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Climate change in asset management of infrastructure: A risk-based methodology applied to disruption of traffic on road networks due to the flooding of tunnels

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This paper presents a risk-based method to quantify climate change effects on road infrastructure, as a support for decision-making on interventions. This can be implemented in climate adaptation plans as an element of asset management. The method is illustrated by a specific case in which traffic on a road network is disrupted by the flooding of a tunnel due to extreme rainfall.

Novel techniques to describe both probability of occurrence and consequences of an event are integrated into the proposed risk-based approach. To model a typical climate-change related phenomenon, i.e. rainfall intensity-duration, a model using copulas is proposed as well as a method to account for uncertainty using structured expert judgement. To quantify the consequences, an existing quick scan tool is adopted. The method calculates the risk of flooding of a tunnel, expressed in both probability of occurrence and subsequent additional travel duration on the road network. By comparison of this evolving risk to a societally acceptable threshold, the remaining resilience of the tunnel is evaluated. Furthermore, the method assesses the development of the resilience over time as a result of projected climate change. The maximum time-to-intervention is defined as the period up until the moment when the resilience is depleted. By application of the method to a tunnel in two different contexts, i.e. in a regional road network and a highway network, it is shown that the consequences of tunnel flooding may differ by an order of magnitude (25-fold for the example). Using a risk-based decision-making perspective leads to significant differences in the maximum time-to-intervention. In the example case the year of intervention is determined at 2020 for a tunnel in a highway network, while interventions can be postponed until 2140 in a regional road network.

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1. Introduction

Over the years, road authorities have been professionalizing their management and maintenance processes. Amongst others, budget cuts, more efficient organization or economic and environmental trends are the driving forces. Asset management provides a structured approach to efficiently maintain property and support decision-making. Road authorities have implemented this methodology to optimise costs, performance and risks and thereby achieve their organisational goals.

However, climate change, a major contemporary issue, is only starting to be taken into account in management of infrastructure. Increase in both frequency and intensity of extreme weather events associated with climate change pose a potential threat to the future performance of road networks. At the time being, extreme weather already puts a strain on the transportation sector, with annual costs running to €2.25 billion in the European Union alone, mainly related to the road network (Nemry and Demirel, 2012). The primary mechanisms leading to losses are floods and winter conditions. Floods are expected to increase in severity, as a result of intense downpours (Collins et al., 2013), increased river discharges (Dankers and Feyen, 2009) or storm surges (Hunter, 2010). Heavy rainfall, defined as precipitation exceeding 30 mm per day is expected to soar by 15–25% in almost all of Europe by the end of the century, even though overall rainfall will likely decrease in many countries (Jacob et al., 2014). Sea levels are projected to rise by as much as 2 meters (Pfeffer et al., 2008), leading to bigger storm surges. Increased temperature and more freeze-thaw cycles can also incur losses.

Losses to transport infrastructure could be both direct and indirect; in the United Kingdom the 2007 summer floods inferred losses of £191m (about €280m) in road transport alone. 45% of this was direct spending on bridge and surfacing repairs as well as slope stabilisation works, while the remaining sum is the estimated costs due to disruption of traffic. Closure of the M1 motorway for 40 hours was assessed to cost £2.3m (Chatterton et al. 2010). For railways the proportion of direct to indirect damages was estimated to be 29 to 71. Heavy rainfall in Chicago in 1999 caused $48m losses in the railways sector, of which $12m was the cost of train re-routings due to the incapacitation of bridges and tracks (Changnon, 1999).

Dealing with these threats in professional asset management requires a structured approach, in order to quantify the potential effects on the road infrastructure and to assess the efficiency of adaptive measures. Despite extensive research carried out in climate science, the quantification of potential impacts of climate change and extreme weather on transport infrastructure, such as road networks, is a question for ongoing research (Chappin and van der Lei, 2014; Koetse and Rietveld, 2009). Ryghaug and Solli (2009) investigated in depth how climate science is perceived and utilised by road managers in Norway. Besides concluding the need of translating climate science to practically applicable models for road managers, they identify a gap in studies addressing the question of how to handle the potential impacts of climate change and extreme weather events on transportation infrastructure.

In the past years, some studies have addressed the need of quantifying the impact of climate change on transport infrastructure. For example, Chinowsky et al. (2013) determined the influence of climate change on the cost of the road infrastructure on the US focusing solely on pavement replacement. They adapt two climate change scenarios and model only the adaptation costs, i.e. they don’t consider possible alternatives. The software tool IPSS (Infrastructure Planning Support System) is advocated to support a holistic, long-term planning approach and is capable of accounting for several factors, including climate change and flooding effects (Schweikert et al., 2014). The use of scenario analysis reflects the findings of Piyatrapoomi et al.

(2004), who state that this is the predominant methodology applied in risk analysis in the field of infrastructure investments, in opposition to sensitivity analysis or risk-based decision-making. To the knowledge of the authors of this paper, a comprehensive probabilistic approach to quantify climate change impacts on road networks has not been adopted to date.

When dealing with a highly complexity system involving both biophysical and social processes, such as the climate, traditional scientific methods (hypothesis testing) for future predictions have limited use (McLain and Lee, 1996). Adaptive management is a concept allowing for switching between strategies when new information becomes available and has been advocated for as a suitable strategy for dealing with consequences of climate change (Arvai et al, 2006, Thompson et al, 2006, McLain and Lee, 1996) . This approach can be implemented in climate adaptation plans as an element of asset management, where short-term decisions about assets should be linked to the long-term issue of climate change. Asset management decisions are based on cost-optimisation, therefore input parameters for direct application should be monetizable.

In this paper a risk-based methodology to quantify climate change effects on road infrastructure and thereby support decision-making is proposed. The basis of this method is defining the resilience of the considered system. This indicator reflects the amount of time left before an unacceptable situation arises and can be used in climate adaptation plans as an element of asset management.

In probabilistic risk assessment in civil engineering applications, risk is defined as the product of failure probability and consequence (Vrouwenvelder et al, 2000). Failure is understood as a state in which the considered asset or system no longer fulfils its performance requirements.

Risk-based decision-making is concerned with the overall risk and therefore requires good understanding of both failure probability and consequences. Adaptation of this approach to risk in road infrastructure and in specific the inclusion of the effects of climate change has been developed in Huibregtse et al. (2013) and is described in Section 2. The proposed risk-based methodology is illustrated by a test case, where the frequency and effects of flooding of a fictitious tunnel in The Netherlands due to (extreme) rainfall are studied. This variable is influenced by climate change. The possible failure of the tunnel will have a consequence on the functioning of the system, where costs will arise due to increased travel time.

When attempting to determine the influence of climate change on the failure probability of any system, a major challenge is to find a suitable probabilistic model describing this phenomena (Huibregtse et al., 2013). The models in question give results with high uncertainty bounds, while their resolution is not always adequate for small-scale analysis. However, these statistical models are necessary to describe the probability of occurrence of extreme weather events in a quantitative manner. Furthermore, the relation of climate change and extreme weather events is a field of ongoing research (Neumann et al., 2014). Therefore, in Section 3, we demonstrate novel techniques to model climate change in relation to extreme weather events and their impact on infrastructure. The proposed method was developed in addition to existing models of the Royal Netherlands Meteorological Institute, from now on referred to as KNMI, and other meteorological research centres.

To create a fully risk-based model, cost shall be defined in terms of extra travel time due to distortions in the road network, caused by blockage of the tunnel. The extra travel time is calculated utilizing a “quick scan tool” (Verstraeten-Jochemsen, 2013). Extra travel time can be easily monetized using data of road authorities, thus failure consequence expressed in these terms can be applicable in decision-making. The methodology is demonstrated in Section 4.

The results of determining both failure probability and consequences are integrated in Section 5, where the benefits of a risk-based approach are also shown.

Finally conclusions, recommendations and a future outlook are presented in Section 6.

This paper is an extension and update of work previously described by Huibregtse et al. (2013). It introduces important new elements to the methodology described therein: structured expert judgement, joint probability distributions and calculations of indirect losses caused by extreme events. This paper was written within the research program INCAH (Infrastructure Networks for Climate Adaptation in Hotspots), which is part of the Dutch Knowledge for Climate Research Programme. The aim of INCAH is to identify, analyse and model the risks associated with climate change and to provide a solid basis for decision-making on adaptation strategies. The research program addresses both transport and utility infrastructure and covers technical, economical and governance aspects (Bollinger, 2014). It also integrates results from of a number of related roadERAnet studies such as IRWIN, P2R2C2, RIMAROCC and SWAMP (RoadERAnet, 2014).

2. Risk-based methodology to quantify climate change effects

To study climate change related risks, time-dependent variability should be considered. An indicator used for decision-making in time-dependent risk problems is the resilience of the system, which, as defined in this paper, reflects the amount of change the system can accommodate until an unacceptable situation arises. Defining the resilience of the considered system forms the basis of the proposed methodology and is illustrated by a test case. The resilience of the tunnel is calculated by determining the risk of the system and comparing it to the acceptable level of risk. The steps of the risk-based methodology are schematically represented in Figure 1 and elaborated in more detail in the remainder of this section.

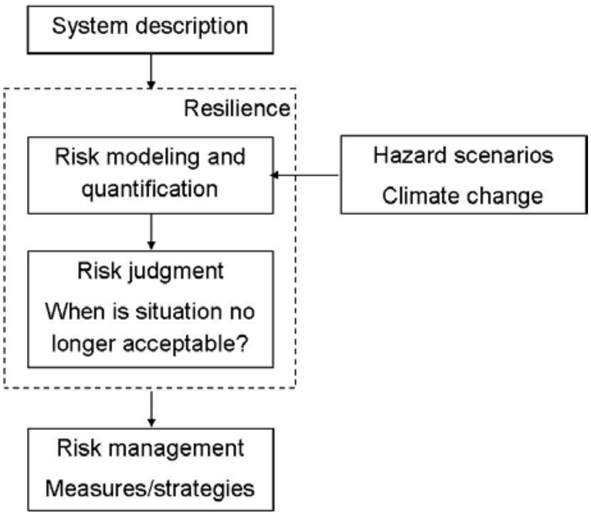

Figure 1. Risk assessment approach

2.1 Hazard scenarios

A hazard is defined as a set of circumstances, possibly occurring within a given system, with the potential to cause events with undesirable consequences. In general, hazard scenarios mathematically describe the likely effect of climate change in terms of relevant parameters.

This study focuses on hazards related to climate change effects in the future. In specific, the effects of extreme rain on the availability of a tunnel are studied. For this case, (alterations in) rain duration and rain intensity are relevant parameters.

In Section 3 it is shown how a joint probability distribution of these two parameters can be derived, which serves as input for the proposed risk-based methodology. To derive this distribution, historic data and climate change scenarios developed by KNMI (KNMI, 2014) are used.

2.2 System description

The system description of a fictitious tunnel is schematically represented in Figure 2. The characteristics of the drainage system in the tunnel are based on an existing tunnel, however, in a simplified format. Rain water is collected at the entrance areas and drained off via the drainage system to the pump cellars, where water is pumped out of the tunnel system. Dimensions of the elements and assumptions regarding for instance the water flow in the drainage system can be found in Huibregtse et al. (2013).

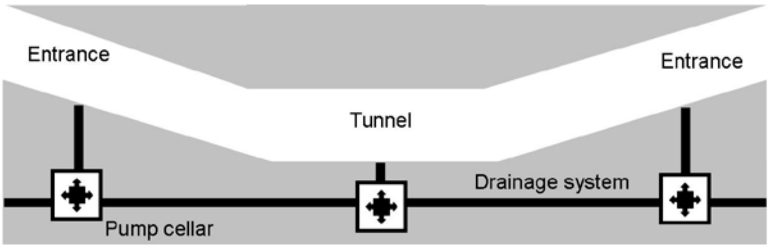

Figure 2. Schematised (not to scale) representation of the tunnel (in longitudinal direction) used as test case. Dimensions can be found in Huibregtse et al.(2013).

2.3 Risk modelling and quantification

In probabilistic risk assessments in civil engineering, e.g. (Vrouwenvelder, 2000), risk is commonly defined as the mathematical expectation of the consequences of failure:

$$Risk = P_f \cdot C \tag{1}$$

where P_f is the probability of failure and C is the consequence of failure. Failure is defined as a state in which the asset or system no longer fulfils its performance requirements.

Probability of failure

The starting point for a quantitative analysis of the failure-probability is the limit state function. This function describes the boundary between the states where the system fulfils its performance requirements (safe domain) and the states where those requirements are not met (failure domain). In this expression the strength of the system is compared to the loads imposed to it, from which the probability of failure can be derived.

For the test case, the limit state (Z) is defined as (Huibregtse et al., 2013):

$$Z = V_{capacity} - \left(A \cdot q_{shower} - Q_{pump} \right) \cdot \Delta t \tag{2}$$

where A is the area where water is collected (m^2) , Q_{pump} is the pump capacity (m^3/min), q_{shower} is the rain intensity (m/min), $V_{capacity}$ is the volume of the pump cellars (m^3) and Δt is the duration of the shower (min).

The capacity of the cellars and the pump capacity represent the strength of the system and are defined in the system description. Similarly, the rain intensity, the duration of the shower and the area where water is collected define the load on the tunnel system. These parameters are given in the hazard scenarios.

The tunnel system fails in case Z is smaller than zero. Thus, the probability of failure P_f equals $P(Z<0)$.

In general, the parameters in the limit state function are random variables, described by (joint) probability distribution functions that express the stochastic nature of these parameters. Given the limit state function and the (joint) probability distribution functions, the probability of failure P_f (for the defined reference period) can be determined by probabilistic calculation techniques, such as Monte Carlo analysis.

In Section 3 it is demonstrated how a joint probability function of the rain intensity and rain duration can be derived by making use of so called copulas. Additionally, it is shown how structured expert judgement can be used to account for time-dependence of the phenomena. These efforts result in the time dependent probability of failure (Pf(t)) as plotted in Figure 3. Note that the strength of the system might also be time dependent, for example the degradation of pumps can reduce the strength of the drainage system over time. In the current study, degradation effects are not accounted for.

Consequences
Consequences are possible outcomes of the failure of an object, expressed for example by the extent of human fatalities and injuries, environmental damage or economic loss. The damage may be expressed for instance in monetary units or in terms of injured or dead per event. In the tunnel case, the consequences will be defined as extra travel time due to unavailability of the road section. This will be illustrated in Section 4.

2.4 Risk judgement
In risk judgement the probability of failure is compared to the acceptable level, in order to determine the resilience of the system. This assessment identifies which resilience the system has at present, how the resilience will develop or diminish over time and at which point in time the resilience will be depleted so that the situation is no longer acceptable. The system resilience can be determined from the combination of the (time dependent) risk quantification and the risk judgement (which may also vary over time). Figure 3 shows schematically how the probability of failure and the acceptable probability of failure are combined to obtain the resilience. The dashed line in Figure 3 represents the acceptable level of probability of failure as determined by authorities. The intersection of the probability of failure and the acceptable level gives an estimation of the time when the situation becomes unacceptable.

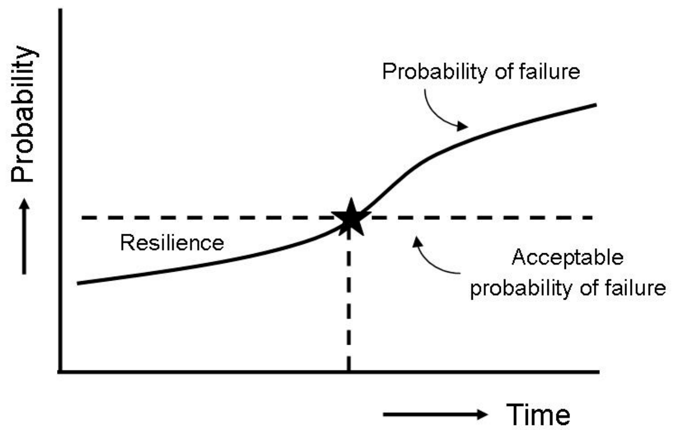

Figure 3. Comparison between the probability of failure of the considered system and the acceptable probability of failure, indicated by resilience (Huibregtse et al., 2013).

The acceptable level of probability of occurrence is a threshold commonly used in decision-making. However, in order to account for the possibly different consequences of failure, it is desirable to use an acceptable level of risk instead. Then, in situations with minimal consequences a higher probability of failure can be accepted, while keeping the risk at or below the acceptable level. The inverse holds for situations with large consequences of failure. As a result, the level of acceptable probability of failure may differ for different assets.

The current resilience of the system is relevant input to develop a plan for measures in the risk management phase.

2.5 Risk management

The resilience of a system gives an indication of when measures are to be implemented in order to prevent an unacceptable situation. In our test case, multiple types of measures can be adopted. First, the probability of failure can be reduced by either increasing the water bearing capacity, installing bigger pump cellars or using stronger pumps. Another option is to prevent rain water from entering the tunnel. Second, the consequences of failure can be reduced. An option is to increase the number of alternative vehicular routes to reduce the extra travel time in case of flooding of the tunnel. Another possibility is to have emergency pump capacity stand-by, to reduce the unavailability-time of the tunnel. These type of measures may result in an adapted acceptable probability of failure.

Both strategies result in an altered system-resilience model and a shifted moment in time at which the requirements are no longer fulfilled.

Determining the resilience of the system as a function of climate change effects and its sensitivity to interventions can be used in climate adaptation plans as an element of asset management.

3. Probabilistic modelling of climate change

To determine probability of failure in terms of flooding of the tunnel in our test case, we use climate data as input for the risk-based model. The required input has to be sufficiently detailed in terms of rain intensity and rain duration of individual showers. Extreme rainfall is often investigated through depth-duration-frequency (DDF) or intensity-duration-frequency curves (IDF). These describe either rainfall depth or intensity as a function of duration for given return periods or probabilities of exceedance. An example is shown in Figure 4.

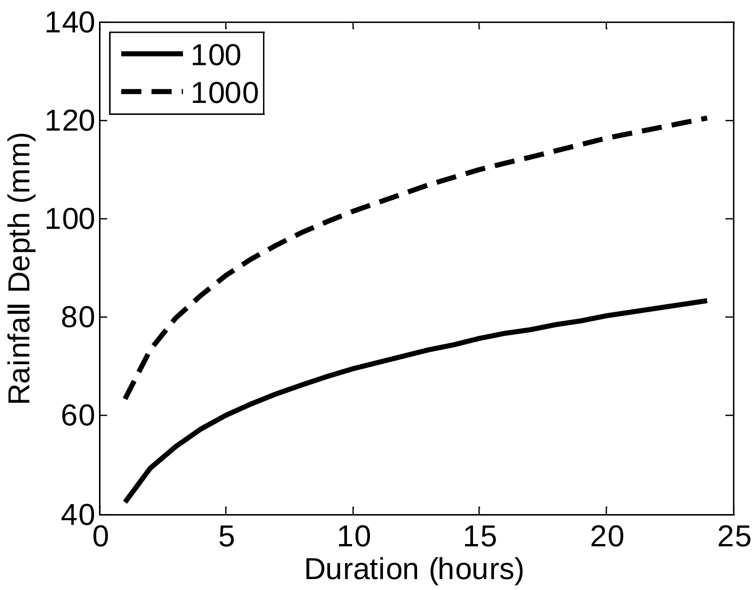

Figure 4. Rainfall DDF curves for 100 and 1000 years return periods (Overeem et al., 2008).

In this section we investigate another approach: how a joint probability function, describing the likelihood of combinations of both intensity and duration of showers, can be derived and applied in the risk-based methodology. This is elaborated in Section 3.1. In addition, the joint probability function is expressed as a function of time, to account for the climate change effects. However, the development of climate change and its effects is very uncertain, with various climate models providing very different outcomes. This is caused by the variety of greenhouse emissions scenarios, model assumptions and inaccuracies, as well as resolution (Kotlarski et al., 2014). None of the models simply outperforms the others, rather each one is good in particular attributes. Inaccuracies in hindcasting, a method of validating the models, are still considerable, especially when modelling precipitation (Knutti and Sedlácek, 2012, Schaller et al., 2011).

Here, the KNMI's climate scenarios, released in May 2014 will be used (KNMI, 2014). These scenarios indicate that precipitation in general and extreme precipitation in particular will soar in the upcoming decades. The amount of winter precipitation, presented in Figure 5, shows uncertainties in the four scenarios around 2050. The G scenarios correspond to an increase in global temperature of 1℃ while the W scenarios to an increase of 2 ℃. L stands for low value changes in air circulation while H to high value changes or the same variable. The mean amount in the reference period is 211 mm for the different scenarios. The following sources of uncertainty are addressed in (KNMI, 2014): a scenario increase factor, natural variations in 30-year averages and year-to-year variations. The uncertainty bars represent roughly one standard deviation from the central estimate assuming sources of uncertainty to be independent. All scenarios differ approximately by a factor of 2.7-2.8 between the lower and upper bounds.

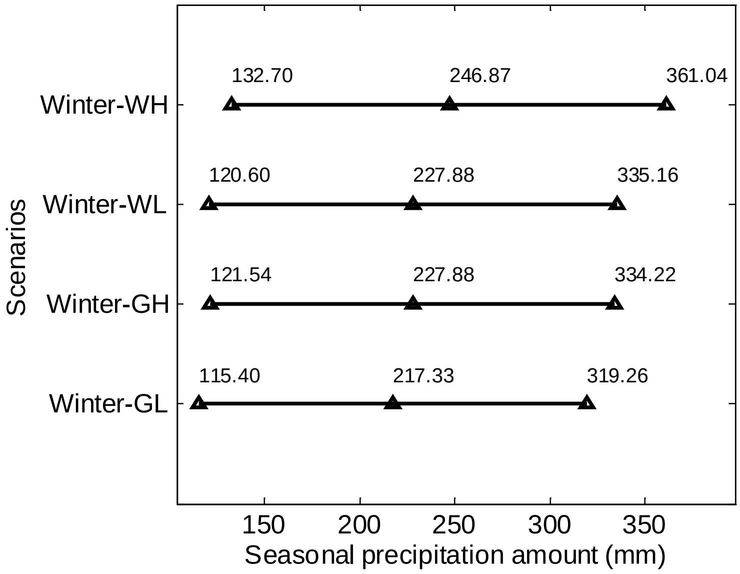

Figure 5. The assessment of KNMI'14 for winter precipitation around 2050. Derived from data in (KNMI, 2014).

As can be seen in Figure 5, even a single assessment of climate change can produce a variety of results. One effective way to account for these type of uncertainties is the use of structured expert judgement (SEJ), presented in detail in Section 3.2. In an expert judgement study uncertainty is considered as an observable quantity. Measurement of this quantity is carried out through an elicitation of experts, who are best suited to filter and synthesise the body of existing knowledge and experimental data. The experts are asked to give their assessments for the variables, e.g. rain intensity and rain duration, in terms of subjective probability distributions, expressing their uncertainty with respect to, for example, the development of these variables or their dependence structure over time (Cooke, 1991). From the derived time dependent joint probability function typical showers are sampled using Monte Carlo simulation, from which the probability of failure of the tunnel as a function of time can be calculated via the limit state function (see Section 2).

3.1 Joint probability function through copulas

Rain intensity in the Netherlands may be derived from data collected by measuring stations of KNMI. There are thirty three measurement stations in the Netherlands where KNMI data concerning rain fall is publicly available. Two variables are measured hourly: rainfall depth (in mm) and the fraction of an hour (in 6 minute intervals) where rain is actually observed.

We are interested in raining periods without interruptions (showers) hence we aggregate the data into two variables: rain duration (hours) and rainfall depth (mm) per shower. Let X_1 be the random variable denoting rain duration (hours) and X_2 the random variable denoting rainfall depth (mm). Rain intensity is then defined as $X_3 = \frac{X_2}{X_1}$, a deterministic function of the previous two random variables, and has units (mm/hours).

Measurements of X_1 and X_2 realise a bivariate probability distribution and may be described through copulas. A bivariate copula is a joint distribution on the unit square with uniform one dimensional margins: $F_{X_1,X_2} = C_\theta\left(F_{X_1}(x_1), F_{X_2}(x_2)\right)$. Notice that C is parameterised by θ. For one parameter copulas, θ may be expressed in terms of usual statistical measures of dependence such as rank correlations. A complete discussion about copulas is out of the scope of the present paper, for this we refer to (Joe, 1997, 2014).

We are interested in finding a low parameter family of copulas that describes adequately the statistical behaviour of showers. The data for the period 1951-2013 at De Bilt transformed to uniform (0,1) through the empirical margins is shown in Figure 6. Spearman's rank correlation coefficient for this dataset is ≈ 0.66. The data present ties (samples realizing the same pair of variables) in the lower tail of the distribution (small values of amount of rain and small values of duration of rain) while it appears that more samples are concentrated in the upper right joint tail of the distribution than elsewhere. That feature suggests upper tail dependence. The upper tail dependence coefficient is defined as:

$$\lambda_u = \lim_{u\to 1} P\left(X_1 > F_{X_1}^{-1}(u) | X_2 > F_{X_2}^{-1}(u)\right) \quad (3)$$

When such characteristics are present in the data, it is most of the times important to model them.

In order to corroborate the existence of upper tail dependence for the random vector (X_1, X_2), firstly, the so called 'Blanket Test' as discussed in (Genest et al., 2009) has been performed. The test is based on the Cramèr- von Mises (CVM) statistic.

The test statistic of interest may be computed for a sample of length n as:

$$CM_n(\boldsymbol{u}) = \sum_{|\boldsymbol{u}|}\left\{C_{\hat{\theta}_n}(\boldsymbol{u}) - B(\boldsymbol{u})\right\}^2, \ \boldsymbol{u} \in (0,1)^2 \quad (4)$$

where $B(\boldsymbol{u}) = \sum_{i=1}^{2} 1(U_i \leq \boldsymbol{u})$ is the empirical copula and $C_{\hat{\theta}_n}(\boldsymbol{u})$ is a parametric copula with parameter $\hat{\theta}_n$ estimated from the sample. Notice that the statistic is the sum of squared differences between the empirical copula and the parametric estimate. We compute the CM statistic for the Gaussian (no tail dependence), Gumbel (upper tail dependence) and Clayton copulas (lower tail dependence). For the data in Figure 6, the value of the test statistic (sum of squared differences between the theoretical model and the empirical copula) for Clayton, Gumbel and Gaussian copulas was respectively 5.46, 4.33 and 4.42, while the respective p-values were 0.05, 0.097 and 0.082. By using the CVM test, it is evident that the Clayton copula is not the preferred model for this data. It is also difficult to distinguish between The Gaussian and Gumbel copulas as a fair model for this data based on the same test.

Other diagnostic tools called semi-correlations are suggested in Joe (2014). The semi-correlations are the Pearson's product moment correlation coefficients computed in the upper and lower quadrants of the normal transforms of the original variables. For positive correlation

$$\rho^{NE} = \rho(Z_1, Z_2 | Z_1 > 0, Z_2 > 0) \text{ , and,} \quad (5)$$

$$\rho^{SW} = \rho(Z_1, Z_2 | Z_1 < 0, Z_2 < 0) \quad (6)$$

where (Z_1, Z_2) are the standard normal transforms of (X_1, X_2). For negative correlation ρ^{NW} and ρ^{SE} are defined similarly (Joe, 2014). Roughly, larger values of the semi-correlations than the "overall" correlation indicate tail dependence. For the data in Figure 6 the Pearson's product moment correlation is ≈ 0.69 while $\rho^{NE} \approx 0.68$ and $\rho^{SW} \approx 0.24$. The semi-correlations indicate thus a preference for a model with upper tail dependence. Finally if we were to approximate the tail dependence coefficient (λ_u) for this data by letting u = 0.95 we would find

$$P\left(X_1 > F_{X_1}^{-1}(0.95) | X_2 > F_{X_2}^{-1}(0.95)\right) \approx 0.68 \tag{7}$$

The same probabilities estimated from a Gaussian and Gumbel with parameters estimated from the data in Figure 6 are 0.38 and 0.60 respectively. The Gumbel copula underestimates the exceedance probability of interest though to a much lesser degree than the Gaussian copula. In general a similar pattern as the one describe above is observed for all the measurement locations in the Netherlands.

Based on these statistical analyses it is concluded that the Gumbel copula is an appropriate model for the joint probability distribution for rainfall amount and duration, which describes the upper tail dependence observed in the data. The Gumbel copula is a one parameter copula. From this joint probability distribution showers are sampled by a Monte Carlo analysis, from which the probability of failure can be calculated (see Section 2). In the next section we will show how structured expert judgement can be applied to adjust the parameter of the copula to represent climate change and how the uncertainties are taken into account.

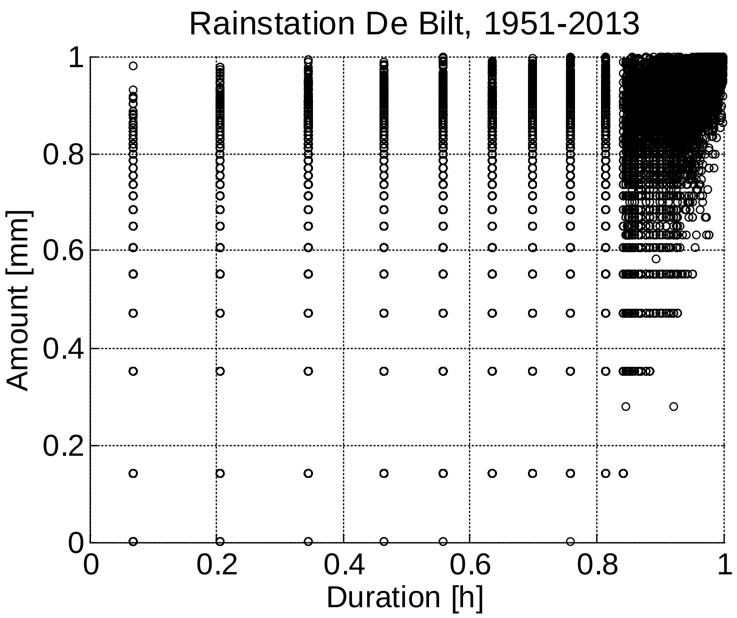

Figure 6. Pseudo observations rain intensity.

The Gumbel copula is an appropriate choice within one parameter copula families for rainfall modelling. It is however worthwhile to investigate other two or three parameters copula-families, which could improve further the description of the data. Desirable properties to include would be tail dependence in the upper right quadrant and skewness towards the upper left quadrant. Notice that in this case the most critical rain intensity is observed with samples in the upper left quadrant. Tail dependence in this case is a desirable property of the data in the sense that very high rainfall depth would occur also over very long periods of time. These refinements of the model are recommended for future research.

3.2 *Modelling climate change through Structured Expert Judgement*

The Gumbel copula described in the previous section, together with the one dimensional margins describe the statistical dependence between rain amount and rain duration. Due to likely climate change, the parameterization of the joint distribution in the future is uncertain. From the asset management perspective, insights in these uncertainties are valuable information for optimising planning of maintenance.

Therefore, for our tunnel case, we are looking for a description, including uncertainty, of the dependencies between the change of rain intensity (or amount of rain) and change of rain duration as a function of time (see the previous section).

One option to account for uncertainties in future scenarios is through Structured Expert Judgement. Structured Expert Judgement (SEJ) has been widely used in uncertainty analysis and could be a suitable way to model these uncertainties in likely climate changes for the future. The main feature of the classical model for SEJ is that experts are evaluated as uncertainty assessors through so called "seed" or "calibration" variables. Experts performing better on the set of seed variables will have higher weight on a pooled opinion. See for example (Cooke and Goossens, 2008) where an account of the use of the classical model for SEJ on 45 studies is presented. Fields of application include nuclear, chemical and gas industries, groundwater/water pollution, dike ring barriers, aerospace sector, occupational sector, health, banking, volcanoes, dam safety and others. SEJ has been recently used in the context of climate change to model future sea level rise from ice sheets (Bamber and Aspinall, 2013; Cooke, 2013).

In a typical SEJ elicitation experts are asked for their estimations on one dimensional distributions. With respect to rain intensity, an example could be an estimation of the amount of winter precipitation up to 2050. The answers are typically expressed in quantiles like 5%, 50% and 95%. Although the majority of the literature on SEJ is dedicated to one dimensional distributions, techniques for elicitation of higher dimensional distributions are being explored, for example by the elicitation of statistical dependence.

According to expert's answers, the parameters or one dimensional margins of the underlying model for climate change scenarios may be inferred under the Gumbel copula assumption. However, an equivalent approach might be used for the assessment of IDF curves by experts. In that case, in the exercise one could ask for different pair of points on an IDF curve similar to Figure 4.

Notice that through this exercise, insight on whether the underlying dependence model has changed (or not) may also be obtained. In other words insight on whether climate change affects the parameters of the underlying statistical model or the underlying statistical model itself may also be obtained.

4. Modelling consequences – quick scan road network

In general, the performance, as well as the consequences of failure of infrastructure is expressed in terms of four aspects: Reliability, Availability, Maintainability and Safety (RAMS)(Stapelberg, 2009). In this paper we focus on the non-availability of the tunnel due to flooding. We express non-availability in terms of extra travel time, as this is an important cost factor as indicated in the introduction of this paper. In this section a quick scan tool (Verstraeten-Jochemsen, 2013) is demonstrated that calculates the amount of extra travel time due to distortions in the road network. This tool is used to determine the extra travel time due to flooding of the tunnel in the main route.

The tool uses a simplified network consisting of a main route and two alternative routes. When the travel time on the main route increases, for example due to closure of a tunnel, traffic will switch to the alternative routes, leading to extra travel time on the network. To calculate the extra travel time, the quick scan tool compares the normal total travel time with the travel time including distortions.

The normal total travel time on the network depends on amongst others the road length, road capacity, traffic volumes, the allowed- and the actual speed. The actual speed depends on the intensity/capacity ratio, as speed will decrease on busier roads. Combining the road lengths and actual speeds gives the time on the network per car. The total travel time can be calculated by taking the sum of the time on the network for all cars.

The travel time with the distortions is found by closing the main route and re-routing the cars to the alternative routes. The impact depends on the duration of the closure, which leads to additional travel times on the alternative routes. Again, the total travel time is calculated by taking the sum of the travel times for all cars on the network, but now with distortion.

The quick scan provides planners with first estimations of consequences of distortions in the network. As the model is simplified compared to real networks, the impact on the network in reality would be different. The alternative roads will get too busy and new alternatives will be used; i.e. the total network gets affected. The quick scan neglects this possibility. In addition, the quick scan model uses a waiting queue model for the main road, meaning that in case it gets too busy, it will take more time before a car starts driving and reaches the end of the trajectory. This waiting queue model is not implemented for the alternative roads. Additional travel time on the alternative routes is calculated by taking the intensity/capacity ratio into account. However, in case more detailed analyses are required, results of the quick scan can be further analysed with high-end dynamic traffic models that use bigger and more complex networks, for example as described in (Snelder, 2011).

To demonstrate the application of this tool in relation to unavailability of a tunnel due to flooding , two cases were considered. The cases illustrate a highway and regional road situation, respectively. The traffic volumes are derived from real highway and regional roads in the Netherlands. These are approximately 38,000 and 5,000 vehicles per day (one way), respectively (see also Table 1). In these cases the main route is closed for one day, simulating a flooded tunnel in this road section.

Table 1. Input and output of quick scan tool for extra travel time due to flooding of a tunnel in a highway and a regional way.

Road characteristics (one way)		
	Highway	Regional road
Traffic volume (vehicles/day)	~38,000	~5,000
Undisturbed travel time [hour]	13,000	3,600
Disturbed travel time [hour]	23,000	4,000
Δ travel time [hours]	10,000	400
Δ travel time [%]	77%	11%

From Table 1 it follows that for the highway case the travel time increases with approximately 10,000 hours in case of flooding, or 77% with respect to the undisturbed situation. For the regional case an increase of 400 hours travel time or 11% results. This implies that the consequences of failure are a factor 10,000/400 = 25 higher on the highway than on the regional road, given that travel time on regional roads is as valuable as it is on highways. Note that costs of for instance draining the water from the tunnel and repairing damages to specific installations are not taken into account.

5. Risk-based decision-making

To calculate the risk of flooding of a tunnel due to extreme rain, both the probability of failure, in terms of unavailability due to flooding of a tunnel, and the consequences of failure have been studied in the foregoing sections. Studies on the probability of failure as a function of time will increase the accuracy of the continuous line in Figure 3. Studies on the consequences of failure will provide insights to the acceptable probability of failure (the dashed line in Figure 3).

In Section 4 it was calculated that the travel time in a highway scenario increases by a factor of 25 compared to the travel time in a regional road scenario, in case the main road is blocked due to flooding of a tunnel. When aiming for a comparable risk in both situations, the acceptable probability of failure of tunnels in regional roads can be adapted, in this example with a factor 25. This leads to the situation sketched in Figure 7. Increasing the originally acceptable probability of failure (1/250 years) with a factor 25 results in an acceptable probability of failure of 1/10 years, resulting in an equal level of risk for the highway- and the regional road scenario. Following from Figure 7, this leads to extra time (or a shift in the resilience of the tunnel) before the performance of the tunnel in the regional road system becomes unacceptable. In this example the time horizon of necessary intervention shifts from 2020 to 2140, underpinning the value of analysing an (apparently critical) situation from a risk-based perspective. Using this approach, additional time can be gained to define appropriate measures, in comparison to using a single requirement for acceptable failure probability which doesn't account for lower consequences.

Over time new models will be developed and additional climate change data will become available, which is expected to lead to new insights into the impact of climate change on stressors of infrastructure systems, such as extreme precipitation. Accordingly, the curve describing the probability of failure over time will be adapted.

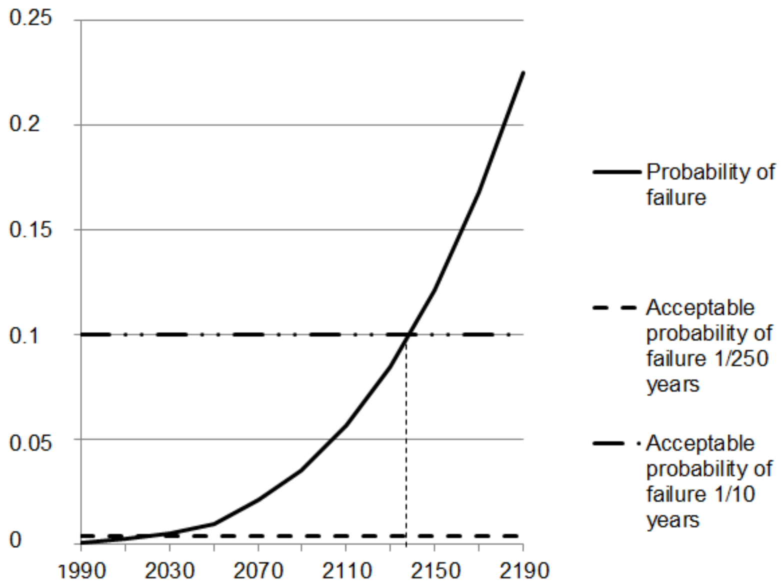

Figure 7. Probability of failure of the drainage system in the tunnel under climate change scenario compared with acceptable levels of risk.

6. Conclusions

In this paper a risk-based method to quantify climate change effects on infrastructure has been presented and illustrated by a specific case, i.e. the consequences of flooding of a tunnel on a road network. Quantifying these effects is of importance for the maintenance and management processes of infrastructure.

It was shown how, using the proposed risk-based method, the resilience of an infrastructural system can be determined, providing insight into the time window before measures have to be taken to avoid a critical situation.

Two elements of probabilistic risk assessment have been elaborated, the probability of failure and the consequences of failure.

The probability of failure in terms of flooding of a tunnel was assessed in more detail by developing a joint probability function (copula) as a function of time. We have concluded that the Gumbel copula is an appropriate choice for rainfall modelling within one parameter families. To determine the input required to model the possible future climate effects (for example in terms of marginal distributions, or the dependence between variables), structured expert judgement (SEJ) is suggested as technique to account for uncertainties.

For future research it is recommended to investigate multiple parameter copula-families, which may be more suited to describe rain data. In specific, tail dependence in the upper right quadrant and skewness towards the upper left quadrant are aspects that may be covered with these types of copulas.

The consequences of failure were quantified by making use of a quick scan traffic model. The results indicated that the consequences in terms of extra travel time can differ by an order of magnitude (in the example, a factor 25) between highway and regional road situations.

The combination of failure-probability and consequence of failure leads to a quantified description of the risk of flooding of the tunnel. In the test case it was demonstrated that the acceptable probability of failure could be significantly increased for tunnels in regional roads, assuming that in both scenarios an equal risk is acceptable. This has shown how an analysis from a risk-based perspective can lead to a more rational evaluation of an apparently critical situation. In some cases additional time may be available to define appropriate measures.

For future research it is recommended to review the quick scan model and add extra functionality, e.g. extending network modelling capabilities and a waiting queue model.

In this paper it was shown how the resilience of the system can be derived as a function of likely climate change. Over time, new insights are expected to lead to a shift in the resilience model, including its uncertainty. An adaptive management approach is expected to be a beneficial strategy to deal with this model uncertainty. For instance, flexible maintenance planning can be carried out using the proposed risk-based model, where the resilience function is adapted when new information becomes available. Embedding the proposed strategy as an element of asset management will allow authorities to account for climate change related effects in a rational way, taking into account currently available information.

The proposed approach was illustrated by calculating the effects of extreme rain on the availability of a tunnel.

The risk-based methodology provides a framework that can be extended to assess the performance of infrastructure as a function of the broad range of climate change effects. We believe that enriching asset management with taking into account the resilience of infrastructure as function of climate change effects will contribute to optimisation of risks, costs and performance of infrastructure.

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