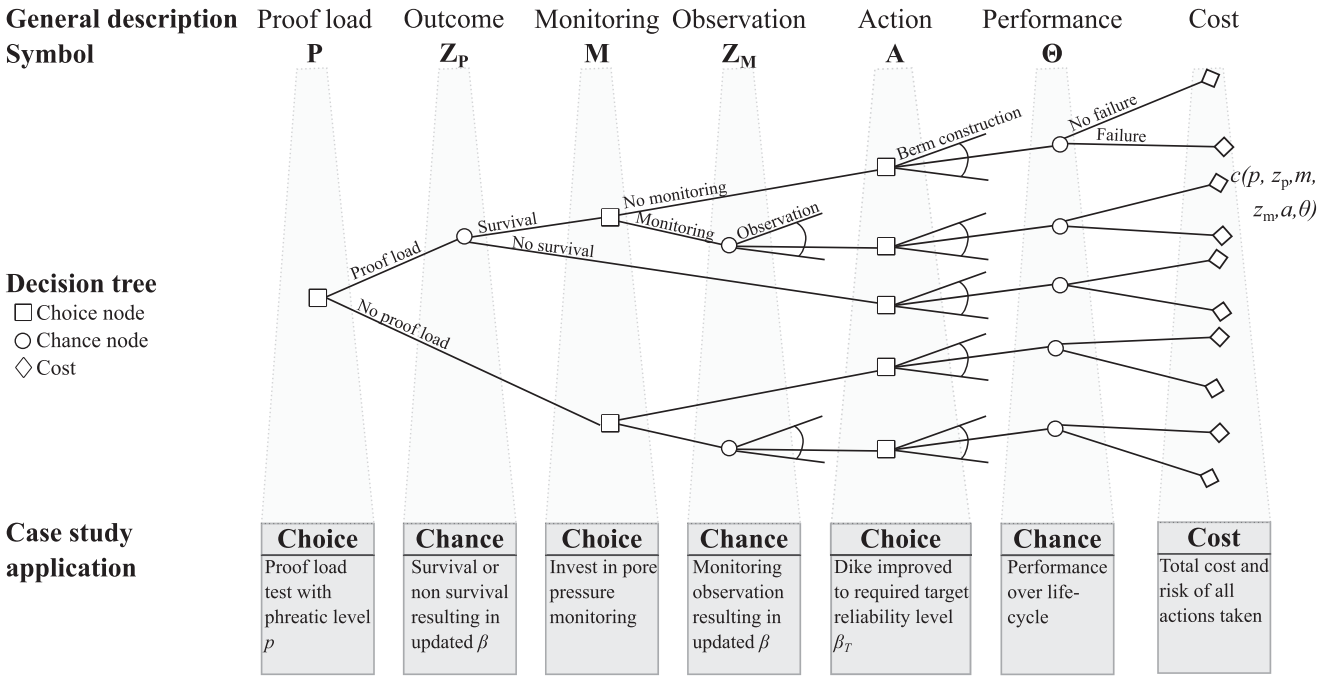

Figure 1. Decision tree for a sequential decision on proof loading, monitoring, and reinforcement of a dike section. The decision tree is a graphical presentation of the choices $p \in \mathbf{P}$, $m \in \mathbf{M}$, and $a \in \mathbf{A}$, and chances $z_p \in \mathbf{Z}_p$, and $z_m \in \mathbf{Z}_m$.

Netherlands), reinforcement can become extremely expensive, for example because adjacent home owners have to be moved and compensated, or because other design options are applied such as expensive sheet pile walls and diaphragm walls. In such cases, methods for reducing uncertainty that might result in lower reinforcement costs can be very valuable as the required reliability can be achieved at much lower cost. For example, a less costly reinforcement method becomes feasible, or reinforcement projects become obviated.

To evaluate the benefits of pore pressure monitoring and proof loading Bayesian pre-posterior analysis is used. The basic idea of pre-posterior analysis is that, based on a priori available information, one can determine the best decision based on an evaluation of all possible outcomes. The principles were first introduced by Raiffa & Schlaifer (1961). Decision trees are the most common approach to visualise and structure pre-posterior decision analysis (Raiffa & Schlaifer, 1961; Spross & Johansson, 2017; Thöns, 2018, 2019). A decision tree shows a sequence of decision (choice) nodes and outcomes (chance). Decision nodes are typically choices made by a decision maker as part of some (optimized) strategy, such as the decision to do proof loading. Chance nodes are outcomes of choices and depend on the action and prior information on the state of the system, for instance failure after a proof load test.

A disadvantage of a decision tree is that it can become cumbersome to visualise and solve if many sequential decisions are considered, in such cases other approaches such as influence diagrams (i.e., an extension of Bayesian networks) are more adequate (Luque & Straub, 2019), possibly combined with heuristic decision rules. This study considers three decision options (proof loading, monitoring and dike reinforcement), hence a decision tree is well suited. Figure 1 presents the decision tree for the sequential decision strategy of proof loading, pore pressure monitoring and dike reinforcement, denoted with p, m, and a, respectively. Note that a specific sequence for proof loading and pore pressure monitoring is assumed, the effect of reversing this is discussed in Section 5.

In the evaluation of choices on proof loading and pore pressure monitoring it is desired to evaluate what is the optimal strategy, given the prior belief $f_{\mathbf{X}}(\mathbf{x})$ of the random variables $\mathbf{X}$. Here $f_{\mathbf{X}}(\mathbf{x})$ is the joint probability density, where $\mathbf{x}$ is the realization of $\mathbf{X}$. The failure probability is then given by $P(F) = \int_{g(\mathbf{x})<0} f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$, the integral over the prior belief for all values where the limit state function evaluates to a value smaller than 0.

The first step is the decision whether to execute a proof load test of a certain magnitude $p \in \mathbf{P}$. The outcome z_p (a survived or failed proof load test) depends on the magnitude of the proof load and the prior belief $f_{\mathbf{X}}(\mathbf{x})$. The higher the magnitude of the survived test load (i.e. the artificially induced phreatic line), the more uncertainty is reduced, and the higher the updated reliability. On the other hand, the higher the magnitude of the survived test load, the higher the probability that the test is not survived. In that case the dike is damaged and needs to be reinforced immediately and the part of the section that was proof loaded has to be repaired such that extra costs are incurred.

After deciding whether to do a proof load test (and on the magnitude of the test load), it can be decided to invest in pore pressure monitoring ($m \in \mathbf{M}$) in order to reduce uncertainty on the response of the phreatic line to outside water levels. Again, two outcomes are possible: either an observation is made or not. The observation z_m depends on the belief after proof loading $f_{\mathbf{X}|z_p}(\mathbf{x})$. Whether an observation is made in the considered time period depends on whether the water level

Table 1. Methods, goals and activities considered in this paper.

Method	Goal	Activity
Proof load test (**P**)	Reduce uncertainty in geotechnical parameters	Artificially raise the phreatic line by infiltrating water in the dike
Monitoring (**M**)	Reduce uncertainty in response of the phreatic line to floods	Monitor the response of pore water pressures during floods using piezometers
Dike reinforcement (**A**)	Increase the reliability of the dike	Increase stability by construction of a stability berm

exceeds a certain threshold required to obtain useful measurements (Frangopol et al., 2008; Klerk et al., 2019). Note that this is time-dependent: the longer the monitoring period, the higher the probability of a useful observation, opposite to a proof load test which is time-independent.

After the outcome of the monitoring, the dike is improved to the required target reliability level. This is done using decision rules that translate combinations of outcomes of proof loading and monitoring to actions: $\mathbf{d}(\mathbf{Z_P}, \mathbf{Z_M}) = \mathbf{A}$, where for an individual decision rule d it holds that $d \in \mathbf{d}(\mathbf{Z_P}, \mathbf{Z_M})$. Note that through an action $a \in \mathbf{A}$ also some variables in $\mathbf{X}$ can be adapted (e.g., the length of the stability berm).

The cost of a branch in the decision tree is determined by the costs of every individual step and the expected damage given the performance θ (failure/no failure): $c(p, z_p, m, z_m, d, \theta)$. The cost of the optimal strategy $c(p^*, m^*, d^*)$ can be computed by combining the cost of different branches over the possible outcomes:

$$c(p^*, m^*, d^*) = \min_{p \in \mathbf{P},\, m \in \mathbf{M},\, d} E_{\mathbf{\Theta}|\mathbf{X}}\left[E_{z_m|\mathbf{X}}\left[E_{z_p|\mathbf{X}}\left[c(p, z_p, m, z_m, d, \theta)\right]\right]\right]. \tag{2}$$

Specifically in this paper, the cost of a strategy *c(p, m, d)* is defined by the sum of costs of each step in the decision tree (decision and outcome):

$$c(p, m, d) = I_p \cdot C_{\text{proof load}} + I_m \cdot C_{\text{monitoring}} + \int_{f_X(\mathbf{x})} P(\bar{S}|p \cap \mathbf{x}) \cdot C_{\text{repair}} + C_{\text{reinforcement}}(d, \mathbf{x}) + C_{\text{failure}}(d, \mathbf{x}) \mathrm{d}\mathbf{x}, \tag{3}$$

where I_p and I_m are indicator random variables (value 0 or 1) that indicate whether proof loading or monitoring is done. C parameters indicate different cost components. The cost components of proof loading and monitoring are independent of the prior belief $f_{\mathbf{X}}(\mathbf{x})$. There are three cost components that depend on the prior belief: the cost of failure after a failed proof load test, where $P(\bar{S}|p \cap \mathbf{x})$ is the probability of not surviving a proof load with magnitude p, and C_{repair} are the repair costs. The costs of reinforcement $C_{\text{reinforcement}}$ depend on decision d and the realization $\mathbf{x}$. The annual failure probability is assumed to be constant in time. Thus, for the Present Value of the failure costs $C_{\text{failure}}(d,\mathbf{x})$ an infinite time horizon can be considered, such that:

$$C_{\text{failure}}(d, \mathbf{x}) = \frac{P(F|d, \mathbf{x}) \cdot D}{r}, \tag{4}$$

where $C_{\text{failure}}(d,\mathbf{x})$ is the cost of failure in €for an infinite time horizon, D is the expected damage in case of a flood (in €), r is the annual discount rate, and $P(F|d,\mathbf{x})$ is the annual failure probability given an action following from decision rule d and a realization of the set of random variables $\mathbf{x}$.

A reference period of 1 year is assumed, in line with common practice for flood defence structures. It should be noted that in some cases for geotechnical structures, the use of other reference periods might be more adequate (Roubos et al., 2018), and for instance the time factors provided in Diamantidis et al. (2019) may be applied. The cost of the reference strategy without monitoring and proof loading is defined as c_0. The Value of Information (*VoI*) of a strategy $\{p,m,d\}$ can be computed by:

$$VoI = c_0(d) - c(p, m, d). \tag{5}$$

The next subsections go further into the choices the decision maker is faced with (summarized in Table 1) in more detail.

Step 1: doing a proof load test (P)

Proof loading involves imposing a representative design load on the dike body, for example a high phreatic line (see Figure 4). If such a proof load is survived, it proves that there is a minimum resistance along a slip plane. Conversely, when the dike fails under the conditions of the proof load test, it reveals that the structure was not safe enough. Note that a higher proof load yields more information, but also results in a higher risk of failure during the test. The outcome of the proof load test is used to update the failure probability based on the outcome z_p of the proof load test, and hence the updated probability of failure is written as:

$$P(F|z_p) = \int_{g(\mathbf{x}) < 0} f_{\mathbf{X}|z_p}(\mathbf{x}) d\mathbf{x}, \tag{6}$$

with:

$$f_{\mathbf{X}|z_p}(\mathbf{x}) = \frac{P(\mathbf{x} \cap z_p)}{P(z_p)} f_{\mathbf{X}}(\mathbf{x}) = \frac{P(z_p|\mathbf{x}) f_{\mathbf{X}}(\mathbf{x})}{\int_{\mathbf{X}} P(z_p|\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}}. \tag{7}$$

where, z_p is the observation of no instability at a proof load level p, for which the performance function for stability at a proof load level p, $g(\mathbf{X}, p) \geq 0$. Instead of updating the probability density $f_{\mathbf{X}|z_p}(\mathbf{x})$, the updated failure probability is directly calculated by applying Bayes' rule:

$$P(F|z_p) = \frac{P(F \cap z_p)}{P(z_p)} = \frac{P(g(\mathbf{X}) < 0 \cap g(\mathbf{X}, p) \geq 0)}{P(g(\mathbf{X}, p) \geq 0)}. \tag{8}$$

This formulation in terms of conditional probability avoids the explicit calculation of the updated joint probability distribution $f_{\mathbf{X}|z_p}(\mathbf{x})$. Note that a proof load test does not update all parameters, for example for those related to response of the phreatic line to an extreme flood water level (e.g., the head

level in the aquifer below the soft soil blanket or pore pressures in the dike body in flood conditions) no additional information is obtained.

The proof load test considered in this paper consists of a controlled experiment to artificially raise the phreatic line, assuming a successful test in the sense that it always succeeds in increasing the water pressures to the desired level, throughout the dike body. The cost of such a proof load test involve the set-up of a test, equipment, analysis, and monitoring to substantiate the observations of a survived proof load, such as deformation monitoring to indicate that a rotational shear failure was not initiated under the observed loading conditions (e.g., Tavenas et al., 1979). Subjecting a structure to a proof load also involves the possibility that instability occurs during the test, with additional repair costs involved.

Step 2: setting up a pore pressure monitoring campaign (M)

After or instead of proof loading, uncertainty can be reduced by setting up a pore pressure monitoring campaign. Pore pressure monitoring aims to reduce uncertainty about the response of the phreatic line in the dike. The parameters characterizing this response are part of the belief $f_{\mathbf{X}|z_p}(\mathbf{x})$, where conditioning on z_p is not needed if proof loading was not done beforehand. If a pore pressure monitoring campaign yields an observation z_m, $f_{\mathbf{X}|z_p}(\mathbf{x})$ can be updated to a posterior estimate including z_m:

$$f_{\mathbf{X}|z_p\cap z_m}(\mathbf{x}) = \frac{P(\mathbf{x}\cap z_m)|f_{\mathbf{X}|z_p}(\mathbf{x})}{P(z_m)} = \frac{P(z_m|\mathbf{x})|f_{\mathbf{X}|z_p}(\mathbf{x})}{\int_{\mathbf{X}} P(z_m|\mathbf{x})f_{\mathbf{X}|z_p}(\mathbf{x})d\mathbf{x}}. \quad (9)$$

Note that the likelihood $P(z_m|\mathbf{x})$ is calculated with the updated probability distribution $f_{\mathbf{X}|z_p}(\mathbf{x})$. Then it holds for the posterior probability of failure with monitoring and proof load:

$$P(F|z_m\cap z_p) = \int_{g(\mathbf{x}<0)} f_{\mathbf{X}|z_p\cap z_m}(\mathbf{x})d\mathbf{x}. \quad (10)$$

Note that the parameters in $\mathbf{X}$ related to the response of the phreatic line are now directly updated, as there are direct observations of input parameters, contrary to proof loading.

As was indicated by Klerk et al. (2019), an important parameter for pore pressure monitoring is the probability that a useful observation is obtained. Often discontinuities in a dike body (e.g., an older clay dike), or different permeability values in general can result in different responses of the phreatic line for different outside water levels, and therefore, an observation z_m is to give more useful information if measurement conditions are closer to design conditions. To incorporate this, it is assumed that a valuable measurement (i.e., uncertainty reduction) is only obtained if the annual maximum water level h exceeds a predefined threshold water level h_{thresh}. Thus the probability of obtaining a valuable measurement z_m can be computed using the following formula:

$$P(z_m) = 1 - F(h > h_{thresh})^t \quad (11)$$

where $F(h > h_{thresh})$ is the cumulative probability per year that the outside water level exceeds the threshold water level h_{thresh}, and t is the duration of monitoring in years.

Step 3: dike reinforcement (A)

In practice, numerous reinforcement methods are available to increase the stability of dikes, for example: stability berms, sheet pile or diaphragm walls, or soil anchoring techniques. Here, only the most common (and often cheapest) method of stability berm construction is considered. Adding a stability berm at the inner toe of the dike increases the weight on the passive side of the slip plane and increases the resisting shear stress.

The target reliability that has to be satisfied after a dike reinforcement is often predetermined, and typically based on an optimization of various risk indicators and costs of reinforcement (see e.g., Eijgenraam et al., (2017); Voortman, (2003); Vrijling, (2001). If the reliability of dikes is changing significantly in time, one also has to consider reinvestments. However, due to the dependence of slope stability reliability on time-independent ground-related uncertainty, slope stability of dikes (and other geotechnical structures, see e.g., Roubos et al. (2018)) is typically rather time independent. Therefore, in an economic optimization one can estimate the annual target reliability by considering an infinite time horizon, such that the optimal level of protection β_T, follows from the following minimization:

$$\beta_T = \arg\min_{\beta}\left(C(\beta) + \frac{\Phi^{-1}(\beta)\cdot D}{r}\right) \quad (12)$$

where D is the annual expected damage in case of flooding, r is the annual discount rate and $C(\beta)$ is the cost of achieving a certain reliability index. It has to be noted that in practice reliability targets are typically specified in standards and are not based on a case-specific optimization. This will be further addressed in the sensitivity analysis in Section 4.

3. Case study

3.1. Description of the reference case

The reference case is a dike section of 1 kilometre in length, inspired by an actual dike section currently being reinforced. It is slightly simplified such that it contemplates a typical dike section in the Dutch riverine area. The dike cross section, displayed in Figure 2, consists of a traditional clay dike which has been reinforced with sand in the past. It is assumed that the dike is scheduled for reinforcement in 5 years as it currently does not meet the safety standard. Until that time there is opportunity to do a proof load test and pore pressure monitoring to reduce uncertainty on the resistance parameters and the position of the phreatic line in the dike body, respectively. The goal is to determine the optimal course of action for the coming 5 years.

The dike consists partly of clay and partly of sand, has a crest level at 14.0 m + ref. (reference level), a landside elevation of 6.0 m + ref., an inner slope of 1:3 (v:h) and is situated on (Holocene) clay layers on top of a (Pleistocene)

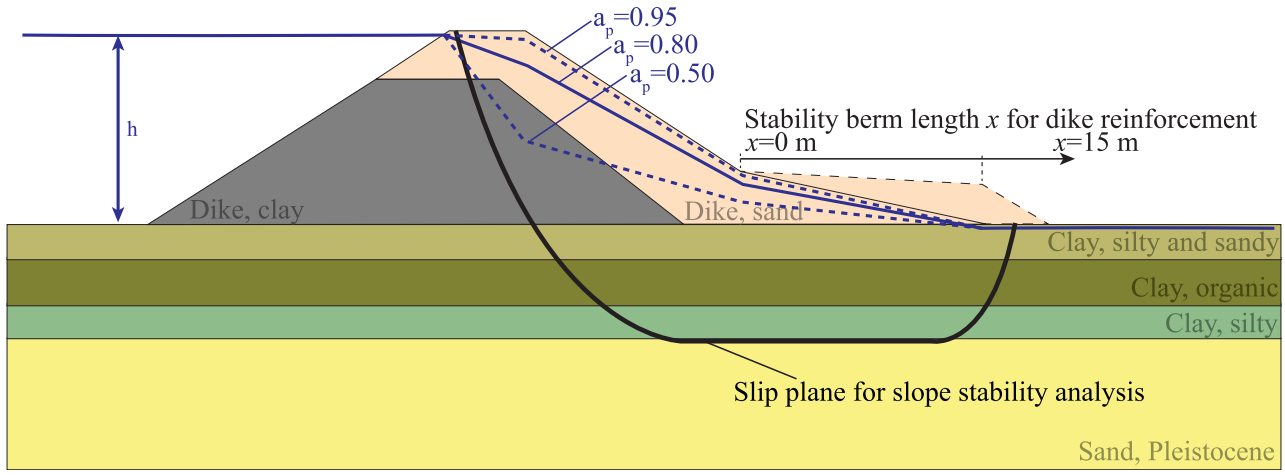

Figure 2. Cross section of the considered case study. Blue lines indicate the simplified schematization of the phreatic line for different response factors a_p (at an extreme water level).

aquifer. A cross section of the considered dike is shown in Figure 2. The strength of the soil is modelled according to the Critical State Soil Mechanics framework (Schofield & Wroth, 1968) with a critical state friction angle (φ) or undrained shear strength (s_u) calculated using the SHANSEP formulation (Ladd & Foott, 1974):

$$s_u = \sigma'_v \cdot S \cdot OCR^{m_{SHANSEP}} \tag{13}$$

where, S is the undrained strength ratio for normally consolidated soil, $m_{SHANSEP}$ is the strength increase exponent, and OCR is the over-consolidation ratio: the ratio of in situ vertical effective stress (σ'_v) and pre-consolidation stress $\sigma'_p = \sigma'_v + POP$, where POP is the pre-overburden pressure. The vertical effective stress is the total vertical soil stress σ_v minus the pore pressure σ_p : $\sigma'_v = \sigma_v - \sigma_p$. Note that a high phreatic line leads to higher pore pressures, thus lower s_u, and lower stability (F_s). Additionally, the stability decreases because a higher phreatic line corresponds to a higher weight of the dike body.

In the case study, only monitoring of the phreatic line in the dike body is considered, not of the pore water pressures in other soil layers. The position of the phreatic line in the dike at flood conditions typically depends on the permeability of the dike material which is often heterogeneous and uncertain. Especially when a dike has a long history of reinforcements with various materials, the phreatic line is uncertain. For example the considered case study of a traditional clay dike reinforced with sand. Therefore, the position of the phreatic line in steady state seepage conditions is parametrised, using an uncertain response factor (a_p).

The response factor represents the degree of saturation of the dike body at the inner crest line, in response to an extreme water level. Values can range between a_p=0 (phreatic level at the landside elevation level) and a_p=1 (phreatic level equal to the outside water level). For intermediate values of a_p, the phreatic line is interpolated accordingly, see Figure 2. Because the dike body will always saturate to some degree, and in case of a fully saturated dike (a_p=1) other mechanisms such as micro-instability become dominant, the value of a_p is limited between 0.5 and 0.95. The bounds represent realistic values based on physical considerations. Furthermore, the lower bound has a limited influence on the reliability, indicated by the results in the next paragraph.

To facilitate the probability updating outlined in Section 2, 3-dimensional fragility surfaces are derived, where the failure probability is conditional to response factor a_p and the water level h. These surfaces are derived both for the prior situation, and the situation posterior to surviving a certain proof load level p. Figure 3 presents this fragility surface, plotted in terms of reliability index for convenience. The reliability is calculated at discrete intervals of h and a_p, and linearly interpolated to obtain intermediate values. The fragility surface directly shows the influence of the response factor a_p (mainly at high water levels), and clearly illustrates the potential benefit of reducing uncertainty herein.

Separate fragility surfaces $\beta(h, a_p)$ are derived for berm lengths of 5, 10, 15 and 20 meters. For other values fragility surfaces are interpolated or extrapolated. Table 2 lists the input probability distributions for parameters in the reference case. The probability distributions for these spatially averaged soil parameters are derived from regional data for typical geological deposits of the Dutch situation, see Rijkswaterstaat (2019). Integration of the fragility surface with the prior probability distribution of a_p and h along the lines of Equation (1), results in a prior failure probability of $2.7{\cdot}10^{-4}$ ($\beta = 3.46$).

3.2. Implementation of risk reduction strategies

Proof loading

Proof loading is done by artificially raising the phreatic line in the dike by infiltrating water into the dike from the crest (similar to van Hoven & Noordam (2018)), see Figure 4. Survival of the situation with an imposed phreatic level leads to a higher reliability because of an implicit update of the probability density of soil parameters involved (which are a subset of $\mathbf{X}$). The higher the phreatic level, the larger the uncertainty reduction, and hence, the larger the reliability update; but also the higher the probability the proof load is not survived.

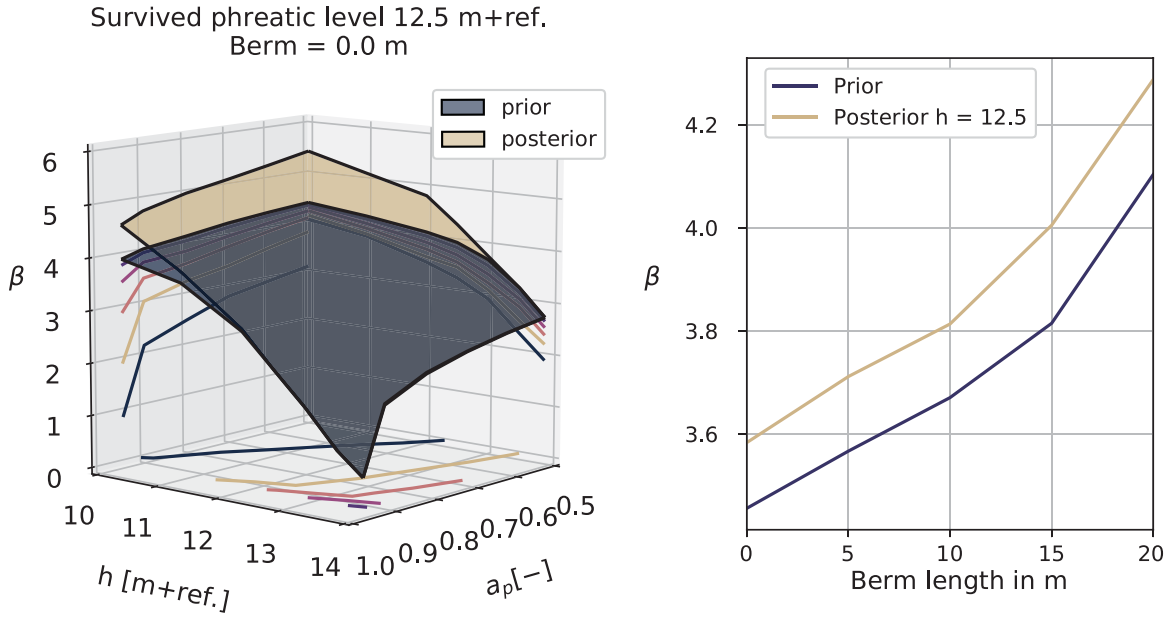

Figure 3. (left) Prior and posterior fragility surface (in terms of reliability index β) for the considered case study without berm. The overall reliability index (integrated with the prior probability density of a_p and h) is 3.46. (right) Relationship between berm length and overall reliability index β for the prior situation and posterior after a proof load level of 12.5 m + ref.

Table 2. Random variables in the reference case.

Property	Symbol and Unit	Soil type	Distribution*
Normally consolidated undrained shear strength ratio*	S [–]	Clay, silt and sand	Lognormal($\mu = 0.36$, CoV = 0.15)
		Clay, organic	Lognormal($\mu = 0.29$, CoV = 0.15)
		Clay, silt	Lognormal($\mu = 0.32$, CoV = 0.25)
Strength increase exponent	m [–]	Clay, silt and sand	Lognormal($\mu = 0.84$, CoV = 0.05)
		Clay, organic	Lognormal($\mu = 0.93$, CoV = 0.05)
		Clay, silt	Lognormal($\mu = 0.83$, CoV = 0.05)
Pre-overburden Pressure at daily stress conditions (no flood)	*POP* [kPa]	Clay, silt and sand	Lognormal($\mu = 27.0$, CoV = 0.45)
		Clay, organic	Lognormal($\mu = 27.0$, CoV = 0.45)
		Clay, silt	Lognormal($\mu = 27.0$, CoV = 0.45)
Critical state friction angle	φ' [°]	Dike, sand	Lognormal($\mu = 32.6$, CoV = 0.05)
		Dike, clay	Lognormal($\mu = 35.0$, CoV = 0.05)
		Clay, silt and sand	Lognormal($\mu = 32.3$, CoV = 0.05)
		Sand, Pleistocene	Lognormal($\mu = 35.0$, CoV = 0.05)
Model factor stability model	m_d [–]	n/a	Lognormal($\mu = 0.995$, CoV = 0.033)
Parameter for phreatic line	a_p [–]	n/a	Uniform(a = 0.5, b = 0.95)
Water level	h [m + ref.]	n/a	Gumbel(loc = 11.9, scale = 0.2)

*Note that μ is the mean value, not the lognormal distribution parameter, CoV is the coefficient of variation.

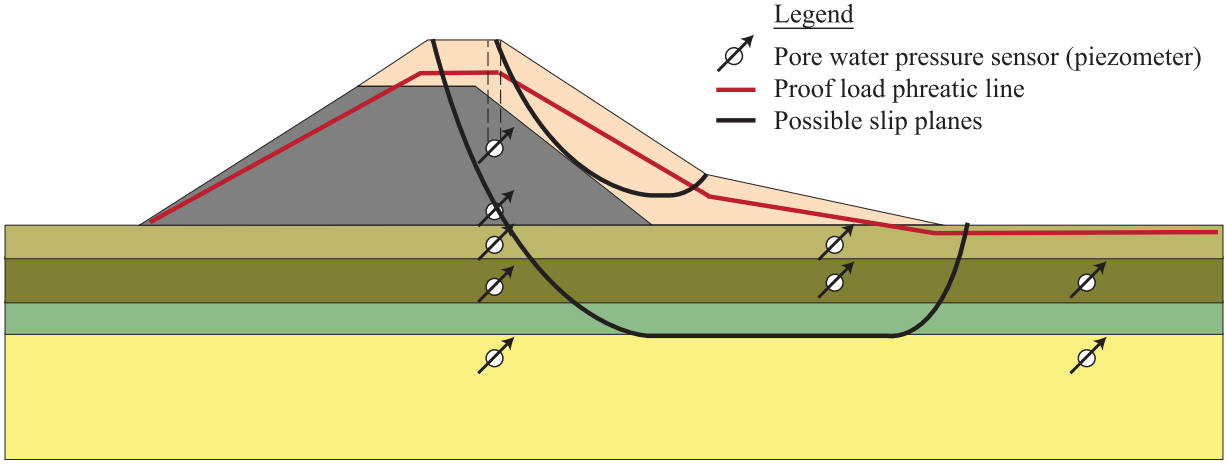

Figure 4. Overview of the positioning of sensors installed for pore water pressure monitoring, and the imposed phreatic level during a proof load test. The larger black line indicates the slip plane relevant for flooding, the smaller slip plane is relevant for failure of the proof load test but does not cause flooding.

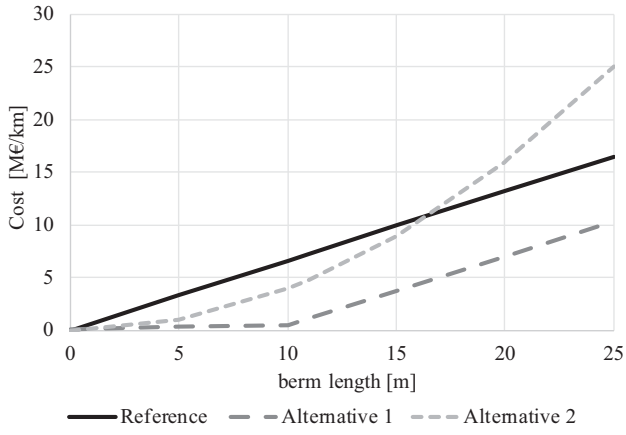

Figure 5. Different cost functions for dike reinforcements.

Contrary to the phreatic level in flood conditions (dependent on amongst others the flood water level, the duration of the flood wave, and permeability of the outer slope cover layer), the phreatic level during proof loading is induced/imposed by infiltrating water into the dike using, e.g., infiltration wells or an irrigation system (see van Hoven & Noordam (2018) for pictures). Therefore, the outcome of the proof load test (and hence the updated reliability) is independent of the response factor a_p, and the posterior reliability β conditional to a_p: $\beta|a_p = -\Phi^{-1}(P(F|z_p, a_p))$ can be computed, using the formulation from Equation (6) to calculate $P(F|z_p, a_p)$.

Figure 3 shows that a significantly updated reliability for water levels lower than the survived proof load of 12.5 m + ref. is to be expected. The reliability update is relatively larger for lower values of a_p. This is in line with expectations because the survived proof load becomes more valuable if a high phreatic line is less likely. Note that the failure probability for water levels lower than the survived proof load level is not reduced to 0 (infinite beta) because of irreducible uncertainty (see Schweckendiek et al. (2017) for a consideration of reducible and irreducible uncertainty). In this case this mostly concerns uncertainty in time-variant variables, such as the rainfall intensity.

It is assumed that the proof load is applied over a stretch of 100 m length. This is considered representative for the 1 km dike section because of a limited variation in the dike body in longitudinal direction as a result of the quite recent reconstruction with sand, see Figure 2. The total cost of a proof load test is assumed to be €500,000 consisting of costs for equipment required for infiltration, monitoring during the test, emergency measures to mitigate slope failures induced by the test and analysis of the test results. It is assumed that the test is carried out in a period where a potential failure does not cause flooding.

Therefore, the costs of not surviving a proof load only consist of repairing the damaged slope. These costs are estimated to be €2,000,000, based on the costs of full reconstruction of the existing dike over a length of 100 meter. Additional costs such as follow-up damage to buildings, transportation infrastructure, agricultural areas etc. are disregarded in this case study. For damage during a proof load test (C_{repair}) occurrence of each slip circle (also very shallow) is considered as failure, contrary to flooding. For flooding damage (D) only larger slip circles which will lead to flooding of the hinterland are considered, as is depicted in Figure 4. After a proof load test failure, no pore pressure monitoring is done.

Pore pressure monitoring

Pore pressure monitoring is carried out by measuring the phreatic line in the dike body (see Figure 4 for location of sensors). The measurement will lead to an update of the probability distribution of a_p ($a_p \in \mathbf{X}$). Because of the chosen limits of the prior distribution of a_p, it is assumed that the posterior distribution of a_p is a truncated normal distribution with μ the observed value (i.e., based on possible state), standard deviation $\sigma = 0.05$ and upper and lower bound equal to the upper and lower bound of the uniform prior. The value of σ accounts for measurement errors and transformation errors, and corresponds with a standard deviation of 0.3 m in the position of the phreatic line. This value is in accordance with commonly found values in the Dutch practice (Kanning & van der Krogt, 2016).

Due to the old clay dike located in the cross section the sensors will only yield relevant results if the water level is somewhat above the crest of the old clay dike (see Figure 2), it is assumed that this threshold is 12.2 m + ref (0.2 m above the top of the clay). With the local probability distribution for water levels, and 5 years of monitoring the probability that a relevant observation is obtained is 67% (using Equation (11)).

While not explicitly modelled, the costs are based on plans for measuring the entire section including redundancy in measurements and multiple cross-sections with sensors. The cost of pore pressure monitoring is estimated at €100,000 for 5 years and include cost for installation, maintenance, decommissioning and analysis of the obtained data, based on the number of sensors in Figure 4, installed at two cross sections.

Dike reinforcement

The reliability requirement for the dike section is determined based on the level of protection with minimal total cost (see Equation (12)). This value is derived based on the prior $f_{\mathbf{X}}(\mathbf{x})$. The costs for reinforcement are shown in Figure 5, both for the reference case and some alternatives that will be used in a sensitivity analysis. Except for alternative 2, these curves have been derived using KOSWAT, a software program used for cost calculations for dike reinforcements in the Netherlands (Deltares, 2014). Only reinforcement through a stability berm is considered (see Figure 2 for dimensions). The costs are calculated using Equation (3). Note that the risk in the 5 years before reinforcement is not considered, as this is the same for each strategy (and thus does not lead to differences in VoI).

4. Results

4.1. Reference case

First, it is evaluated whether proof loading and/or pore pressure monitoring reduces overall total cost for a

Table 3. Cost/Benefit parameters.

Parameter	Description	Unit	Value
R	Annual discount rate	–	0.035
D	Damage in case of flooding	million €	5000
C_{repair}	Cost of repair after failed proof load test	million €	2.5
$C_{monitoring}$	Cost of 5 years of pore pressure monitoring	million €	0.1
$C_{proof\ load}$	Cost of proof load test	million €	0.5
σ	Uncertainty in observation of a_p	–	0.05
h_{thresh}	Minimum water level for a useful observation	m + ref	12.2

reference case. Here, a proof load test where the phreatic line is artificially increased to 12.5 m + ref. is considered. For 5 years of monitoring the probability of having a useful observation is 67%. The parameters used for the cost benefit analysis are shown in Table 3.

Figure 6 displays total cost and Value of Information (see Equation (5)) for all combinations of proof loading and monitoring, compared to a conventional strategy without monitoring and proof loading. Both monitoring and proof loading reduce total cost, with the optimal strategy being a combination of proof loading and monitoring (VoI = 4.0 M€). For the optimal strategy the reduction in total cost is 25% compared to a conventional reinforcement, strategies with only proof loading or monitoring have a lower but also positive VoI. The most important component for the VoI is the reduction in construction cost, which significantly outweighs the costs of monitoring and proof loading.

4.2. Optimization of proof load level

Although Figure 6 clearly shows that a combination of monitoring and proof loading is an effective approach to reduce total cost, another important choice is the phreatic level that is to be tested. While lower levels will result in a smaller reduction of uncertainty, higher levels have higher uncertainty reduction but also the added risk that the dike section fails during the test and has to be repaired.

Figure 7 depicts the relation between phreatic level in the proof load test and the Value of Information. The red line indicates the VoI for different combinations of proof loading and monitoring, for which the optimum is at a proof load phreatic level 13.0 m + ref. If no monitoring is done, the optimal proof load level is 13.5 m + ref. (see yellow bars). However, combined with monitoring, the VoI is highest with a lower proof load level (e.g., 12 m + ref.). For proof load levels above 13.5 m + ref., the VoI becomes negative because of the high risk of failure during the test (i.e., there is a critical proof load level where the VoI = 0).

Another interesting observation is that in this case the VoI of monitoring after a proof load test (purple bars) is higher than the VoI without a preceding proof load test (left purple bar). Thus, the monitoring becomes more valuable after reducing uncertainty through proof loading. Obviously, this can differ per case, and it is also dependent on for instance the shape of the relationship between construction cost and berm length.

4.3. Sensitivity analysis

Dike sections that are part of longer dike segments can differ significantly. This section discusses several of these differences encountered in practical situations, and their influence on the Value of Information, namely:

- Influence of the reliability requirement: in many practical cases reliability requirements are not based on an economic optimization, such that the VoI might be different.
- Influence of different soil parameters: different locations can have significantly different mean values and variance of soil parameters, such that he benefits of different types of uncertainty reduction might shift.
- Influence of different cost functions: due to local circumstances (e.g., density of adjacent buildings) costs of reinforcement can vary, which can influence the VoI.

A proof load level of 13.0 m + ref. is assumed in all cases of the sensitivity analysis, which is (close to) optimal in all cases and strategies (see also Figure 7).

Influence of the reliability requirement

In the reference case an optimal target reliability level is determined based on a Total Cost minimization using prior information. In reality, the section studied is part of a larger flood defence system where other safety requirements (e.g., loss-of-life) might be dominant, or requirements are based on general codes. It would therefore be unlikely that the safety standard is exactly economically optimal for this specific dike section, with its specific characteristics. Figure 9a and b show a comparison of Total Cost and VoI for 4 cases: the reference case with optimized target reliability based on the prior information (β_T = 4.09), a case with 10 times higher requirement (β_T = 4.6 0), 10 times lower requirement (β_T = 3.52), and a case where the optimal target reliability is determined based on the posterior information after a proof loading and/or monitoring.

Without monitoring, the cases with lower and higher reliability requirements are significantly more expensive in terms of Total Cost. For the case with a higher requirement this is mainly caused by higher reinforcement costs, whereas for the case with a lower requirement this is due to higher risk costs. As reinforcement costs for the case with a higher requirement are still high after monitoring, the VoI is limited for this case. For the case with a lower requirement, the VoI of a combination of a proof loading and pore pressure monitoring is very high. The reason is that in case of very unfavourable values of a_p (and therefore high risk costs), observations are very valuable. In addition, it is prevented that an insufficiently safe dike is constructed as a result of an already too low reliability requirement.

The most efficient strategy in terms of Total Cost is if proof loading and monitoring are combined with a posterior optimal reliability requirement. Concretely, the optimal target reliability to be met after the dike reinforcement is determined based on the posterior information after monitoring and/or the proof load test (using Equation (12)),

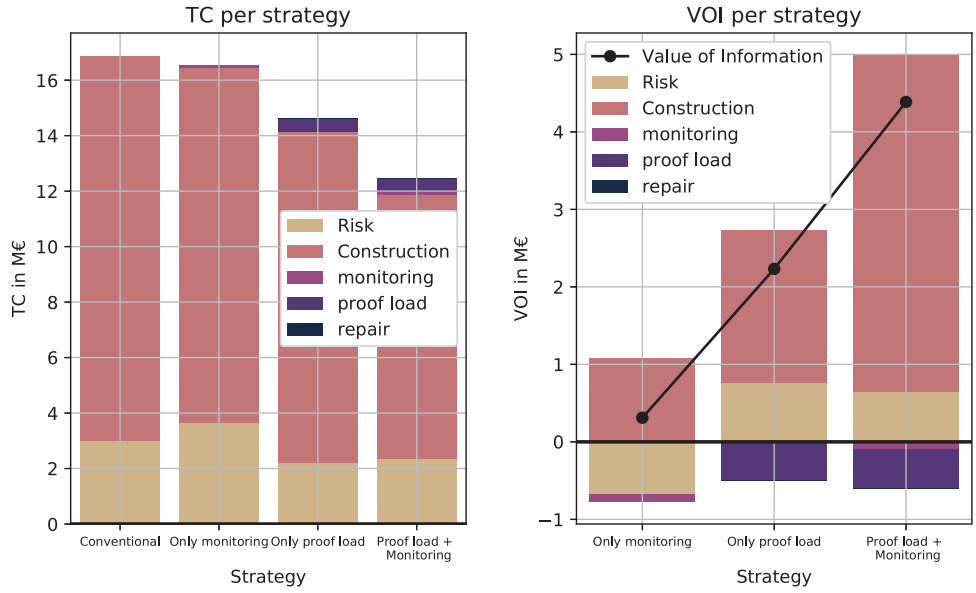

Figure 6. Total Cost (TC) (left) and Value of Information (VoI) (right) per strategy for the reference case. Colors indicate what the contribution is of different components to the TC (left) and VoI (right). The VoI for each strategy (the sum of the components) is calculated relative to the conventional strategy.

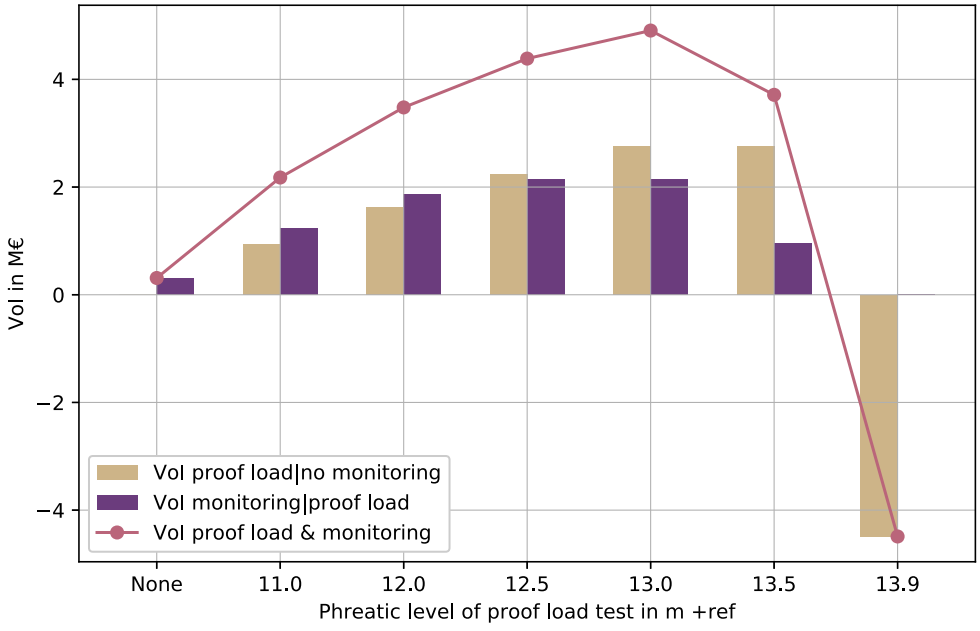

Figure 7. Value of Information (VoI) related to the level of the proof load test. Red line indicates the VoI for a combination of proof loading and monitoring, yellow bars indicate the value of a proof load test without monitoring. Purple bars indicate the added value of monitoring after a proof load test.

rather than the prior information. Consequently, the optimized target reliability depends on the obtained information z_p and z_m, and the determination of β_T becomes a part of the decision rules $\mathbf{d(Z_p, Z_m)}$ in the decision tree.

Hence, each branch in the decision tree can have a different β_T, dependent on the observations. This is slightly more efficient than having a requirement based on prior information, especially in case of a very favourable or unfavourable outcome after monitoring, because the change in expected reinforcement cost can be adjusted in the posterior optimization of the requirement. It has to be noted that the differences with the reference case with (prior) optimized β_T are limited, but it demonstrates that using a suboptimal target reliability has a large influence on the results of a VoI analysis.

Influence of different soil parameters

The reference dike section is characterised by relatively large uncertainties in soil parameters, and therefore the Value of Information of both proof loading and monitoring is found

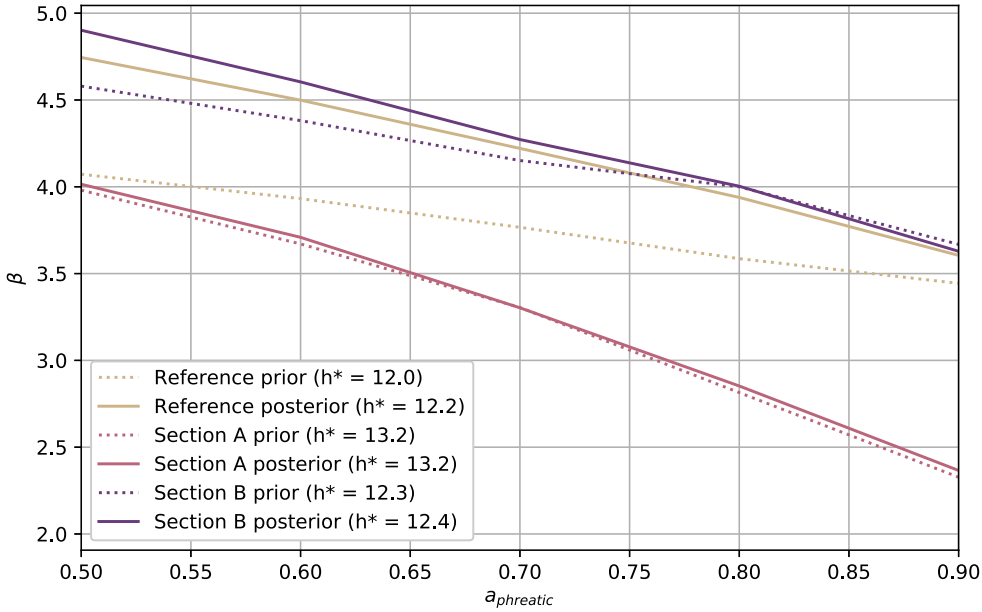

Figure 8. Fragility curves at the design point water level, showing an increasing dependency for the response factor $a_{p(hreatic)}$ after proof loading (steeper curve).

to be relatively large. However, not all dikes might have such large uncertainties, and therefore the VoI is assessed for two other cases: dike section A with lower uncertainty in soil parameters and a prior reliability index of 3.99, with a target reliability of 4.07. Hence, there is only a small reliability deficit, that would in practice likely be accepted as is. Section B also has relatively low uncertainty in soil parameters but lower mean values, so the prior reliability index is 3.61, with a target reliability of 4.02. Figure 9c and d show the Total Cost and VoI for each dike section for 4 different strategies.

Compared to the reference case, section A has considerably lower Total Cost as it is much closer to the target reliability (so the construction costs are much lower). At the same time, the VoI for proof loading is negative, which is due to the fact that the initial reliability is relatively high and the influence of soil parameter uncertainty is limited. Therefore a high proof load has to be applied to learn anything, which results in a higher probability of failure during the test. Thus, for this section proof loading adds very limited value. Although the uncertainty of soil parameters for section B is similar to that of section A, the fact that the initial reliability is lower results in a small but positive VoI for proof loading.

For pore pressure monitoring the VoI is positive in all cases. While the absolute VoI for section A is quite low compared to the other cases, relatively speaking monitoring reduces total cost by 22%. One thing that is quite apparent for the reference case is that monitoring only becomes relevant once it is combined with a proof loading, which is not the case for the other cases with lower uncertainty in soil parameters. This can be explained as follows: a priori, the reliability in the reference case is hardly influenced by the response factor a_p, whereas, a posteriori, the reliability is dependent on the response factor.

This is shown by the less steep fragility curve for the reference case in Figure 8. These curves are plotted conditional to the design point (i.e. most probable failure point) of the water level such that it best illustrates the contribution to the failure probability. Thus, the results illustrate that when geotechnical uncertainty is the dominant uncertainty in the prior failure probability (as it is only in the reference case), pore pressure monitoring is much less effective than proof loading. After proof loading, geotechnical uncertainty is reduced, and pore pressure monitoring becomes much more effective.

Influence of different cost functions

Local differences in density of buildings, land prices, and available space for reconstruction, can significantly influence the costs for reinforcing dikes using stability berms. The reference dike section is considered for three different cost functions (see Figure 5). Figure 9e and f present Total Cost and VoI for the three different functions. Alternative 2 has relatively large benefits for proof loading, compared to the reference case (relative to Total Cost). This is caused by the lower marginal cost of the berm in €/m' after proof loading, due to the fact that part of the cost function is less steep than the reference case.

However, for alternative 2 the benefits of monitoring are much larger if the reliability requirement is optimized based on the posterior information after monitoring, rather than the prior information. Note that the same holds for alternative 1, but results are not shown. The reason is that the marginal costs of reinforcement differ per berm length. Henceforth, if the posterior reliability estimate differs significantly from the prior estimate, the marginal costs of reinforcement might change significantly as well. Thus, especially if a cost function is highly non-linear, such a

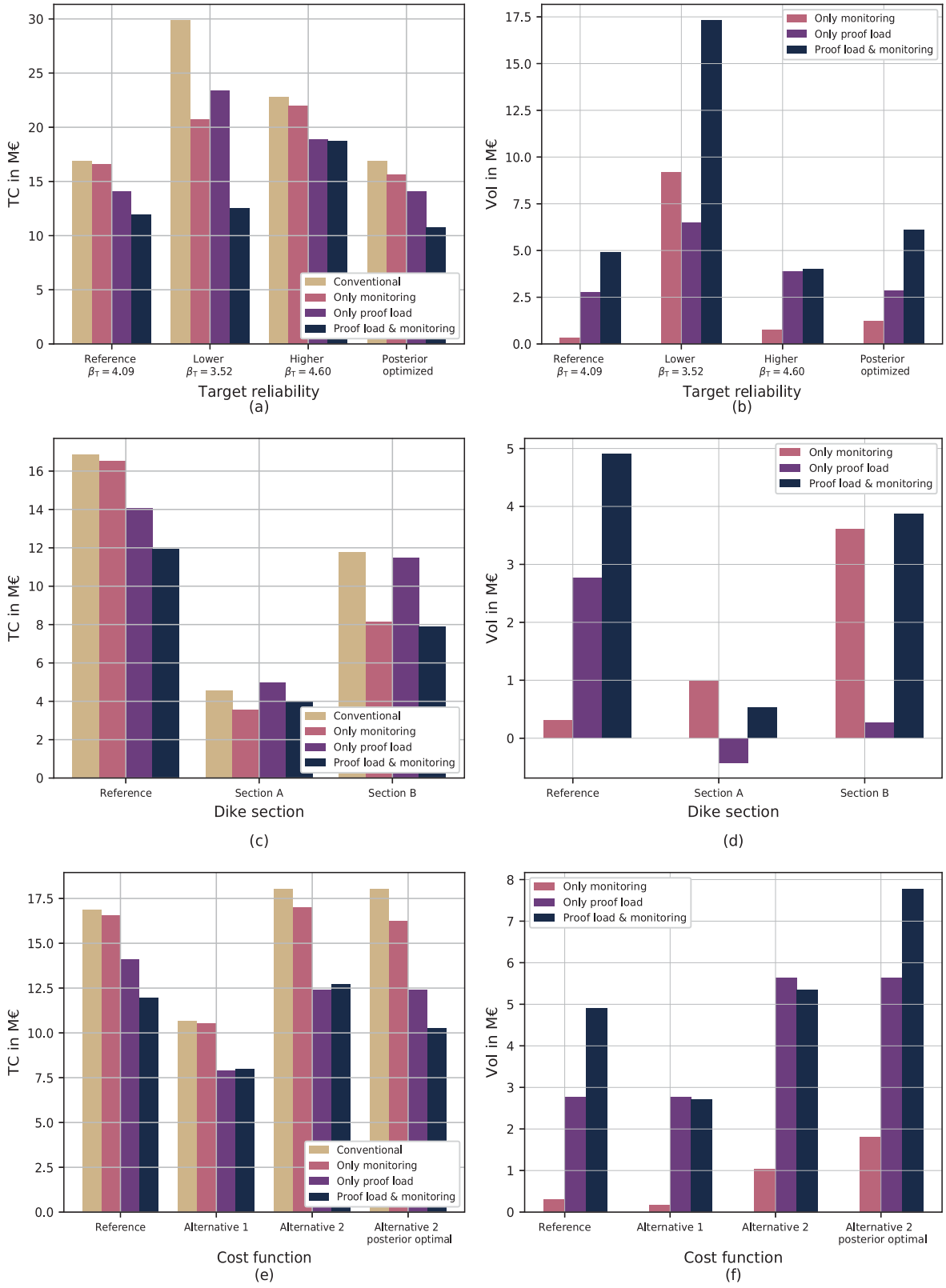

Figure 9. Total Cost and Value of Information for different target reliability values (a and b), for different dike sections (c and d) and for different reinforcement cost functions (e and f). Proof load test level for all strategies is 13.0 m + ref. Conventional strategy has no proof load test and no monitoring.

posterior optimization of the target reliability might yield significant benefits. For these cases it is even so that monitoring without posterior optimization of the reliability target, has a negligible or slightly negative VoI, as the findings are not properly translated into a more optimal design (i.e., the reliability requirement is suboptimal).

5. Towards practical implementation of the framework

The analysis in this paper demonstrates that in most cases some combination of pore pressure monitoring and proof loading yields a positive VoI for dikes that are sensitive to slope stability failures. However, proof loading is not economically efficient in all cases, and in some cases also pore pressure monitoring has very limited benefits. In a practical situation, decision makers therefore have to carefully consider what are the uncertainties that dominate the reliability, and from that determine measures to reduce these uncertainties (if available). For example, the design point (the approach used in this paper, see Figure 8) can provide indications to estimate the relative influence of different uncertain parameters, after which the proposed decision tree framework can be used to structure sequential decisions.

It has to be noted that this paper only slope stability failures are considered, whereas in practical situations there are often multiple failure modes that can be of relevance. This will change the VoI for reduction of uncertainties in slope stability reliability, for instance if an increase in crest level is also required to mitigate risks from overtopping failure. However, the presented framework facilitates such a straightforward extension.

In this paper it is assumed that failure probabilities in different years are uncorrelated. While this is in line with common practice in flood defence reliability analysis, knowledge uncertainties on soil parameters are typically correlated in time. Consequently the future failure probability might be overestimated in cases with large knowledge uncertainty, most notably the case without uncertainty reduction. However, as the failure probabilities are relatively small, the overall effect is expected to be small as well (Klerk et al., 2018; Roubos et al., 2018).

In practice, reliability requirements are often prescribed by law, and are not necessarily derived solely on a local optimization of total cost, for instance requirements to loss of life can also determine the target reliability. The sensitivity analysis in Section 4 shows that this can have a large influence both on Total Cost and on Value of Information. Aside from different target reliability levels that are optimal for prior information, a case where the target reliability level is optimized based on the posterior information after reducing uncertainty is also presented. It is found that this increases the VoI, in particular if the marginal cost of a dike reinforcement varies for different dimensions of the reinforcement (i.e., different increases in berm length).

Specifically for cases with highly non-linear cost functions or jumps in cost functions, a local optimization based on posterior information after uncertainty reduction efforts can increase the effectiveness of uncertainty reduction, and flood risk management in general. The cases in this paper do not explicitly consider a fixed cost component, which could slightly lower the marginal costs. However, if 3 M€ starting costs are added to the reference case the influence on VoI is still minor. Analysing different cost functions is straightforward within the presented framework.

While the influence of several important influential factors is explored, some are not. First of all, repair costs and other costs involved with proof loading can differ significantly depending on the design of the test. For example, damage and repair costs can be much larger than solely costs for fixing the dike itself, for instance if buildings are close by. In addition, there could also be immaterial consequences of a failing proof load test.

Second, it is assumed that proof loading is executed first, and after that pore pressure monitoring. However, in practice it might also make sense to alter the sequence of testing, for instance if it is expected that the outcome of pore pressure monitoring is already sufficient to ensure that the target reliability is met. Such strategies can be incorporated in the presented framework as well.

A third point concerns the inclusion of other methods for uncertainty reduction, most notably carrying out additional site investigation. This paper, in comparison to other decision analysis on reduction of geotechnical uncertainty (e.g., Schweckendiek & Vrouwenvelder, 2013; Spross & Johansson, 2017), does combine multiple sequential uncertainty reduction effects. However, in a practical consideration also other approaches for uncertainty reduction such as additional soil investigation should not be overlooked and included in the analysis if they are found to be relevant based on an analysis of the most influential uncertainties. Next to that, it has to be noted that in this paper does not include potential uncertainty reduction on dike body permeability through a proof load test. This is an assumption that might influence the VoI estimates for the proof load test and in reality at least some information on this permeability might be obtained.

Spatial variability of the dike body in longitudinal direction might hinder the extrapolation of proof load test results from cross-section to dike section. In the present case study, it is assumed that the tested section is representative for the full dike section because of the relatively recent reconstruction of the inner slope. However, in other practical situations, additional site investigation might be required to substantiate the representativeness of the tested section, or else it remains uncertain how to translate the test results to other parts in longitudinal direction. Such site investigation efforts could then also be considered as a step in the presented framework.

Practical applications of pore pressure monitoring might or might not concern cross-sections with a threshold, such as the old clay dike in the cross section considered in this study. If there is not such a clear threshold, including monitoring can be done in a similar manner, although more monitoring outcomes have to be considered than merely (no) observation. Another point of attention is that in this case a useful observation is obtained at a water level that occurs approximately once per 5 years. There might be situations where useful observations are less (or more) frequent, which obviously has an influence on the VoI of pore pressure monitoring. These considerations have been elaborated further in Klerk et al. (2019). The presented

Table 4. Overview of influential factors for decisions on proof loading and/or pore pressure monitoring. Some of these factors are influenceable by the decision maker (e.g., the proof load level), others are autonomous (e.g., amount of geotechnical uncertainty). For each factor a positive impact is named and potential remarks for practical implementation are given.

Influential factors for decision	Positive impact	Remark
Proof load level	Higher proof load, more uncertainty reduction.	The increased risk of failure does not always outweigh the potential benefits, especially if consequential damage is high.
Optimization of target reliability before uncertainty reduction	Can lead to significant reduction of total cost	In practice only possible if economic risk is the governing risk indicator rather than e.g., individual risk.
Optimization of target reliability after obtaining information	Reduction of total cost through inclusion of obtained information in target reliability	If target reliability was already optimized this will only be beneficial in very specific cases where information results in a posterior that strongly differs from the prior.
Larger geotechnical uncertainty	Proof loading is more effective	Pore pressure monitoring might become attractive only after reducing geotechnical uncertainty. It is recommended to determine the sequence of measures based on their relative uncertainty contribution and consider other methods (e.g., site investigation).
Higher construction cost of stability berms	Uncertainty reduction methods are more attractive as the benefits are larger.	Other methods for reinforcement might be more effective.

framework using a decision tree approach does facilitate adding additional outcomes or changing the threshold level.

6. Conclusions

This paper demonstrates the applicability of a decision tree framework in a sequential application of methods for reduction of geotechnical uncertainty. This framework can answer the question under what conditions to invest in different measures to reduce uncertainty for a dike section. The considered uncertainty reduction measures are a proof loading, which consists of artificially infiltrating the dike body with water and thus increasing the phreatic level in order to reduce uncertainty in soil properties, and pore pressure monitoring to reduce uncertainty in the response of the phreatic level to extreme hydraulic loads.

It is found that a strategy consisting of a proof load test and/or pore pressure monitoring has a positive VoI. The effectiveness of both methods depends greatly on the specific case. The relative reduction in total cost for all cases considered in this paper is $>18\%$, of which the main contribution is a reduction in construction costs. However, the optimal strategy is not the same in all cases. Proof loading is most beneficial for cases where the uncertainty in soil properties is dominant and where the initial reliability is relatively low. Obviously the potential benefit must outweigh the additional risk of a failing proof load test and its costs. Pore pressure monitoring is most beneficial for cases where the uncertainty in the phreatic response is dominant.

Additionally, the influence of several factors is considered through a sensitivity analysis. The main findings are enlisted in Table 4, together with practical advice and remarks for implementation. For example, it is found that the choice of the target reliability requirement has a large influence on the estimate of the VoI. Therefore it is important that reliability requirements are adequately chosen, either by economic optimization or by other (optimized) requirements (e.g., Individual Risk). Only then the value of measures to reduce uncertainty can be quantified properly. Typically target reliability requirements are determined upfront (i.e., before monitoring and or proof load testing), but in this paper it was also considered whether optimizing reliability requirements after obtaining additional information improves decisions. It is found that this is typically the case, which is in line with the findings that a suboptimal choice of reliability requirements can obscure the results of the Value of Information analysis.

Decision makers can determine which measure might be worthwhile to consider in a VoI analysis by first identifying the dominant uncertainties determining the probability of failure. For example, plotting the conditional failure probability in fragility surfaces (as demonstrated in this paper) is found to be an effective and practical approach in identifying whether the soil properties or pore pressure are the dominant uncertainty; and thus whether to invest in proof loading or pore pressure monitoring. It was also shown that, in cases with large geotechnical uncertainty, the value of monitoring increases after a proof load, which demonstrates the relevance of considering multiple methods for uncertainty reduction in a single decision tree. In case other failure modes also have a significant contribution to flood risk, it is recommended to extend the approach to include these failure modes in the analysis.

Overall, this work puts in evidence to decision makers the criticality of carefully considering how and which uncertainties can be reduced, is essential in achieving efficient flood defence asset management.

Notations list

a	decision on dike reinforcement design action (berm length)
a_{p}	response factor of the phreatic level to flood water levels
c	cost for each step in the decision tree (decision and outcome)
c_0	total cost of the reference case (without proof loading and monitoring)
d	decision rule
f	probability density function
g	performance function
h	water level
h_{thresh}	threshold water level from where valuable measurements are obtained

m	decision whether or not to invest in pore pressure monitoring
$m_{SHANSEP}$	strength increase exponent
p	decision on whether or not to execute a proof load test of a certain magnitude
r	annual discount rate
s_u	undrained shear strength
t	duration of monitoring
$\mathbf{x}$	realization of random variables
z_m	outcome of pore water pressure monitoring (observation of phreatic level reaction to flood)
z_p	observation of survival of a proof load test (at the imposed phreatic level)
$\mathbf{A}$	set of dike reinforcement actions
C	cost components (proof load, monitoring, repair, reinforcement, failure)
D	annual expected damage flooding
F	Failure event
F_S	Factor of safety
I_m	indicator whether monitoring is done
I_p	indicator whether proof loading is done
OCR	over-consolidation ratio
POP	pre-overburden pressure
S	event of survival of a proof load
S	normally consolidated undrained shear strength ratio
TC	total cost
VoI	Value of Information
$\mathbf{X}$	random variables
$\mathbf{Z_p}$	set of all possible outcomes of a proof load test
$\mathbf{Z_m}$	set of all possible outcomes of pore water pressure monitoring
β	reliability index
β_T	optimal target reliability index
θ	performance (failure/no failure)
μ	mean value
σ	standard deviation
σ_p	pore pressure
σ_v	total vertical soil stress
σ'_p	preconsolidation stress
σ'_v	effective vertical stress
φ	critical state friction angle
Φ^{-1}	inverse standard normal cumulative distribution function

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Data availability statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Deltares. (2014). KOSten voor versterking WATerkeringen. KOSWAT, systeemdocumentatie. https://www.helpdeskwater.nl/publish/pages/130414/koswat_v2_3_-_systeemdocumentatie.pdf.

Diamantidis, D., Sykora, M., & Sousa, H. (2019). Quantifying the value of structural health information for decision support: Guide for practising engineers. In *COST Action TU1402*.

Eijgenraam, C., Brekelmans, R., Hertog, D., Den., & Roos, K. (2017). Optimal strategies for flood prevention. *Management Science*, *63*(5), 1644–1656. doi:10.1287/mnsc.2015.2395

Frangopol, D. M., Strauss, A., & Kim, S. (2008). Use of monitoring extreme data for the performance prediction of structures: General approach. *Engineering Structures*, *30*(12), 3644–3653. https://doi.org/doi.org/10.1016/j.engstruct.2008.06.010. doi:10.1016/j.engstruct.2008.06.010

Jongejan, R. B., & Maaskant, B. (2015). Quantifying flood risks in the Netherlands. *Risk Analysis : An Official Publication of the Society for Risk Analysis*, *35*(2), 252–264. doi:10.1111/risa.12285

Jonkman, S. N., van Gelder, P. H. A. J. M., & Vrijling, J. K. (2003). An overview of quantitative risk measures for loss of life and economic damage. *Journal of Hazardous Materials*, *99*(1), 1–30. doi:10.1016/s0304-3894(02)00283-2

Kanning, W., & van der Krogt, M. (2016). *Memo: Pore water pressure uncertainties for slope stability*. http://publications.deltares.nl/1230090_034.pdf.

Klerk, W.J., Kanning, W., & Kok, M. (2018). Time-dependent reliability in flood protection decision making in the Netherlands. *Safety and Reliability – Safe Societies in a Changing World: Proceedings of ESREL 2018*, 3167–3174.

Klerk, W.J., Kanning, W., van der Meer, M. T., & Nieuwenhuis, J. W. (2016). Structural health monitoring in life-cycle management of dikes: a case study in the north of the Netherlands. *Life-Cycle of Engineering Systems: Emphasis on Sustainable Civil Infrastructure: Proceedings of the Fifth International Symposium on Life-Cycle Civil Engineering (IALCCE 2016)*.

Klerk, W. J., Schweckendiek, T., den Heijer, F., & Kok, M. (2019). Value of information of structural health monitoring in asset management of flood defences. *Infrastructures*, *4*(3), 56. doi:10.3390/infrastructures4030056

Koelewijn, A. R., De Vries, G., van Lottum, H., Förster, U., van Beek, V. M., & Bezuijen, A. (2014). Full-scale testing of piping prevention measures: Three tests at the IJkdijk. *Physical Modelling in Geotechnics*, 891–897. doi:10.1201/b16200-124

Ladd, C. C., & Foott, R. (1974). New design procedure for stability of soft clay. *Journal of the Geotechnical Engineering Division*, *100*(7), 763–786.

Li, D.-Q., Zhang, F.-P., Cao, Z.-J., Tang, X.-S., & Au, S.-K. (2018). Reliability sensitivity analysis of geotechnical monitoring variables using Bayesian updating. *Engineering Geology*, *245*, 130–140. doi:10.1016/j.enggeo.2018.07.026

Luque, J., & Straub, D. (2019). Risk-based optimal inspection strategies for structural systems using dynamic Bayesian networks. *Structural Safety*, *76*, 68–80. doi:10.1016/j.strusafe.2018.08.002

Phoon, K. K., & Retief, J. V. (2016). Reliability of geotechnical structures in ISO2394. In *CRC Press* (Issue September). 10.3208/jgssp.KL-1.

Raiffa, H., & Schlaifer, R. (1961). *Applied statistical decision theory*. Boston: Cambridge University Press.

Rijkswaterstaat. (2019). Schematiseringshandleiding Macrostabiliteit WBI-2017 version 3.0, in Dutch.

Roubos, A. A., Steenbergen, R. D. J. M., Schweckendiek, T., & Jonkman, S. N. (2018). Risk-based target reliability indices for quay walls. *Structural Safety*, *75*(January), 89–109. doi:10.1016/j.strusafe.2018.06.005

Schofield, A., & Wroth, P. (1968). *Critical state soil mechanics*. New York: McGraw Hill.

Schweckendiek, T. (2014). *On reducing piping uncertainties: A Bayesian decision approach*. doi:10.4233/uuid:f9be2f7e-7009-4c73-afe5-8b4bb16e956f

Schweckendiek, T., van der Krogt, M. G., Teixeira, A., Kanning, W., Brinkman, R., & Rippi, K. (2017). Reliability updating with survival information for dike slope stability using fragility curves. *Geo-Risk*, 2017, 494–503. doi:10.1061/9780784480700.047

Schweckendiek, T., & Vrouwenvelder, A. C. W. M. (2013). Reliability updating and decision analysis for head monitoring of levees. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, *7*(2), 110–121.

Schweckendiek, T., Vrouwenvelder, A. C. W. M., & Calle, E. O. F. (2014). Updating piping reliability with field performance observations. *Structural Safety*, *47*, 13–23. doi:10.1016/j.strusafe.2013.10.002

Sousa, H., Wenzel, H., & Thöns, S. (2019). Quantifying the value of structural health information for decision support: Guide for operators. In *COST Action TU1402*.

Spross, J., & Johansson, F. (2017). When is the observational method in geotechnical engineering favourable? *Structural Safety*, *66*, 17–26. doi:10.1016/j.strusafe.2017.01.006

Tavenas, F., Mieussens, C., & Bourges, F. (1979). Lateral displacements in clay foundations under embankments. *Canadian Geotechnical Journal*, *16*(3), 532–550. doi:10.1139/t79-059

Thöns, S. (2018). On the Value of monitoring information for the structural integrity and risk management. *Computer-Aided Civil and Infrastructure Engineering*, *33*(1), 79–94. doi:10.1111/mice.12332

Thöns, S. (2019). *Quantifying the value of structural health information for decision support: Guide for scientists*. In *COST Action TU1402*.

van Hoven, A., & Noordam, A. (2018). *POVM Infiltratieproef II -Analyse Infiltratieproef IJsseldijk (in Dutch)*. https://www.povmacrostabiliteit.nl/wp-content/uploads/2019/12/POVM-Analyse-Infiltratieproef-IJsseldijkII_v03-definitief.pdf.

Voortman, H. G. (2003). *Risk-based design of large-scale flood defence systems*. https://repository.tudelft.nl/islandora/object/uuid:31d3672a-0062-465d-b30a-bacc2ed4b79d?collection=research.

Vrijling, J. K. (2001). Probabilistic design of water defense systems in The Netherlands. *Reliability Engineering & System Safety*, *74*(3), 337–344. doi:10.1016/S0951-8320(01)00082-5

Zhang, J., Zhang, L. M., & Tang, W. H. (2011). Slope reliability analysis considering site-specific performance information. *Journal of Geotechnical and Geoenvironmental Engineering*, *137*(3), 227–238. doi:10.1061/(ASCE)GT.1943-5606.0000422

Zhang, L. (2004). Reliability verification using proof pile load tests. *Journal of Geotechnical and Geoenvironmental Engineering*, *130*(11), 1203–1213. doi:10.1061/(ASCE)1090-0241(2004)130:11(1203)