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

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Abstract

Adaptations in infrastructure may be necessitated by changes in temperature and precipitation patterns to avoid losses and maintain expected levels of service. A roster of adaptation strategies has emerged in the climate change literature, especially with regard to timing: anticipatory, concurrent, or reactive. Significant progress has been made in studying climate change adaptation decision making that incorporates uncertainty, but less work has examined how strategies interact with existing infrastructure characteristics to influence adaptability. We use a virtual testbed of highway drainage crossings configured with a selection of actual culvert emplacements in Colorado, U.S.A., to examine the effect of adaptation strategy and culvert characteristics on cost efficiency and service level under varying rates of climate change. A meta-model approach with multinomial regression is used to compare the value of better climate change predictions with better knowledge of existing crossing characteristics. We find that, for a distributed system of infrastructural units like culverts, knowing more about existing characteristics can improve the efficacy of adaptation strategies more than better projections of climate change. Transportation departments choosing climate adaptation strategies often lack detailed data on culverts, and gathering that data could improve the efficiency of adaptation despite climate uncertainty.

Key Words: Infrastructure adaptation; stormwater management; climate change; scenario simulation

1. Infrastructure Adaptation Strategies

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, 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 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? Answers to these questions may help system managers respond to calls by the communities they serve for strategic adaptation plans. While not a complete decision support tool, this study explores methods whereby scenarios of climate change could be incorporated into transportation asset management.

Adaptations in infrastructure may be necessitated by changes in temperature and precipitation patterns to avoid losses and maintain expected levels of service (Gibbs 2012; 2015). The climate change adaptation literature, back to at least the early 1980s (Kates, 1985), has been framed by a relatively simple classification of the type and timing of adaptation: reactive, concurrent, or anticipatory (Smit et al., 2000). Other distinctions have emerged, 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 the further notion that some adaptations could be counted as *no regret*. No (or low) regret options pay off by better adapting systems to current climate risks while also providing adaptive benefit as the future climate unfolds (Field et al., 2012; Thomalla, Downing, Spanger-Siegfried, Han, & Rockström, 2006), though the literature also offers some misgivings whether true no-regret solutions exist (Dilling, Daly, Travis, Wilhelmi, & Klein, 2015). Adaptation has been enhanced with concepts of 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). Adaptation is also now analyzed as "pathways", recognizing the dynamic, time-transgressive nature of adaptation to trends that affect system performance, and accounting for options, 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 (Convertino et al., 2013) 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; Dittrich, Wreford, and Moran, 2016); or explicitly value future options (Woodward, Kapelan, & Gouldby, 2014). One over-riding theme stresses the value of systematic analysis of options (Gibbs 2015), especially to avoid unused capacity, as in the framework offered by Hoss et al. (2014).

A common concern in the contemporary adaptation literature is 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 more common applications have been in coastal flood protection (Linquiti & Vonortas, 2012; Lin e t al., 2014). However, managers of more dispersed systems may also need to adopt climate adaptation strategies. Given a commitment to adapting, 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 dispersed climate-sensitive infrastructure via a virtual testbed of simulated stormwater conveyance structures.

2. 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 intermittent 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 (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.

Regardless of climate change many stormwater systems in the US face threats to their continued functionality. Historically, culvert installations by state and county departments of transportation have been poorly documented and not always consistently maintained (Venner, 2014). The design lives of culverts described above are rough estimates and myriad factors (i.e. environmental, installation techniques, maintenance etc.) can shorten or lengthen those values. Regular inspection for blockage and structural deterioration is needed to ensure that culverts remain functional, but budgets, other priorities, and the sheer number of emplacements mitigates against timely maintenance. Like much of the national infrastructure, good engineering and construction limit failures even when maintenance is deferred, but lack of inspection and knowledge of existing systems has led to both premature failure and failures in runoff events significantly smaller than crossings were designed to accommodate (Perrin Jr & Jhaveri, 2004). In the parlance of adaptation theory, the deficit in knowledge and maintenance of existing systems is an “adaptation deficit” (Burton, 2009) the correction of which would be a “no regrets” climate change adaptation (Dilling et al., 2015), a suggested specifically for culverts by Gersonius et al. (2010). Even with better maintenance and knowledge of existing systems additional adaptive postures maybe necessary to prepare stormwater systems for climate change, especially if it yields more large-scale extremes like the Hurricane Irene floods in Vermont (Irene Recovery Coordination Team, 2011). In this study we focus on examining those options.

A variety of adaptive strategies identified in the literature apply to stormwater 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's capacity can be increased. 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 soft 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).

More robust adaptation strategies often mean installing a larger crossing with greater capacity than traditional minimum specifications. This 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 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 in 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 discover the preferred strategy based on cost, and if so, how much better are predictions when climate change is known?

3. 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 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), or as a decision-support or asset management system. In other words, the culvert model is a ‘what-if’ tool rather than an attempt to predict future climate conditions or prescribe particular maintenance and construction practices. The testbed structure is meant to provide for changing and enlarging the assemblage of simulated culverts and their crossing characteristics, as well as a range of external stresses, similar to the infrastructure and storm surge testbed developed by Francis, Falconi, Nateghi, & Guikema (2011). Simulation outputs 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). The code is available from the authors [and will be archived and available from http://wwa.colorado.edu/ after review of this paper]. Figure 1 diagrams the modeling process described in detail below.

3.1 Climate Scenarios

We intersect crossing characteristics and climate change using scenarios (Schwartz, 1996) of climate trends. 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 the model 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/) 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 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; Kwakkel et al., 2014; 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); a trend projected to continue in some global warming model results (Guinard, Mailhot, & Caya, 2015). But, reflecting the tendency of model outputs to vary with scale, down-scaling to our study region in Colorado points both to intensification of heavy precipitation events (Mahoney, Alexander, Thompson, Barsugli, & Scott, 2012; Tebaldi et al., 2006) and to no significant change (Alexander, Scott, Mahoney, & Barsugli, 2013; Mahoney, Alexander, Scott, & Barsugli, 2013). The important signal in this research is not the differences among models, but the effect of increasing precipitation intensity on infrastructure adaptation strategies; and thus 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.

3.2 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 (Meegoda, Juliano, & Tang, 2009), except as they are specified in construction bids and plans; most road infrastructure management agencies in the U.S. do not keep systematic data on culverts (Maher, 2015). Analysts thus turn to hypothetical examples (Mailhot & Duchesne, 2009; Gersonius et al., 2010), 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 the testbed. By including a range of system characteristics, we varied the ease of adapting crossings, crossing sensitivity to increased flows, and the consequences of crossing failure.

3.3 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. Each crossing is specified using the following variables: crossing road, design flood, material, install date, service life, replacement delay (days with reduced traffic capacity or speed due to replacement), and cost. These variables are reviewed in detail below and listed table 1.

Table 1-Fixed Crossing Characteristics

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

The crossing road, cost, replacement delay, and material characteristics are from 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 specifications are taken from CDOT's Drainage Design Manual (Colorado Department of Transportation, 2004). The manual provides individual specifications for rural and urban areas, and we focus here on rural crossings, where multi-lane roads have culverts designed to the 50-year recurrence interval (RI) and two lane roads are 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

Road Name	AADT	Percent Truck	Delay Planned (hrs.)	Delay Unplanned (hrs.)
SH145	2000	12.3	0.2	1
US40	4600	11.7	0.1	0.3333
US550	5900	4.2	0.1	2
SH12	2200	5.5	0.1	3
SH125	1800	12.3	0.2	0.5
US491	7100	9.2	0.1	0.1
SH139	2000	8.5	0.1	0.1
SH82	960	1.9	0.1	1

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). Specifically we determined when a vehicle would leave and rejoin the disrupted roadway to avoid a non-functioning crossing. We then subtracted the driving time for the undisrupted route from the detoured route to determine delay time.

3.4 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 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 3-Variable Crossing Characteristics

System Characteristic	Reference Value	Step	Range
Cost to Increase Capacity	2.0	0.5	1.0-4.0
Capacity Increase	2.0	0.25	1.5-2.5
Post Increase Discount	0.5	0.1	.03-.07
Emergency Cost	1.5	0.1	1.3-1.7
Resilience Factor	0.1	0.05	.05-0.25

Three variables represent the adaptability of a crossing: Cost to Increase Capacity, Capacity Increase, and Post Increase Discount. Cost to Increase Capacity is proportional to the capacity increment and to the crossing's original cost. This cost is dependent on the individual circumstances of the crossing. In some cases increasing the capacity of a crossing may only entail a small increase proportional to the original cost, i.e. the increase in capacity can be accomplished by a larger pipe with minimal extra labor and excavation. In other cases increases in crossing capacity 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 Cost to Increase Capacity multipliers based on the original install cost allows us to explore a realistic range of these possibilities. The Capacity Increase is the degree to which a crossing's capacity is increased under the different adaptation strategies. All increases in capacity are proportional to the original design storm. The Post Increase Discount allows replacements after the initial increase in capacity 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. In this simulation Resilience Factor is abstraction used to stand in for a variety of other variables that can impact the resilience (or vulnerability) of a crossing to extreme events. Simulating each of the many factors that can increase or decrease a crossing's resilience is beyond the scope of this work, but is addressed in other literature on infrastructure vulnerability evaluation both under climate change (Wall, 2013), and under stationary climates (Cahoon, Baker, & Carson, 2002).

Reference values for variable characteristics were calibrated such that the current infrastructure is more cost effective than increasing capacity under scenarios with no climate change. The validity of this assumption will vary for specific infrastructure. Given concerns about deferred maintenance, it is argued that some current infrastructure is underspecified for the present climate, 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 to fill an adaptation deficit (Burton, 2009). Empirical analysis of this intriguing hypothesis would be a valuable contribution to the climate adaptation literature.

3.5 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):

$$F(x) = \exp\left\{-\left[1+\xi\,\frac{(z-\mu)}{\sigma}\right]^{-\frac{1}{\xi}}\right\} \quad (1)$$

where z is the annual maximum precipitation over the a given duration, μ is the location parameter, σ is the shape parameter, and ξ is the scale parameter. We fit the original GEV distribution to a block maxima of yearly precipitation events from western Colorado 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 precipitation record covers 1900-2015. The extRemes package in R (Gilleland & Katz, 2011) was used for to fit distributions. Fitting was accomplished using maximum likelihood estimation, assuming stationarity, and model selection was based on AIC. We fit models based on the GEV and Gumbel distributions. The GEV distribution used for event simulation had the following parameters with standard error in brackets location 171.68 [5.43], scale 56.868 [4.08], and shape -.0123 [.0124]. 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 impact, and high impact on the frequency of extreme events. Following Mailhot and Duschesne (2009), we apply all changes to climate by altering the location parameter of the GEV distribution used to simulate extreme precipitation events. This effectively decreases the recurrence interval of the events. The low and high scenarios reduce the recurrence interval of the design storm by 33% and 50% respectively, which comports with a 6 to 15% increase in precipitation. Shifts in the distribution are accomplished by applying a climate factor which alters the magnitude of a design event to that of an event with a higher recurrence 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.

3.6 Adaptation Strategies

Four adaptation strategies were tested: 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 culvert replacement. In this simulation each crossing's normal lifespan was shortened by 10% to accelerate the rate of replacement. 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, costs to increase capacity are calculated as a percent of the original cost per unit of incremented capacity. We explore the implications of different capacity increase cost in the sensitivity analysis.

3.7 Simulating Crossing Failure

Whenever a crossing's capacity is exceeded by a runoff event, cost are incurred. Cost associated with overtopping can include: physical damage to the culvert, embankment, or roadway; expenses related to setting up a detour; or the cost of inspection, and cleaning the crossing. In this analysis we refer to all cost incurred from a flood event as damages. 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:

$$d = \frac{E}{R} * Cul_{cost} \qquad (2)$$

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 Cul_{cost} is the cost of replacing the culvert. A crossing is replaced any time the damage exceeds the current value calculated using equation 3:

$$Cul_{value} = Cul_{cost} * \frac{Cul_{life} - (t_c - Cul_{install})}{Cul_{life}} \quad (3)$$

where t_c is the current year, $Cul_{install}$ is the culvert's install year, and Cul_{life} is the service life of the culvert. If the damage exceeds the current value of the crossing the model assumes that the crossing has failed and it is replaced. This method allows us to incorporate the increased rate of failure in older crossings due to structural degradation (Cahoon, Baker, & Carson, 2002).

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 values are used to determine how many days the delays listed in table 1 are experienced for. 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.

3.8 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 (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 (Meegoda, Juliano, & Wadhawan, 2007).

3.9 Example Model Run

Figure 2 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 among strategies. Figure 2a shows the Nominal Strategy with a no climate change. In this particular iteration the crossing experienced two small flood events that damaged it but did not require replacement, and then at approximately year 70 the crossing is replaced at the end of its useful life. Figure 2b 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 2c) 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.

3.10 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 (the number of delay hours incurred by both normal replacements and unexpected failures or overtopping events) 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, replacements create delays by reducing traffic speed and capacity of a road or by requiring an alternate route. Replacements have potential for adverse environmental impacts, additional noise and disturbance in the area, and externalized impacts on local residences and business. Delay hours have a clear economic impact by increasing users' travel time and slowing freight delivery. The impact of delay hours is calculated in dollars using equation 4 as specified by Perrin et al. (2004):

$$D = AADT * t * d * (c_v * v_v * v_{of} + c_f * v_f) \tag{4}$$

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), v_{of} is the occupancy factor for passenger vehicles (average number of persons in a vehicle), 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.

3.11 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 the first research question, about adaptation timing, with visualizations from both one-at-a-time local sensitivity analysis and global sensitivity analysis. We address the second research question, on the role of crossing characteristics in adaptation efficiency, with a multinomial regression on the results from the global sensitivity analysis. In all analyses, we combined performance and cost metrics for the eight culverts in our testbed and assumed that all culverts were treated with the same adaptation strategy, in a companion paper we investigate the possibility of allowing individualized adaptation strategies for each culvert (McCurdy & Travis, 2016).

3.11.1 One-at-a-time Sensitivity Analysis

During this stage, we vary the Crossing Characteristics described above under no change, low, and high climate scenarios. One Crossing Characteristic is altered in each model run according to a specified step; reference 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 limited to plausible values reflected in engineering guidelines for such crossings.

3.11.2 Global Sensitivity Analysis

We used Monte Carlo sampling to alter 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.

3.11.3 Multinomial Regression

We use a multinomial regression to assess the predictability of the preferred strategy (Hosmer Jr, Lemeshow, & Sturdivant, 2013). By preferred we mean the strategy which results in the lowest cost at the end of a simulation. Much of what determines the preferred strategy is inherently random as it depends on the occurrence of rare but costly extreme events. Predictability refers to how well information known at the beginning of the simulation could help a manager chose the strategy with the lowest cost. 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).

4. 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 absolutely advantageous or at least minimize increases in losses and additional cost as the climate changes. Below we present specific findings and results for the two main questions addressed by this research.

4.1 How do adaptation strategies with different timing qualities perform under different climate realizations and crossing parameters?

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 Increase Discount and the Capacity Increase had little impact on the resulting cost; thus, we do not depict them here. Key results are plotted in figure 3 and 4 showing physical cost against crossing characteristic values, and in figure 5, showing the value of delay cost against changes in crossing characteristics. In the latter we only include the Climate and Resilience Factors as the others only affect cost and not performance of crossings.

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 of previously installed crossings. That is each simulation begins with previously installed culverts, all of which have useful life remaining; the anticipatory strategy erases the value of this infrastructure by replacing it prior to the end of useful life. In 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 nominal 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.

4.1.1 Cost to Increase Capacity

We varied the Cost to Increase Capacity 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 capacities are increased. Under the Concurrent Strategy total costs increase linearly with the costs to increase capacity. 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 Concurrent Strategy crossing the Nominal Strategy curve at different points depending on climate the change scenario (figure 3 a-c). These results imply that as rate of climate change increases the cost-effective price to increase capacity rises, and the manager should be willing to pay more per unit upgrade because it helps reduce overall costs.

4.1.2 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 4d and 5d). 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.

4.1.3 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 the No Climate Change scenario the Nominal Strategy remains preferable to both the Concurrent and Reactive strategies (figure 3 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 transportation managers convinced that climate change is worsening, or will worsen, stormwater performance are trying to avoid by adopting more anticipatory strategies.

4.1.4 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. This is likely an effect of particular statistical nature of extreme events, represented in the shape of the underlying GEV distribution (figure 3 a-c and 4 a-c). As the capacity of a 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. This might be intentional in some cases or the inadvertent effect of the available precast culvert sizes.

4.2 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?

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 excluding the climate change 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.

$$Optimal\ Strategy \sim Emergency\ Factor + Upgrade\ Cost + Climate\ Factor + Resilience\ Factor + Upgrade\ Factor + Upgrade\ Factor * Climate\ Factor + Upgrade\ Cost * Climate\ Factor + Emergency\ Factor * Climate\ Factor \quad \text{(EQ 4)}$$

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 4-RPSS Results for Multinomial Models

Model	**RPSS vs Nominal**	**RPSS vs Nominal and Concurrent**	**RPSS vs Climatology**
Aggregate	0.72	0.4	0.42
Aggregate w/o CF	0.68	0.36	0.32
Climate Alone	0.58	0.17	0.11

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.

5. 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 forward-looking plans for design and maintenance. This follows trends in the climate change adaptation literature stressing flexibility (Walker, Haasnoot, & Kwakkel, 2013) and attention to the range of options (Hoss et al., 2014). We found that the choice of when and how to implement adaptation is affected by both the degree of climate change and crossing characteristics, but that there is more opportunity and benefit from reducing uncertainty about crossing characteristics rather than about climate change. Even for climate change that halved the recurrence 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 structures prior to the end of their useful life, a maladaptive strategy that incurs larger opportunity costs compared to other strategies and may create path dependencies that reduce options for future adaptation (Magnan et al., 2016).

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. Yet many transportation agencies would need additional data collection to learn this information and to benefit from the finer distinctions in choices allowed by simulation modeling (Maher, 2015), and the additional cost of that information may eliminate benefits gained by using it to choose appropriate adaptation strategies. Future work could assess the cost and value of additional information about culverts to judge whether the investment in data collection is likely to pay off in terms of more efficient adaptation.

Our simulation describes a simple but realistic testbed of road crossings served by culverts. Future work could elaborate on this model in several ways. First, 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), and economic analysis has shown that increasing the capacity of crossings by installing stream-simulation culverts would be beneficial in many cases under the current climate (Levine & Keene Valley, 2013; Long, 2010). Second, climate change is implemented in our model through a shift in the location parameter, the simplest way to simulate 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. Finally, this study focused on incremental adaptation but it is likely that systems in some settings (e.g., where freshwater and coastal flooding interact) will require transformative adaptation at some time in the future, perhaps involving relocation of infrastructure. The findings from incremental adaptations suggest that investing now in anticipatory infrastructure capacity without attention to possible transformations needed in the future (Barnett & O'Neill, 2010; Kates, Travis, & Wilbanks, 2012), makes those changes less likely to pay off.

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Figure Captions

Fig 1 Diagram of the modeling process. Rounded rectangels with bold text are inputs, diamonds are processes, and rounded rectangles without bold text are results from processes. Event simulation is repeated for a 100 year timeline

Fig 2 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

Fig 3 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 cost to increase capacity under high, low, and no change climate scenarios. (d-f) Changes in mean physical cost vs changes in in the emergency factor under high, low and no change climate scenarios. For example in the emergency factor plots (d-f) the cost of the Nominal Strategy increases from typically being the lowest cost under normal climate (d) to mostly the highest cost under the high climate change scenario (f)

Fig 4 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 resilience factor under high, low, and no change climate scenarios. (d) Changes in mean physical cost vs changes in the climate factor

Fig 5 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 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 costs are not included. Despite the earlier increase in capacity the Anticipatory Strategy has higher delay cost from premature replacement events

Figure 1

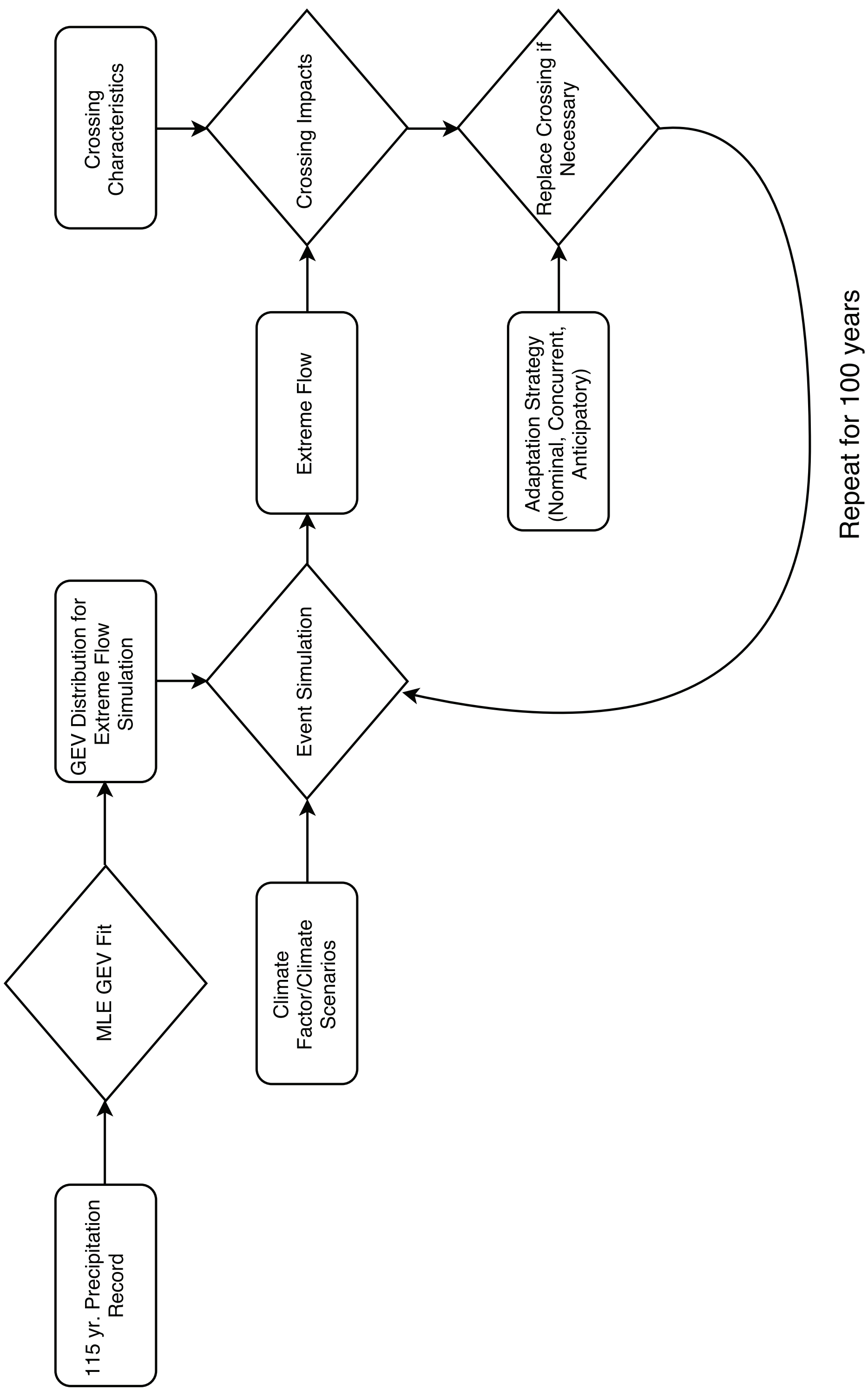
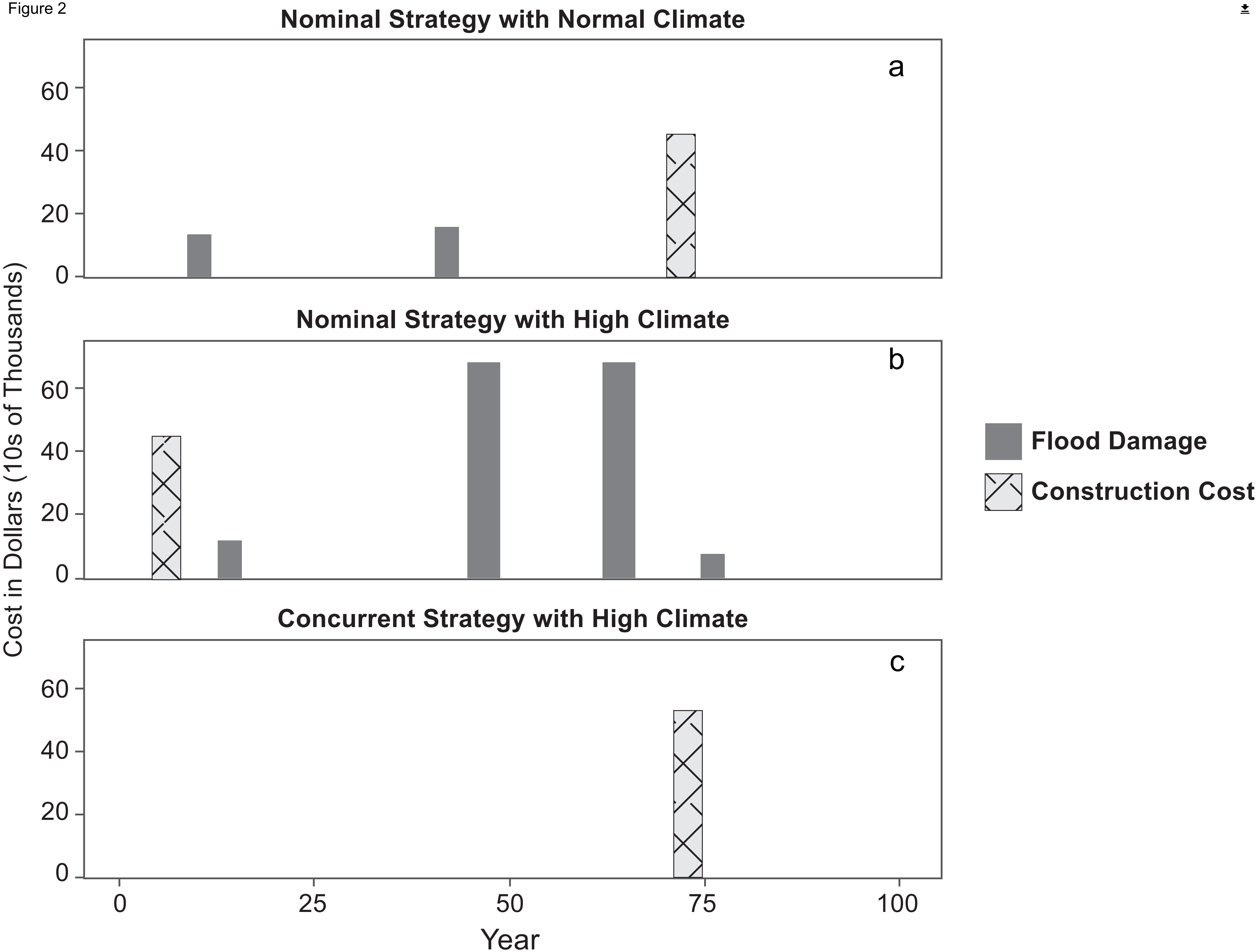
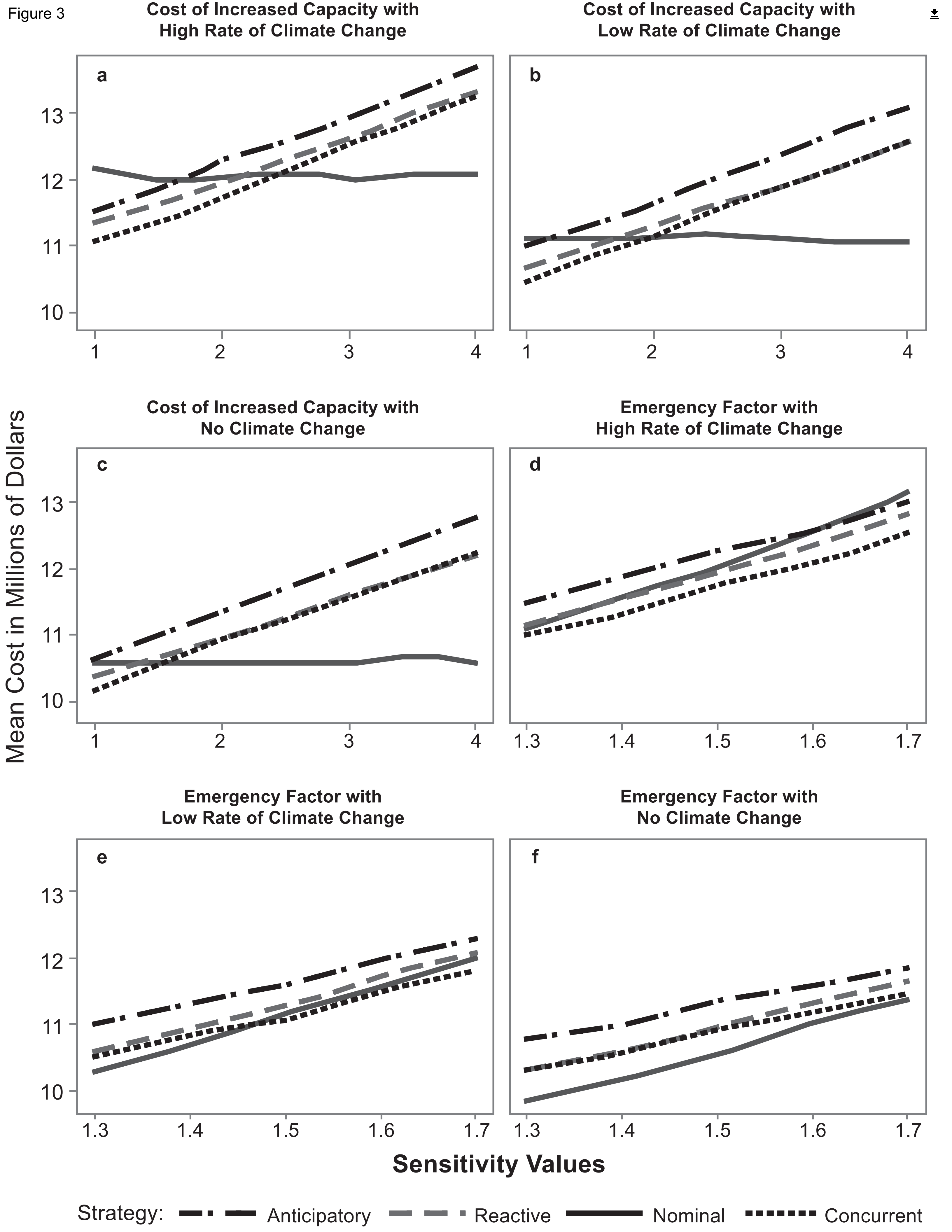

115 yr. Precipitation Record
MLE GEV Fit
GEV Distribution for Extreme Flow Simulation
Climate Factor/Climate Scenarios
Event Simulation
Extreme Flow
Crossing Characteristics
Crossing Impacts
Adaptation Strategy (Nominal, Concurrent, Anticipatory)
Replace Crossing if Necessary
Repeat for 100 years

Figure 2



Nominal Strategy with Normal Climate
a
Nominal Strategy with High Climate
b
Concurrent Strategy with High Climate
c
Cost in Dollars (10s of Thousands)
60
40
20
0
0
25
50
75
100
Year
Flood Damage
Construction Cost

Figure 3



Cost of Increased Capacity with High Rate of Climate Change
Cost of Increased Capacity with Low Rate of Climate Change
Cost of Increased Capacity with No Climate Change
Emergency Factor with High Rate of Climate Change
Emergency Factor with Low Rate of Climate Change
Emergency Factor with No Climate Change
a
b
c
d
e
f
10
11
12
13
1
2
3
4
1.3
1.4
1.5
1.6
1.7
Mean Cost in Millions of Dollars
Sensitivity Values
Strategy:
Anticipatory
Reactive
Nominal
Concurrent

Figure 4

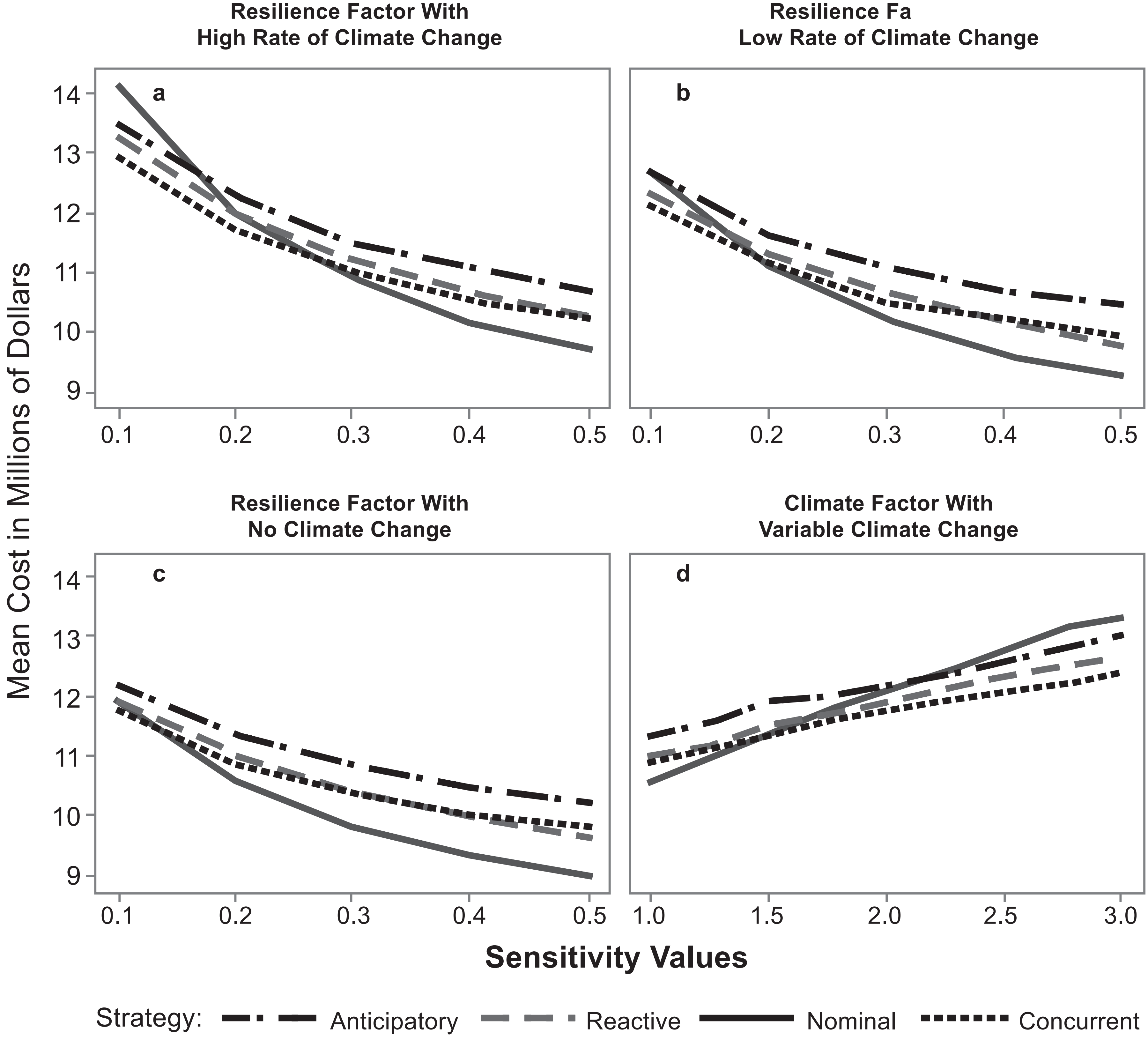
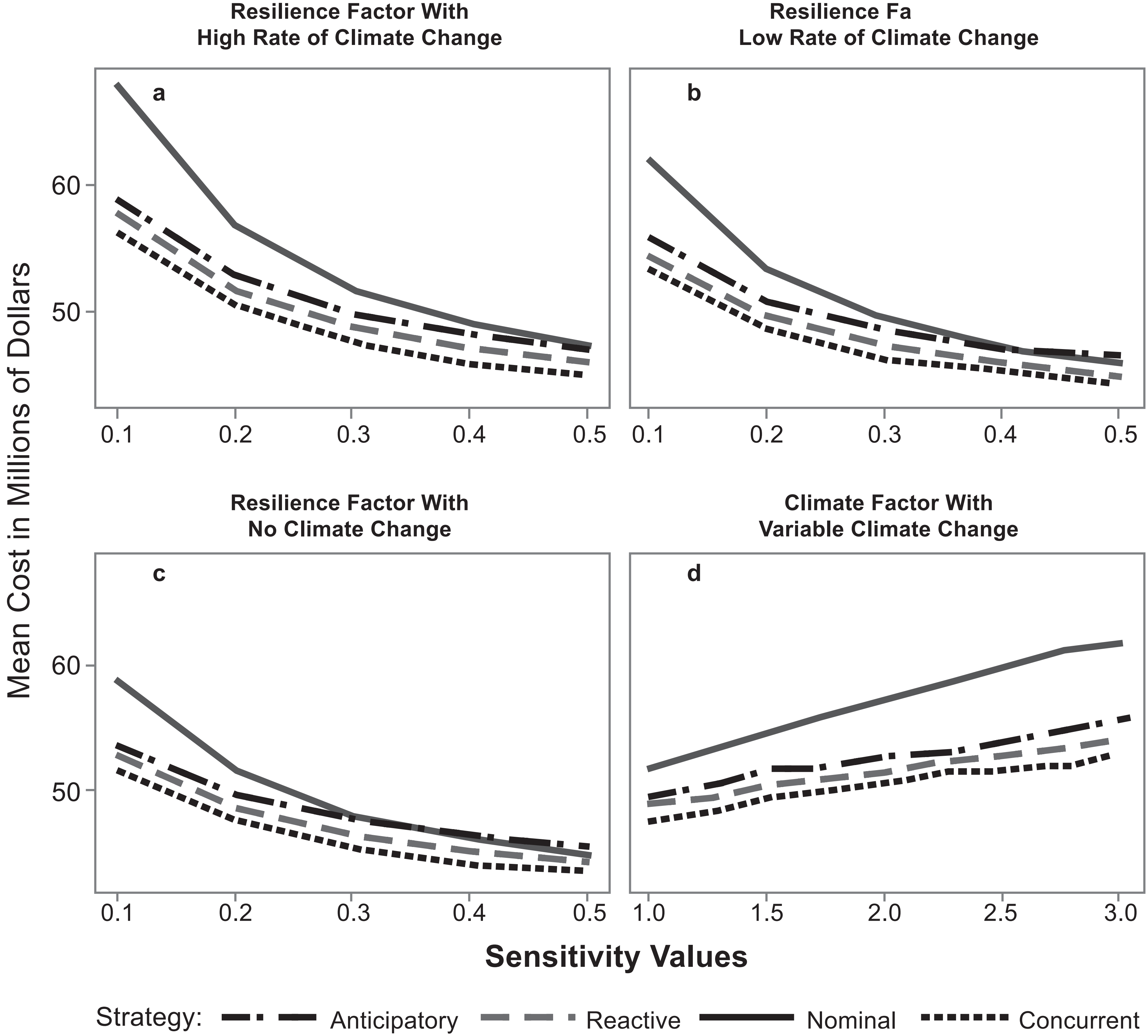

Resilience Factor With
High Rate of Climate Change
Resilience Fa
Low Rate of Climate Change
Resilience Factor With
No Climate Change
Climate Factor With
Variable Climate Change
a
b
c
d
Mean Cost in Millions of Dollars
14
13
12
11
10
9
0.1
0.2
0.3
0.4
0.5
1.0
1.5
2.0
2.5
3.0
Sensitivity Values
Strategy:
Anticipatory
Reactive
Nominal
Concurrent

Figure 5



Resilience Factor With
High Rate of Climate Change
Resilience Fa
Low Rate of Climate Change
Resilience Factor With
No Climate Change
Climate Factor With
Variable Climate Change
a
b
c
d
Mean Cost in Millions of Dollars
60
50
0.1
0.2
0.3
0.4
0.5
1.0
1.5
2.0
2.5
3.0
Sensitivity Values
Strategy:
Anticipatory
Reactive
Nominal
Concurrent