Simulated climate adaptation in stormwater systems:
Evaluating the efficiency of adaptation pathways

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A range of strategies is available to infrastructure managers attempting to adapt to climate change. As more system managers have become convinced, by current trends or projected future change, of the need for some explicit adaptive posture, studies of alternative adaptation strategies have attracted interest and evoked studies providing initial foundations for evaluating their relative efficiency and efficacy. In this paper we apply exploratory policy modeling and to a testbed of simulated stormwater infrastructure to examine the efficiency of alternative adaptation pathways. The analysis is aimed at two main questions: (1) how do adaptation strategies with different timing qualities perform with varying crossing characteristics and climate change trends? and (2) can system characteristics be used to predict the preferred strategy based on cost, and if so, how much better are predictions when climate change is known?

Adaptation Strategies

The climate change adaptation literature, back to at least the early 1980s (Kates, 1985), offered simple classifications of the type and timing of adaptation: reactive, concurrent, or

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1 Corresponding author. AM developed the model and ran the simulations and prepared the first draft of results. AM and WT jointly conceived of the analysis, and jointly prepared the final paper.
anticipatory (Smit et al., 2000). Other distinctions evolved, including incremental adaptations that adjust systems but leave their overall structure in place, and transformative adaptations that fundamentally alter system organization, scale, location or goals (Kates et al., 2014). Recent attention to extremes, in concert with continuing uncertainty about future climate change, has yielded a notion that some adaptations could be counted as no regret. No regret options pay off by better adapting systems to current risks while also providing adaptive benefit as the future climate unfolds (Dilling, Daly, Travis, Wilhelmi, & Klein, 2015; Field et al., 2012; Thomalla, Downing, Spanger-Siegfried, Han, & Rockström, 2006). A more subtle framing replaces adaptation with resilience. Traditionally defined as a system’s ability to recover after a shock without transforming, resilience has been elaborated into a more inclusive property of systems characterized by measures of preparation, absorption, recovery, and adaptation (Linkov, et al., 2013), especially in the face of unpredictable stresses (Sikula et al., 2015). Other approaches explore elaborated adaptation “pathways”, recognizing the dynamic, time-transgressive nature of adaptation to trends that affect system performance, and account for learning and revision, over the long term (Haasnoot, Middelkoop, Offermans, Beek, & Deursen, 2012; Wise et al., 2014). Finally, adaptation is increasingly evaluated with the tools of risk and decision analysis that search for the points at which systems fail (Brown, Ghile, Laverty, & Li, 2012), seek dynamic optimization (Kasprzyk, Nataraj, Reed, & Lempert, 2013; Jan H. Kwakkel, Haasnoot, & Walker, 2014), maintain future options (Hallegatte, 2009; Hultman, Hassenzahl, & Rayner, 2010; Jones & Preston, 2011; Moss et al., 2014), provide robustness (Lempert, Popper, & Bankes, 2003), or explicitly value future options (Woodward, Kapelan, & Gouldby, 2014).

One common component of the contemporary adaptation literature is a grappling with the persistence, despite progress in climate science, of deep uncertainty associated with climate
change projections. This weighs against a “predict-and-act” approach, and supports proposals for dynamic decision strategies that emphasize continual learning and revision (Walker et al., 2003; Walker, Haasnoot, & Kwakkel, 2013). In the climate change context, these techniques have mostly been applied to planning large, integrated systems characterized by a diverse option space and low tolerance for failure. The two most common applications have been in water supply systems and coastal flood protection. However, managers of more dispersed systems also need to adopt climate adaptation strategies. Given a commitment to adapting to climate change, the universal questions abide: what to do and when to do it? We test answers to these questions with exploratory modeling analysis (Bankes, 1993) applied to climate-sensitive infrastructure via a virtual testbed of simulated stormwater conveyance structures.

**Evaluating Adaptation in Dispersed Stormwater Infrastructure**

Runoff must be conveyed across or through road alignments in some way or it will impound against, and perhaps wash out, the roadbed. The most common device, referred to in this paper as a crossing or culvert, is:

….a conduit which conveys stream flow through a roadway embankment or past some other type of flow obstruction. Culverts are constructed from a variety of materials and are available in many different shapes and configurations. Culvert selection factors include roadway profiles, channel characteristics, flood damage evaluations, construction and maintenance costs, and estimates of service life. (Federal Highway Administration, 2012, p. 15).

Some culverts pass permanent streams under roads, while others are emplaced to convey stormwater or peak flows caused by short-term, intense rainfall or snowmelt. All are designed, more or less formally, with a peak discharge in mind, and sized accordingly. With design lives of
up to 100 years (Maher, 2015) and actual service lives sometimes greater than 120 years (J. Meegoda & Zou, 2015), crossing capacity is sensitive to climate change. Deep-fill culverts, with 10-20 or more feet of cover, are extremely expensive and disruptive to replace and thus counted on to perform for several decades.

A variety of adaptive strategies remain available for such systems. One soft strategy is to relax expectations, reckoning that performance marginally outside nominal limits, perhaps routine incursion into what were originally defined as safety buffers, is acceptable during some period after climate change has moved the system out of specification and before the structure can be upgraded. Accepting more frequent “graceful failures,” like temporary impoundment or over-topping road surfaces, may be less costly and less disruptive than active adaptation.

Shortening the lifespan of infrastructure to reduce the decision horizon, another generic strategy for adapting to uncertain climate change (Hallegatte, 2009), may be poorly suited to the case of road beds and culverts due to the fixed cost associated with each replacement, though it might apply to the smallest devices and lowest service levels (as with driveways or backcountry roads). Such strategies are problematized, but perhaps also incentivized, by the difficulty of discerning the effect of climate change from natural variability in something as noisy as extreme precipitation (National Academies of Sciences, Engineering, and Medicine, 2016).

With dynamic options limited, robust strategies often mean installing a larger crossing with greater capacity than traditional minimum specifications. This strategy can be inefficient, and invokes the potential, rarely analyzed in climate change literature, for over-adaptation or adapting sooner than necessary (De Bruin & Ansink, 2011). Over-adaptation in one area reduces resources available for other adaptations or future unforeseen consequences, possibly reducing overall adaptive capacity (Smit & Wandel, 2006).
We explore options for when to adapt using a virtual testbed of road crossings, and test an adaptation typology common in the literature (Smit et al. 2000), including anticipatory, concurrent, and reactive, along with the nominal (no adaptation) case in which culvert capacity is not increased even when destroyed by extreme runoff. Rather than focus on the climate change forcing, we examine the efficacy of basing decisions on the more reducible uncertainty associated with characteristics of the crossings themselves, such as cost of damage or difficulty of upgrading a culvert, “which influence their propensity to adapt and/or their priority for adaptation measures” (Smit, Burton, Klein, & Wandel, 2000, p. 14). We then compare the influence of these characteristics to influence of changes in flood frequency and total cost. We address these dimensions with two main research questions:

1. How do adaptation strategies with different timing qualities perform with varying crossing characteristics and climate change trends?

2. Can system characteristics be used to predict the preferred strategy based on cost, and if so, how much better are predictions when climate change is known?

Methods

We created a virtual testbed of culverts whose performance and costs can be simulated over specified timespans, henceforth referred to as the “culvert model” or simply the testbed. Our model follows the tradition of an exploratory tool for policy analysis, focusing on computational experiments to explore possible futures rather than a consolidative model acting as a surrogate for actual systems (Bankes, 1993; Jan H. Kwakkel, Walker, & Marchau, 2012). In other words, the culvert model is a ‘what-if’ tool rather than an attempt to predict future conditions, though it simulates actual culverts. The testbed structure is meant to provide for changing and enlarging the assemblage of simulated culverts, their crossing characteristics, and the external stresses.
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applied (Francis, Falconi, Nateghi, & Guikema, 2011). Simulation results include individual and aggregate cost of flood damage, cost of normal and emergency construction, cost of delay hours, and the number of replacement events over a simulated life span. The model was written in the R programming language (see: R Project for Statistical Computing (Venables & Ripley, 2002)).

**Climate Scenarios**

We intersect crossing characteristics and climate change using a scenario approach (Schwartz, 1996) for climate trend. Changes especially in precipitation intensity, if not overall amounts, have the potential to stress stormwater infrastructure and result in premature failure and increased operating cost (Neumann et al., 2014). While climate change projections for impact and adaptation studies can be derived from global climate model output, we follow the approach of several infrastructure researchers and apply a feasible, though simple, climate trend guided by model output and climatological logic. Climate model output comes with deep uncertainty and a mismatched scale, large multi-thousand-member ensembles (e.g. those available from [http://www.climateprediction.net/](http://www.climateprediction.net/)) which explicitly resolve regional details have shown climate sensitivity (mean temperature response to a doubling of CO$_2$) ranging from 2° K to 11° K (J. H. Kwakkel, Haasnoot, & Walker, 2012; Stainforth et al., 2005). There is additional concern that changes in the many initial parameters can have large and unknowable effects on long term simulations (Bradley, Frigg, Du, & Smith, 2014), and that model outputs downplay extremes (Jones & Preston, 2011). In light of these concerns we followed other decision researchers and used a scenario based approach to climate change aimed at capturing broad uncertainty (Hulme, Pielke, & Dessai, 2009; Hultman et al., 2010; Kunreuther et al., 2013; Kwadijk et al., 2010; Jan H. Kwakkel et al., 2014; J. H. Kwakkel et al., 2012).
Our climate scenarios do reflect meteorological logic and climate change modeling. Climate models show increases in precipitation totals and intensification of individual events on the global scale, especially in higher-latitudes, over the coming century of anthropogenic warming (Tebaldi, Hayhoe, Arblaster, & Meehl, 2006). Significant precipitation intensification has already been observed in the latter half of the 20th century (Donat, Lowry, Alexander, O’Gorman, & Maher, 2016; Groisman et al., 2005), including in the north-central and northeastern sectors of the U.S. (Walsh et al., 2014; Romero-Lanko et al., 2014). But, reflecting the tendency of model outputs to vary with scale, down-scaling to Colorado yields results that point both to intensification of heavy precipitation events (Mahoney, Alexander, Thompson, Barsugli, & Scott, 2012; Tebaldi et al., 2006) and no significant change (Alexander, Scott, Mahoney, & Barsugli, 2013; Mahoney, Alexander, Scott, & Barsugli, 2013). Rather than using specific or ensemble climate models in our simulations we vary changes in precipitation frequency/intensity continuously over a plausible range as described below.

**Constructing the Crossing Test Bed**

Data on culverts is more difficult to obtain than for bridges. Other stormwater researchers confirm this, finding that most transportation infrastructure agencies do not have a centralized system for tracking culvert installations and condition (Jay Meegoda, Juliano, & Tang, 2009), except as they are specified in construction bids and plans. A recent survey found that 60% of road infrastructure management agencies in the U.S. did not keep systematic data on culverts (Maher, 2015). Analysts thus turn to hypothetical examples (Mailhot & Duchesne, 2009), or to specific crossing cases, often ones brought to the fore by recent failure (Gillespie et al., 2014). We used construction bid and project records for actual crossings in Colorado to choose a set of crossing characteristics to populate our testbed. By including a range of system characteristics,
we varied the ease of adapting crossings, the consequences of crossing failure, and crossing sensitivity to increased flows.

**Fixed Crossing Characteristics**

To assign realistic characteristics to the crossings in our testbed, we selected eight recent culvert replacements bid by contractors for the Colorado Department of Transportation (CDOT) (Colorado Department of Transportation, 2016a). The cases include all of the costs associated with replacement, such as removal of previous structures, excavation and fill, mobilization, and paving. We characterize each crossing using the following variables: crossing road, design flood, material, service life, replacement delay (days with reduced traffic capacity or speed due to replacement), and cost. We review these variables in detail below and list their values in table 1, along with the actual install dates for the culverts on which the results reported here were based.

**Table 1-Fixed Crossing Characteristics**

<table>
<thead>
<tr>
<th>County</th>
<th>Road</th>
<th>Design Storm</th>
<th>Material</th>
<th>Design Life</th>
<th>Replace Delay</th>
<th>Cost</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dolores</td>
<td>SH145</td>
<td>100</td>
<td>Concrete</td>
<td>80</td>
<td>25</td>
<td>$497,747</td>
<td>7/18/2013</td>
</tr>
<tr>
<td>Routt</td>
<td>US40</td>
<td>100</td>
<td>Concrete</td>
<td>80</td>
<td>50</td>
<td>$1,385,135</td>
<td>2/5/2015</td>
</tr>
<tr>
<td>Ouray</td>
<td>US550</td>
<td>100</td>
<td>Concrete</td>
<td>80</td>
<td>30</td>
<td>$1,281,625</td>
<td>10/29/2015</td>
</tr>
<tr>
<td>Huerfano</td>
<td>SH12</td>
<td>100</td>
<td>Concrete</td>
<td>80</td>
<td>45</td>
<td>$995,000</td>
<td>1/15/2015</td>
</tr>
<tr>
<td>Jackson</td>
<td>SH125</td>
<td>100</td>
<td>Concrete</td>
<td>80</td>
<td>40</td>
<td>$453,761</td>
<td>5/8/2014</td>
</tr>
<tr>
<td>Montezuma</td>
<td>US491</td>
<td>50</td>
<td>Steel</td>
<td>50</td>
<td>25</td>
<td>$270,105</td>
<td>7/18/2013</td>
</tr>
<tr>
<td>Mesa</td>
<td>SH139</td>
<td>50</td>
<td>Steel</td>
<td>50</td>
<td>25</td>
<td>$189,363</td>
<td>10/6/2014</td>
</tr>
<tr>
<td>Lake</td>
<td>SH82</td>
<td>100</td>
<td>Concrete</td>
<td>80</td>
<td>43</td>
<td>$709,426</td>
<td>6/5/2014</td>
</tr>
</tbody>
</table>

The crossing road, cost, replacement delay, and material characteristics are based on the CDOT bid tabulations. We estimated culvert service life based on material and previous research (Maher, 2015; Perrin Jr & Jhaveri, 2004). These values are static in the model. The bid tabulations do no list the design flood so we assume all construction follows the specifications in
CDOT’s Drainage Design Manual (Colorado Department of Transportation, 2004). The manual provides individual specifications for rural and urban areas; based on the location of crossing we assumed that all of the culverts in our testbed are considered rural. The manual specifies that multi lane roads in rural areas should have culverts designed to the 50-year return interval (RI) and two lane roads should be designed to the 25-year RI if the 50-year flow is less than 4,000 cfs and 50-year flow is greater than 4,000 cfs. The manual also suggest increasing capacity where “associated damaged is judged to be severe”. Of the culverts in the testbed we assumed that all but the Mesa and Montezuma culverts are designed to the 100-year flow due to the lack of alternative routes and severe consequences should they fail.

Each crossing road is characterized by four variables: average annual daily traffic (AADT), proportion of traffic from freight (trucks), delay in hours during a planned replacement, and delay in hours due to failure and emergency replacement (table 2).

Table 2-Road Characteristics

<table>
<thead>
<tr>
<th>Road Name</th>
<th>AADT</th>
<th>Percent Truck</th>
<th>Delay (planned)</th>
<th>Delay (unplanned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SH145</td>
<td>2000</td>
<td>12.3</td>
<td>0.2</td>
<td>1</td>
</tr>
<tr>
<td>US40</td>
<td>4600</td>
<td>11.7</td>
<td>0.1</td>
<td>0.3333</td>
</tr>
<tr>
<td>US550</td>
<td>5900</td>
<td>4.2</td>
<td>0.1</td>
<td>2</td>
</tr>
<tr>
<td>SH12</td>
<td>2200</td>
<td>5.5</td>
<td>0.1</td>
<td>3</td>
</tr>
<tr>
<td>SH125</td>
<td>1800</td>
<td>12.3</td>
<td>0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>US491</td>
<td>7100</td>
<td>9.2</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>SH139</td>
<td>2000</td>
<td>8.5</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>SH82</td>
<td>960</td>
<td>1.9</td>
<td>0.1</td>
<td>1</td>
</tr>
</tbody>
</table>

We used CDOT’s Traffic Data Explorer to determine the AADT and percent truck traffic (Colorado Department of Transportation, 2016b). Delays from planned replacements for the crossings in the testbed are likely to be minor due to the relatively low volume of traffic handled.
by each road. We calculated delay due to failure using Google Maps driving times and finding the shortest alternate route (Google Maps, 2016).

**Variable Crossing Characteristics**

Many culvert characteristics affect adaptability, and a crossing’s sensitivity to climate. The characteristics we explore are shown in table 3 and elaborated on below. Over thousands of simulations, we test a range of values for each characteristic. To explore the possible impacts of these variables we conduct extensive sensitivity analysis on each of the variables.

<table>
<thead>
<tr>
<th>System Characteristic</th>
<th>Starting Value</th>
<th>Step</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upgrade Cost</td>
<td>2.0</td>
<td>0.5</td>
<td>1.0-4.0</td>
</tr>
<tr>
<td>Upgrade Amount</td>
<td>2.0</td>
<td>0.25</td>
<td>1.5-2.5</td>
</tr>
<tr>
<td>Post Upgrade Factor</td>
<td>0.5</td>
<td>0.1</td>
<td>.03-.07</td>
</tr>
<tr>
<td>Emergency Cost</td>
<td>1.5</td>
<td>0.1</td>
<td>1.3-1.7</td>
</tr>
<tr>
<td>Resilience Factor</td>
<td>0.1</td>
<td>0.05</td>
<td>.05-.25</td>
</tr>
</tbody>
</table>

We use three variables to represent the adaptability of a crossing: Upgrade Cost, Upgrade Amount, and Post-upgrade Factor. Upgrade Cost determines the cost of increasing the capacity of a crossing. The cost is proportional to the capacity increment and to the crossing’s original cost multiplied by the Upgrade Cost. This cost is dependent on the individual circumstances of the crossing. In some cases upgrades may only entail a small increase proportional to the original cost, i.e. the upgrade can be accomplished by a larger pipe with minimal extra labor and excavation. In other cases the upgrade could invoke a significant cost increase, for example moving from a precast concrete box to a reinforced concrete box that is cast in place. Using a range of Upgrade Cost multipliers based on the original install cost allows us to explore a realistic range of these possibilities. The Upgrade Amount is the degree to which a crossing’s
capacity is increased under the different adaptation strategies. All upgrades are proportional to the original design storm. The Post-upgrade Factor allows replacements after the initial upgrade to be less expensive in line with cost estimates based on life cycle.

Emergency Cost and Resilience Factor are used to represent a crossing’s sensitivity to changes in climate. Emergency Cost reflects the increased cost of replacement and repair after a failure. To find the cost of replacement after failure, the original cost is multiplied by the Emergency Cost Factor. The Resilience Factor describes the degree to which a flow can exceed design capacity before a crossing is damaged. Starting values for variable characteristics were calibrated such that the current infrastructure is more cost effective than an upgrade under scenarios with no climate change. The validity of this assumption will vary depending on specific infrastructure. Some researchers argue that current infrastructure is underspecified for the present climate (Burton, 2004), echoing a broad sense that resource and infrastructure systems are under-adapted to current extremes (Field et al., 2012), and implying that increasing capacity may be beneficial regardless of climate change, a form of no regret action (Burton, 2004). Empirical analysis of this intriguing hypothesis would be a valuable contribution to the climate adaptation literature.

**Simulating Climate Change and Extreme Events**

Climate change is incorporated into the simulations using a linear change in the location parameter of a generalized extreme value (GEV) distribution following the methods used in (Mailhot & Duchesne, 2009). The cumulative distribution function for the GEV distribution is shown in Equation 1 (Coles, 2001):

\[
F(x) = \exp \left\{ - \left[ 1 + \xi \frac{(x - \mu)}{\sigma} \right] \right\}^{-\frac{1}{\xi}} \quad (1)
\]
where \( z \) is the annual maximum precipitation over a given duration, \( \mu \) is the location parameter, \( \sigma \) is the shape parameter, and \( \xi \) is the scale parameter. We fit the original GEV distribution to a block maxima of yearly precipitation events to approximate the shape and scale of yearly maximum stream flow, a technique used by CDOT when making infrastructure decisions (Colorado Department of Transportation, 2004). The extRemes package in R (Gilleland & Katz, 2011) was used for to fit distributions. Fitting was done using maximum likelihood estimation, assuming stationarity, and model selection was based on AIC. We fit models based on the GEV and Gumbel distributions. The effect of climate change is only realized in the location parameter of the GEV distribution. There is evidence that climate change could possibly cause changes to the shape parameters and other moments of distributions (Field et al., 2012; Read & Vogel, 2015). This possibility is important to explore and should be addressed in future work.

In one-at-a-time sensitivity analysis, we apply three climate change scenarios: no change, low and high impact from climate change on the frequency of extreme events. Following Mailhot and Duschesne (2009), we apply all changes to climate by altering the return interval of the storm. The low and high scenarios reduce the return interval of the design storm by 33% and 50% respectively, which comports with a 6 to 15% increase in stream flow. Shifts in the distribution are accomplished by applying a climate factor which changes the magnitude of a design event to that of an event with a higher return interval. For example, given a climate factor of two, the magnitude of the 100 year event will have shifted, by the end of the simulation, to be equivalent to the original 200 year event. Each year the location parameter is linearly increased to simulate this non-stationary risk.
Adaptation Strategies

We test four adaptation strategies: Nominal, Anticipatory, Reactive, and Concurrent. The Nominal strategy assumes no change in culvert replacement strategy over the entire simulation; in the event that a crossing’s lifespan is reached, or the crossing is destroyed by a runoff event, it is replaced with a crossing of the same capacity. Under the Anticipatory strategy, all crossings are replaced with higher capacity crossings prior to the end of their normal lifespans. This would be the case if a manager decided that climate change is a significant enough threat that it requires increasing the capacity of culverts in anticipation, but where budgets restrict the rate of upgrade. In this simulation each crossing’s normal lifespan was shortened by 10% to accelerate the rate of replacement and upgrades. Under the Concurrent Strategy the capacity of each crossing is increased at the time of normal replacement. The Reactive Strategy begins with the Nominal Strategy and switches to the Concurrent Strategy when a crossing is replaced following damage by an extreme event. We do not specify the method for increasing capacity as this will vary by site, but the most obvious action is to increase the size of the pipe or to re-engineer the inlet and outlet controls. Because the model is agnostic to the method of increasing capacity, upgrade costs are calculated as a percent of the original cost per unit of incremented capacity. We explore the implications of changing upgrade cost in the sensitivity analysis.

Simulating Crossing Failure

Whenever a crossing’s capacity is exceeded by a runoff event, damage is incurred. Damage is calculated based on the original cost of the crossing and the Resilience Factor. The Resilience Factor specifies how much the crossing’s design capacity can be exceeded before it is damaged to the point of replacement. Damage less than that required to destroy the crossing is assumed to linearly increase to the point at which the crossing is destroyed. Damage is calculated via equation 2:
\[ d = \frac{E}{R} \times C_{cost} \]  

(2)

where \( E \) is how much the event exceeded the crossing’s capacity, \( R \) is how much the crossing can be exceed and not be replaced (Resilience Factor), and \( C_{cost} \) is the cost of replacing the crossing. A crossing is replaced any time the damage exceeds the current value calculated using equation 3:

\[ C_{value} = C_{cost} \times \frac{t_c-C_{install}}{C_{life}} \]  

(3)

where \( t_c \) is the current year, \( C_{install} \) is the install year, and \( C_{life} \) is the service life of the crossing. If the damage exceeds the current value of the crossing, it is replaced.

The number of delay days associated with crossing damage are estimated from a triangular distribution with a minimum of .1, a max of 3 and a mean of .6 days. If the culvert is destroyed the road is considered impassible for a number of days determined using a triangle distribution with a minimum of 1, a maximum of 4 and a mean of 2 days. These parameters are based on cases examined in Perrin et al. (2004) and could be improved by increasing the number of cases investigated. The model calculates delays according to the formula described in the Measures of Success section. In the case of failure, the cost of delay is added to the cost of delay incurred during normal replacement.

**Replacing Culverts**

Full replacement occurs if either the culvert reaches the end of its service life or it is destroyed during an extreme event. We assume that replacement will always occur at the end of the culvert’s specified service life. Research has shown that replacement is often delayed due to budget constraints (J. Meegoda & Zou, 2015). We also assume that all crossings have a static service life based on the shape of the culvert and the materials used for construction. In reality crossing service lives are affected by many factors, including chemical composition of water,
velocity of flow, scouring, and direction of flow, amongst others (J. N. Meegoda, Juliano, & Wadhawan, 2007).

Figure 1 shows three examples of actual model runs, selected from the hundreds of thousands of simulations, to show how the model operates and to illustrate a few key differences between strategies. Figure 1a shows the Nominal Strategy with no climate change. In this particular simulation iteration the crossing experienced two small flood events that damaged the crossing but did not require replacement, and then at approximately year 70 the crossing is replaced at the end of its useful life. Figure 1b shows the Nominal Strategy with high climate change (climate factor of 2). In this run the crossing is replaced three times, once at the end of its useful life at year 6 (crossing emplacement dates, which start the lifetime clock, are randomly assigned in the testbed so routine replacements may occur anytime in the simulation), and twice after being damaged by extreme events. Damage from the events is higher due to the increased cost of failure-induced replacement. A Concurrent Strategy sample run with high climate change (figure 1c) experienced no flood events but note that the cost of normal replacement is higher than under the Nominal Strategy because the crossing’s capacity is increased.
Figure 1-Flood damage and construction cost from sample model runs. (a) A sample run with no climate change and the Nominal Strategy. The sample run has two small flood events that damage the crossing but do not necessitate replacement and one normal replacement event. (b) A sample run with high climate change (climate factor of 2) and the Nominal Strategy. The run has a normal replacement event early in the simulation followed by a damaging flood and then two floods within 20 years that both result in enough damage to require replacement. Note that the cost for failure-induced replacement is higher than for normal replacement. (c) A sample run with high climate change and the Concurrent Strategy. This run experienced a normal replacement at about year 74 and no flood events. The normal replacement event is more expensive than replacements in (a) or (b) because the capacity of the crossing is increased.

Measures of Success

Measuring the success of climate change adaptation is a challenging and multifaceted problem, including multiple temporal and spatial scales (Adger, Arnell, & Tompkins, 2005). In many business and engineering applications, measures of success can be conflicting, with no optimal solution, requiring satisficing by the decision maker (Clemen & Reilly, 2014). We use
service level and cost of maintaining the system to evaluate the performance of adaptation strategies. Crossings have the potential to be part of an interconnected system where adapting one crossing can increase impacts on others. This problem is described by Adger et al. (2005) as a spillover effect. We assume that each of the crossings in our testbed is independent, and network effects are beyond the scope of this study. Even for our relatively simple testbed, the two criteria for success can be conflicting, with increased service level causing larger maintenance costs. To avoid making assumptions about manager decision preference we examine these measures independently.

To assess cost we simulate normal construction events, and repairs or replacement after flood events. Periodic maintenance and inspections could also be included but since these are unlikely to appreciably change under different climate scenarios or adaptation strategies, we do not explicitly model them. To determine success on the metric of cost we compare adaptation strategies to the Nominal Strategy under the same climate scenario. We refer to these costs as physical costs as they are the only costs directly incurred by operators. While the cost of impacts to users are real there is some evidence that decision makers do not always incorporate them into cost benefit analysis (Chang & Shinozuka, 1996; Perrin Jr & Jhaveri, 2004).

Service level is assessed by two metrics: number of replacements and the cost of delay. The number of replacements affects service on a variety of levels. First and foremost, replacement events create delays by reducing traffic speed and capacity of a road or by requiring an alternate route. Replacement events have potential for adverse environmental impacts, additional noise and disturbance in the area, and externalized impacts on local business. Delay hours have a clear economic impact by increasing the amount of travel time by users and slowing
freight delivery. The impact of delay hours is calculated in dollars using equation 4 as specified by Perrin et al. (2004):

\[ D = AADT \times t \times d \times (c_v \times v_p \times v_{of} + c_f \times v_f) \]  

where AADT is the average annual daily traffic of the road, t is delay experienced by each vehicle, d is the number of days delays are experienced, \( c_v \) is the cost per hour of person delay ($17.18), \( c_f \) is the cost per hour of freight delay ($50), \( v_v \) percent of AADT that are passenger cars, and \( v_f \) is the percent of AADT composed of truck traffic.

**Sensitivity Analysis**

To investigate the impacts of adaptation timing on the efficiency of adaptation, we compare the measures of success described above over a number of different simulations. We address Question One using visualizations from a one-at-a-time local sensitivity analysis and a global sensitivity analysis. We address Question Two using a multinomial regression on the results from the global sensitivity analysis.

**One-at-a-time Sensitivity Analysis**

During this stage, we vary the Crossing Characteristics described above under no change, low and high climate scenarios. In each model run we alter one Crossing Characteristic according to a specified step; starting values and steps are detailed in table 3. The simulation is then run for 2,500 iterations for each strategy and climate scenario combination. To understand the impacts of variable crossing characteristics we use one-at-a-time sensitivity analysis (Hamby, 1994), varying each of the model parameters over the ranges in table 3. In this method each variable is altered over a specified range while all other variables are held constant. All of the ranges were selected as plausible values reflected in engineering guidelines for such crossings.
Global Sensitivity Analysis

We used Monte Carlo sampling to vary all variable crossing characteristics simultaneously. Because crossing characteristics are dependent on the specifics of each site and we are unable to determine a distribution we drew all values from uniform distributions over the ranges specified in table 3. During this exercise we switched from using discrete climate scenarios to varying the climate factor continuously between 1 and 3. The global sensitivity analysis consisted of 2,000 realizations of crossing characteristics. Each set of crossing characteristics was simulated 104 times for 832,000 total simulations each containing 100 time steps, and using 2,000 model parameter combinations.

Multinomial Regression

We use a multinomial regression to assess the predictability of the preferred strategy (Hosmer Jr, Lemeshow, & Sturdivant, 2013). Since the Concurrent Strategy will almost always result in an increased service level, we judged the preferred strategy as the one that minimizes cost. As a training set we use the model simulations described above in the global sensitivity analysis, and for a test set we use the same procedure described above but repeated 100 instead of 2,000 times. We fit the multinomial models using the “mnnet” package in the R Project for Statistical Computing (Venables & Ripley, 2002). Initially we use all model parameters including climate as covariates and a bidirectional stepwise AIC to select the best combination. We include all predictors with p<.05 in the final model. Prediction skill was assessed by comparing results to random assignment of strategies, and the climatology of the training was set with a ranked probability skill score (RPSS).

Results
We found that the climate sensitivity and adaptability of individual crossings can alter crossing performance such that the preferable strategy switches under specified levels of adaptation. Furthermore our results show that these differences can be used to effectively select adaptation strategies that are either advantageous or at least minimize increases in losses and additional cost. Below we present specific findings and results for both questions addressed by this research.

**How do adaptation strategies with different timing qualities perform under different climate realizations and model parameterizations?**

To address this question we used one-at-a-time sensitivity analysis as described above, altering one variable at a time while holding all others constant. Total cost and the total value of delay hours represent measures for cost and service level, respectively. Our analysis found that the Post-upgrade Factor and the Upgrade Amount had little impact on the resulting cost; thus, we do not depict them here. Key results are plotted in figure 2, showing physical cost against crossing characteristic values, and in figure 3, showing the value of delay cost against changes in crossing characteristics. In this plot we only include the Climate and Resilience Factors as the others only impact cost and not performance of crossings.
Figure 2 One-at-a-time local sensitivity analysis showing changes in mean physical cost vs changes in variable crossing characteristics for adaptation strategies with different timing. (a-c) Changes in mean physical cost vs changes in the upgrade cost under high, low, and no change climate scenarios. (d-f) Changes in mean physical cost vs changes in the emergency factor under high, low and no change climate scenarios. (g-i) Changes in mean physical cost vs changes in the resilience factor under high, low, and no change climate scenarios. (j) Changes in mean physical cost vs changes in the climate factor. For example in the emergency factor plots (d-f) the cost of the Nominal Strategy vs. emergency factor goes from almost always being the lowest cost under normal climate (d) to almost always being the highest cost under the high climate (f).
Figure 3 One-at-a-time local sensitivity analysis showing changes in user cost based on delay vs changes in variable crossing characteristics for adaptation strategies with different timing. (a-c) Changes in mean user cost vs changes in the resilience factor under high, low and no change climate scenarios. (d) Changes in mean user cost vs changes in the climate factor. Here the Concurrent Strategy is always preferred as the increased cost are not included. Despite the earlier increase in capacity the Anticipatory Strategy has higher delay cost from premature replacement events.

It works out that the Anticipatory Strategy is inferior in level of service and cost; that is, it is outperformed by the other strategies under all parameters. One reason for this result is that each simulation inherits some value of previously installed infrastructure. Under the Anticipatory Strategy this value is sacrificed by shortening the lifespan previously installed crossings.
addition to increasing cost, these “premature” replacements actually yield a decrease service level due to delays occasioned by the replacements additional to what would occur under normal replacement cycles. It is conceivable that scenarios exist where this is the preferred strategy, but either the risk of damaging events would need to increase dramatically or the potential damage would need to be very large. In our simulation the crossings do not protect property other than themselves and the road, thus limiting the potential for very large losses. In situations where infrastructure protects additional investments, impoundment might cause additional damage, or where failure has a high risk of fatalities, an Anticipatory Strategy may be preferable.

Below we analyze in more detail the results for the Nominal, Concurrent, and Reactive strategies for both cost and service measures of success.

**Upgrade Cost**

We varied the Upgrade Cost between 1 and 4 with a .5 step. Under all climate scenarios the Nominal Strategy is flat (a slope of about 1), because none of the crossings are upgraded. Under the Concurrent Strategy total costs increase linearly as the upgrade costs increase. There is a slight modifying effect of the climate scenario, such that the slope increases with increased rate of climate change. We also find a modifying effect on the y-intercept under the Nominal Strategy, with an increase in cost from No Change to High Change climate scenarios because of the increased flooding. These effects result in the cost curve for the Upgrade Strategy crossing the Nominal Strategy curve at different points depending on climate the change scenario (figure 2 a-c). These results imply that as rate of climate change increases the cost-effective upgrade price increases, and the manager should be willing to pay more per unit upgrade because it helps reduce overall costs.
Rate of climate change

Climate change was simulated in the model as a linear increase in the probability of exceedance events. For example, a climate change factor of 2 represents a doubling of the probability, or halving of the return period. We vary the climate change factor from 1 to 3, while holding all other variables constant. As expected, the total costs increase as the climate change factor increases under all strategies (figure 2j & 3d). Anticipatory and Concurrent strategies reduce the rate of increase, with the Concurrent Strategy becoming preferable to the Nominal Strategy under higher rates of climate change. Under all three strategies, the cost of delay hours increased as the probability of extreme events increased. Similarly, the slope of increase is greater for the Nominal strategy.

Emergency Factor

The Emergency Factor represents the increased cost of replacement after a flood event has damaged the crossing. The Emergency Factor’s sensitivity is notable for the pronounced moderating effect of the climate scenario. Under No Climate Change the Nominal Strategy remains preferable to both the Concurrent and Reactive strategies (figure 2 d-f). Under the high rate of climate change this is reversed and the Concurrent Strategy is preferred under all Emergency Factor values. This shows the increased importance of the Emergency Factor as exceedance events become more common. Presumably this is what managers convinced that climate change is worsening, or will worsen, stormwater performance are trying to avoid by adopting more anticipatory strategies.

Resilience Factor

The Resilience Factor determines how much a crossing’s capacity can be exceeded before it is destroyed. The initial value is 10% and we vary it between 5 and 25%, in 5% steps. This is the only sensitivity plot that does not exhibit a clear linear relationship between the
change in $y$ with respect to $x$. We believe this is caused by the shape of the underlying GEV distribution (figure 2 g-i & figure 3 a-d). As the capacity of the crossing is increased linearly it is able to handle an increasingly large number of rare storms. The results indicate that maintaining a crossing with a high resilience factor would be more advantageous than upgrading it. In many cases this would be a crossing already built in excess of its specified design flood or engineered for graceful failure. It is conceivable this might be intentionally done in some cases or the effect of the available precast culvert sizes.

Summary

All of the model parameters behave in a predictable manner which comports with our understanding of how stormwater systems function. Several parameter values have the potential to change the preferred strategy under different climate scenarios. Additionally we see clear interactions between climate and several of the parameters, with climate altering both the y-intercepts and slopes. The interactions and potential changes motivate a global sensitivity analysis to better understand the nature of the decision space, including which combinations of variables make one strategy preferable over another and whether we can use our understanding of specific crossings to inform the strategy choice.

Can system characteristics be used to predict the preferred strategy based on cost, and if so, how much better are predictions when climate change is known?

To determine the predictability of strategy choice using System Characteristics, we constructed two multinomial models, one using the climate change factor as a covariate and the second not including the climate factor. We evaluated both models using Rank Probability Skill Score (RPSS) calculated with data not included in the training set (Weigel, Liniger, & Appenzeller, 2007). RPSS measures the skill of a prediction by comparing it to a baseline forecast. An RPSS of 1 indicates perfect prediction, 0 shows equivalent skill to the baseline, and
negative numbers indicate less skill than the baseline. When assessing the efficiency of adaptation strategies there is no known climatology for how often a strategy will be preferred. For this reason we compare the results to always selecting the Nominal Strategy, selecting Nominal 50% of the time and Concurrent 50% of the time, selecting only the Concurrent strategy, and finally to climatology. All initial models were created using Equation 4 with interaction decisions guided by the results from local sensitivity analysis.

\[
\text{Optimal Strategy} \sim \text{Emergency Factor} + \text{Upgrade Cost} + \text{Climate Factor} \\
+ \text{Resilience Factor} + \text{Upgrade Factor} + \text{Upgrade Factor} \\
* \text{Climate Factor} + \text{Upgrade Cost} * \text{Climate Factor} + \text{Emergency Factor} \\
* \text{Climate Factor}
\]

Selection based on bidirectional stepwise AIC removed all the interaction effects for the first model which included the climate factor as a predictor, and retained all linear predictors. A Wald-Significance test showed all remaining covariates for both models to be significant at \( p > 0.01 \) level. Both models show skill compared to all the reference probabilities, including the climatology. RPSS results for both models are in table 4.

<table>
<thead>
<tr>
<th>Model</th>
<th>RPSS vs Nominal</th>
<th>RPSS vs Nominal and Upgrade</th>
<th>RPSS vs Climatology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate</td>
<td>0.72</td>
<td>0.4</td>
<td>0.42</td>
</tr>
<tr>
<td>Aggregate w/o CF</td>
<td>0.68</td>
<td>0.36</td>
<td>0.32</td>
</tr>
<tr>
<td>Climate Alone</td>
<td>0.58</td>
<td>0.17</td>
<td>0.11</td>
</tr>
</tbody>
</table>

RPSS assessment of the three multinomial models used for model selection suggest that both improved predictions of future climate and knowledge of crossing characteristics have the potential to improve adaptation strategy decisions. The model which utilized all crossing characteristics was the most effective. Removing climate factor as a predictor in the multinomial
model reduced model skill by a small amount. This amount is further reduced to a .2 increase in RPSS if simulations that allow for a decreasing intensity of extreme events are not analyzed. Finally, we see that using predictions of climate change alone offer the lowest skill in selecting appropriate adaptation strategies. This suggests that investments in the arguably easier to reduce uncertainties associated with crossing characteristics may offer greater benefits than investing in improved climate predictions. We further explore this point in the conclusions below.

**Conclusions**

In this study we simulated a realistic testbed of culverts varying their characteristics and the frequency of extreme runoff events affecting them, and tested different adaption strategies that might be adopted by a manager convinced that climate change required some change in their design and maintenance. We found that the choice of when and how to implement adaptation is affected by both the degree of climate change and crossing characteristics. Even for rather large climate change that halved the return interval of damaging runoff events, anticipatory adaptation performed poorly as evaluated by both cost and level of service. This was caused by the increased number of replacements that sacrificed the value of the system prior to the end of its useful life. This finding emphasizes the need for continued and improved decision support for climate adaptation decisions. In addition to being ineffective we find that anticipatory adaptation, at least in the case of rural crossing, may even be maladaptive.

Barnett and O’Neil (2010, p. 1) define maladaptation as “action taken ostensibly to avoid or reduce vulnerability to climate change that impacts adversely on, or increases the vulnerability of other systems, sectors or social groups.” Anticipatory adaptation in our simulation has a much higher opportunity cost compared to the other options and likely compared to many other strategies not modeled. Anticipatory adaptation also creates path dependencies that may reduce
the options for future adaptation. Here we simulate incremental adaptation but it is likely that systems in some settings (e.g., where freshwater and coastal flooding interact) will require transformative adaptation in the future, perhaps involving relocation of infrastructure; investing now in anticipatory infrastructure capacity makes those changes less likely to pay off (Barnett & O’Neill, 2010; Kates, Travis, & Wilbanks, 2012).

Additionally we found that under moderate levels of climate change, crossing characteristics, which influence the adaptability of infrastructure and its climate sensitivity, can be used to effectively predict which crossings are most likely to benefit from increased capacity. In developing a predictive model we assume these characteristics are known by agencies. Based on the current state of culvert information management systems, it seems reasonable to assume that many agencies would need additional research and field work to learn this information and to benefit from the finer distinctions in choices allowed by this level of simulation modeling (Maher, 2015). The additional cost of that information may eliminate benefits gained by using it to choose more appropriate adaptation strategies. Future work should assess the uncertainty in important system characteristics and determine the cost of reducing that uncertainty to assess whether the benefits of flexibility are greater than the increased cost.

In this study we used a testbed of culverts that share many parameters, while differing in their design flows, cost, material, and expected service life. Because all cost and damages are based on a proportion of the original crossing value, we found no significant difference in the choice of best strategies for individual crossings and no difference in cost effectiveness for individual crossings. However, crossings are often elements in an interconnected infrastructure network that conveys flows and protects against flooding. Changing one piece of this
infrastructure can have impacts on the rest of the system, and integrated modeling, including of system hydraulics, might yield different results.

Our simulation describes a simple but realistic testbed of road crossings served by culverts. Future work should elaborate on this model in several ways. We use a limited view of benefits associated with increasing the capacity of a crossing: only the decrease in flood damages and increased service level. Recent research shows that replacing traditional culverts with stream-simulation culverts can both increase the capacity of crossings and provide a number of environmental and aesthetic benefits (Gillespie et al., 2014). Economic analysis including these benefits has shown that increasing the capacity of crossings by installing stream-simulation culverts would be beneficial under the current climate (Levine & Keene Valley, 2013; Long, 2010).

Climate change is implemented in our model through a shift in the location parameter, the most simple way of simulating change (Mailhot & Duchesne, 2009). Changes in precipitation and streamflow may shift not only the location of the distribution but also the shape and even the distribution itself (Field et al., 2012; Read & Vogel, 2015). Future work should explore the nature of these changes, how they interact with system characteristics, and how they will influence adaptation decisions.


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