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Adaptive water infrastructure planning for nonstationary hydrology

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ABSTRACT

The uncertainty of a changing climate raises challenges for water infrastructure planning and design. Not accounting for nonstationarity may result in under-designed structures that fail too frequently, or over-designed structures that are economically inefficient. This concern is magnified by uncertainty in the long-term frequency and magnitude of future extreme events. Planning strategies that allow adaptations over a structure's life could improve both reliability and economic efficiency. This study develops a method to inform adaptive water infrastructure planning with uncertain hydrologic and other forms of nonstationarity, applied to levee system planning. A stochastic dynamic programming model including a Markov process is developed for infrastructure planning with uncertain nonstationarity in flood frequency. Bayes' theorem is used to update peak flow probabilities conditioned on observed past peak flows and to update expected residual flood damages over time. A levee system planning problem with a numerical example from California illustrates the approach to derive optimal levee heights over time, and economic values of adapting to uncertain nonstationary flood risk. The projected range of probabilistic hydrology scenarios affects the optimal results, particularly in later planning stages as hydrology scenarios diverge with time. Adaptive planning strategies allowing more levee upgrades over time slightly lowers the overall cost and provides better flood protection than one-time construction under nonstationary hydrology for any climate in the example. Compared to a known future nonstationary hydrology, incorporating uncertain nonstationary climate results in higher levees being planned for observed severe hydrology scenarios in later stages. The overall present value cost with uncertain nonstationary climate depends on rates of change in peak flow distribution parameters in future hydrology scenarios.

1. Introduction

We know the climate is changing, but we aren't sure exactly how and how much. Water infrastructure planning traditionally requires a stationary assumption that the probability distribution of extreme events will not change significantly over time (Milly et al., 2008; Jakob, 2013). However, in a nonstationary hydrology, the intensity, duration and frequency of climatic extremes will change (Alexander et al., 2006; Field, 2012; Gregersen et al., 2013; Jakob, 2013; Cheng and AghaKouchak 2014). A nonstationary hydrology would affect the reliability of existing water infrastructure and planning of new infrastructure, particularly flood protection infrastructure such as dams and levees (Read and Vogel, 2015; Dettinger et al., 2016). The assumption of stationarity in planning is evolving to include climate change and other dynamic considerations (e.g. Zhu et al., 2007; Smith et al., 2017). More severe droughts from climate warming increases the need for storage capacity, while more severe floods encourage release of more stored water, together creating a need to re-balance infrastructure design and operation plans between conflicting purposes (Dettinger et al., 2016). Long-term water infrastructure planning should not only achieve economic, environmental, and social goals, but also be robust and adaptable to nonstationary hydrology.

Infrastructure planning is driven by economic benefits and costs (Layard and Glaister, 1994). Flood protection design, from an economic perspective, should consider benefits from reduced flood risk and costs of construction and maintenance over time (Loucks et al., 2005; DWR, 2016). Economic flood risk is calculated by summing over all possible events the probability of each flood magnitude multiplied by its economic consequences (Van Dantzig, 1956; Samuels et al., 2008; Eijgenraam et al., 2014; Hui et al., 2016a,b). Since flood protection infrastructure reduces, but does not eliminate, flood risk, some residual flood damages always exist (Deverel et al., 2016; Hui et al., 2016b). In the United States, Bulletin 17C has updated the early guidelines for determining flood flow frequency to include consideration of nonstationary climate conditions (Subcommittee, 1982; England et al., 2015). To achieve economically rational flood protection, risk-based infrastruc-

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ture planning usually aims to minimize the sum of expected construction, maintenance, and residual damage costs discounted over time.

In flood planning, traditional flood frequency analysis assumes that the statistical properties of extreme events are stationary, independent, and identical (Stedinger and Crainiceanu, 2001; Zhu et al., 2007). Under nonstationary conditions, the statistical parameters of the peak flow distribution would vary with time (Cheng and AghaKouchak 2014; Cheng et al., 2014). This challenge is further complicated by the fact that the long-term changes in these statistical parameters are uncertain. Dynamic programming (DP) is often used to solve water planning problems with stationary hydrology (Yakowitz 1982; Loucks et al., 2005). To deal with climate changes and hydrologic variability, many optimization models have been developed for flood protection systems, using projected hydrology scenarios to represent nonstationarity (Loucks et al., 2005; Zhu et al., 2007; Teegavarapu 2010; Culley et al., 2016). Optimization formulations to address uncertainties through the use of scenarios include scenario optimization, robust optimization, and stochastic programming (Dembo 1991; Wagner et al., 1992; Mulvey et al., 1995). For dynamic hydrologic changes over time, few flood planning studies have examined the probability of each projected hydrology scenario being updated with ongoing hydrologic observations, which incorporates uncertainty into nonstationary hydrology.

The design of sustainable long-term water infrastructure plans should be robust and adaptable over time to changing future conditions. Adaptive plans are designed to be updated over time with new available information, thus should better manage changing future circumstances with uncertainty and better guide future actions. Basic principles for sustainable adaptive plans include exploring a broader range of uncertainties, considering long-term goals while targeting short-term objectives, continued monitoring, and including options that can be adjusted to respond to problems and opportunities (Walker et al., 2013). Several planning frameworks have been proposed in this area. Assumption-Based Planning (ABP) involves adaptive planning using signposts and triggers to detect actions needed to reduce vulnerability to uncertain future changes (Dewar et al., 1993). The principles underlying ABP guide the development of static or robust adaptive plans such as Robust Decision Making (Grove and Lempert, 2007; Fischbach, 2010), Adaptive Policymaking (Walker et al., 2001; Rahman et al., 2008), Adaptation Tipping Points and Adaptation Pathways (Kwadijk et al., 2010; Haasnoot et al., 2012) and Dynamic Adaptive Policy Pathways (Haasnoot et al., 2013; Kwakkel et al., 2015). However, these frameworks have not incorporated probabilistic nonstationarity in hydrological parameters.

To provide an adaptive plan that addresses changing probabilities of projected hydrology scenarios in flood management, this study examines the effects of uncertain nonstationary hydrology on optimal adaptive water infrastructure plans using a stochastic dynamic programming (SDP) method with a Markov process. The conditional probabilities of projected hydrology scenarios are updated with observations over time using Bayes' theorem (Renard et al., 2013). This case is compared to adaptive water infrastructure planning using a deterministic dynamic programming (DDP) model for known nonstationary. The paper proceeds as follows: Section 2 describes the problem of hydro-economic water infrastructure planning with uncertain nonstationary hydrology; Section 3 develops a general SDP model for the planning problem; Section 4 applies the model to risk-based levee system planning, particularly for adaptive planning over time. Section 5 discusses the example results and Section 6 concludes this study.

2. Nonstationary hydrology and infrastructure planning problem

Flood protection planning typically assumes a stationary probability distribution of annual peak flows, where maximum annual peak flows are independent, identically distributed random variables with unchanging mean and standard deviation values over time (Stedinger and Crainiceanu, 2001). With a nonstationary hydrology, the annual flood frequency distribution is likely to change over time with uncertain mean and standard deviation (Cheng and AghaKouchak 2014). Fig. 1(a) illustrates six hypothetical future hydrology scenarios with variations of the annual peak flood flow distribution over time, following a log-normal distribution. Fig. 1(b) shows the current annual peak flow distribution, and Fig. 1(c) shows the annual peak flow distributions in six hypothetical hydrology scenarios in the future, where the mean and standard deviation change at different rates in each scenario (explained further in Section 4.2). Future hydrology scenarios generally vary for different climate projections. Planning studies typically aggregate projected hydrologic data with the probability of each hydrology scenario. However, the probabilities of each scenario will also change given uncertain nonstationary hydrology. The probabilities of different hydrology scenarios evolve as more hydrologic observations become available over time.

For long-term infrastructure planning and capital investment, reliability and economic costs are major concerns. Ignoring the uncertain nonstationary hydrology might cause infrastructure to be over or under-designed in economic terms. Errors in a forecasted uncertain nonstationary hydrology can also cause under or over-design. To balance reliability and economic cost, a risk-based method can minimize the overall average long-term cost. Reliability corresponds to the residual risk, where risk is typically defined as the summed product of failure probability and economic or other consequences.

The economic costs of infrastructure include construction, maintenance, improvements, and expected annual residual failure costs. Infrastructure should be maintained or improved after initial construction. An adaptive planning strategy provides ability to adjust long-lived infrastructure to changing natural and social conditions (Haasnoot et al., 2013; Kwakkel et al., 2015). The benefit of adaptation over time from reduced annual failure cost and other aspects depends on the infrastructure's functionality, estimated for local conditions.

For infrastructure planning, let the overall planning horizon be $n = T \times N_T$, where T is the incremental/adaptive period for improving/upgrading the infrastructure, N_T is the number of intervals over the infrastructure's lifetime. $N_T = 1$ means there are no improvements over its planned lifetime – a one-time construction strategy with no adaptation. At each time step $t = 1{:}\ n$, a vector $\vec{X}_t$ defines the state of the infrastructure, and a vector $\overline{\Delta X}_t$ defines any changes to the infrastructure (maintenance, repair, enhancement, upgrade, etc.), which together lead to the infrastructure's state at next time step $t+1$, $\vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t$, $t = 1 : n$.

Given m forecasted hydrology scenarios $A_t^s(\mu_t^s, \sigma_t^s)$, $s = 1 : m$, $t = 1{:}\ n$ evolving over time t that are assumed to span over all possible hydrology scenarios, each defines a potential nonstationary annual peak flood flow distribution with a changing mean μ_t^s and standard deviation σ_t^s of the annual peak flood flow, although the distribution's functional form remains fixed. The mean annual flood flow μ_t^s in each hydrology scenario A_t^s is assumed to be constant or vary linearly with time (Eq. (1a)), given the initial mean μ^{0s}, time t and change rate of the mean μ^{1s}. Similarly, the standard deviation σ_t^s is assumed to also be constant or vary linearly with time (Eq. (1b)), given the initial standard deviation σ^{0s} and the standard deviation's change rate σ^{1s}. Variation of the mean and standard deviation can take other forms, but linear trends are used here for demonstration and simplicity.

$$\begin{cases} \mu_t^s = \mu^{1s} t + \mu^{0s} & (a) \\ \sigma_t^s = \sigma^{1s} t + \sigma^{0s} & (b) \end{cases} \tag{1}$$

For computational purposes, the peak flow $Q_i (i = 1{:}\ NQ)$ is discretized into ΔQ increments. Each hydrology scenario has a projected constant probability $P_t(A_t^s) = P(A^s)$ at any time $t\,(t = 1{:}\ n)$. At each stage t, the sum of probabilities of all hydrology scenarios should equal one:

$$\sum_{s=1}^{m} P_t\left(A_t^s\right) = 1,\ t = 1 : n \tag{2}$$

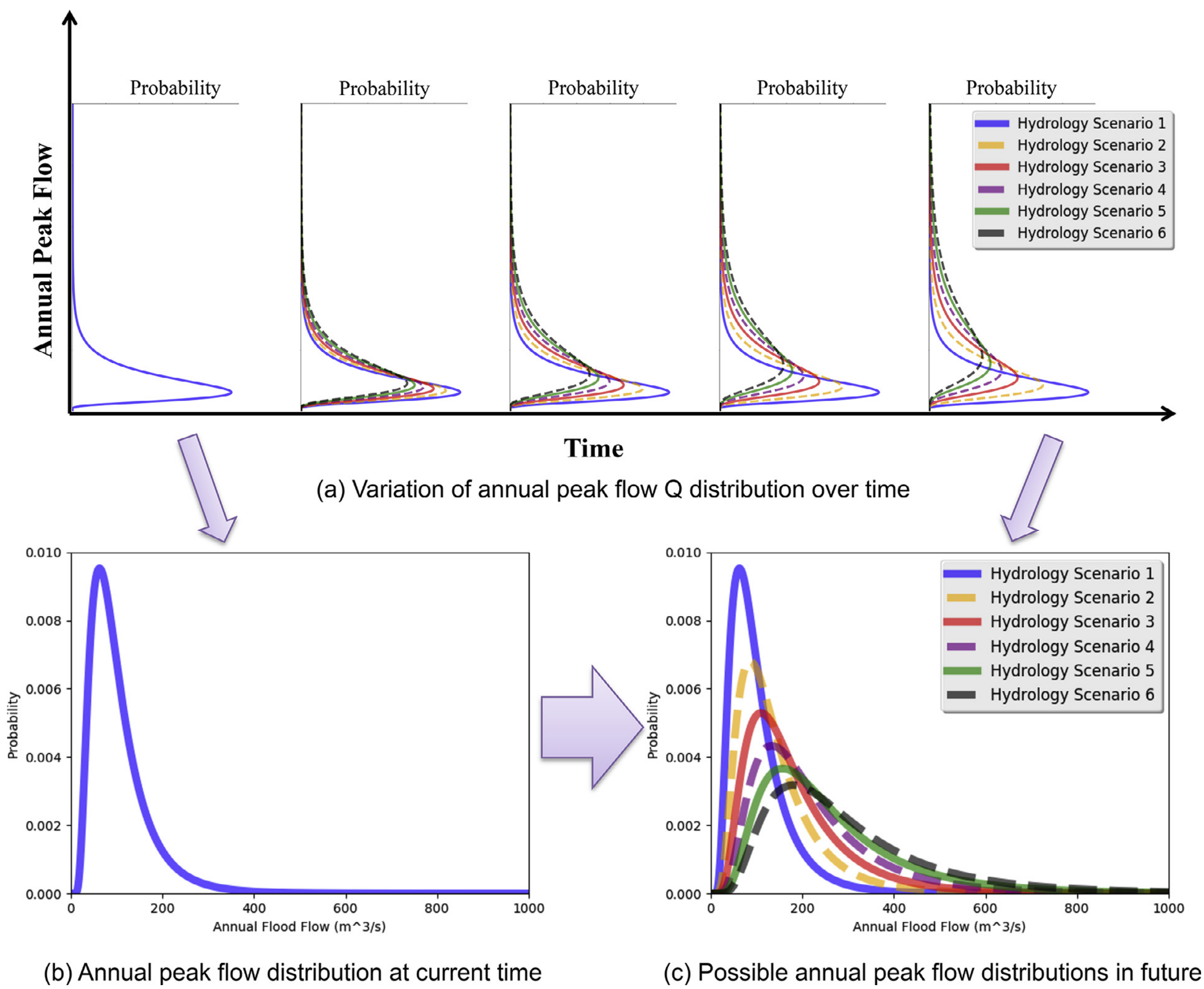

Fig. 1. Illustration of variation of annual peak flood flow distribution over time.

With a deterministic nonstationary hydrology, the probability of a hydrology scenario at any projected time is constant. However, given uncertainty in hydrologic nonstationarity, the "true" probability of a projected hydrology scenario is likely to change with time, referred to as uncertain nonstationary hydrology. Following the Markov process assumption, the future probability of a hydrology scenario would depend on available hydrologic observations (Loucks et al., 2005; Vicuna et al., 2010). Such conditional probabilities reflecting uncertain nonstationarity can be applied to risk-based economic water infrastructure planning calculations.

3. Model formulation for infrastructure planning

A basic dynamic programming formulation to deal with nonstationary hydrology includes elements of decision stage, decision variables, state variables, and objective function. The stage is time $t = 1{:}\ n$, where $n = T \times N_T$ and infrastructure construction or improvement can only occur each T year interval and N_T times over an infrastructure's lifetime. In a deterministic dynamic programming (DDP) model, state variables are the infrastructure's state vector $\vec{X}_t$ of the current stage. Decision variables are the infrastructure's change vector $\overline{\Delta X}_t$ at each time step t, with the relation that $\vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t$ $(t = 1 : n)$. The overall objective is to minimize the summed discounted costs over the planning horizon at an inflation-adjusted discount rate r_t. The discount rate r_t can vary with time, such as a hyperbolic discounting in a societal context (Weitzman, 1998; Dasgupta, 2008), but a simple constant discount rate is used here for illustration purposes (e.g., Zhu et al., 2007).

For a known nonstationary hydrology, the probability of a scenario A_t^s is known exactly at any stage and constant at $P(A^s)$. The backward recursive function for this dynamic programming model is (Zhu et al., 2007):

$$F_t\left(\overline{\Delta X}_t, \vec{X}_t\right) = \begin{cases} C_n\left(\overline{\Delta X}_n, \vec{X}_n\right)\dfrac{e^{r_n}}{e^{r_n}-1}, t = n \\ C_t\left(\overline{\Delta X}_t, \vec{X}_t\right) + \displaystyle\sum_{s=1}^{m} P(A^s) f_{t+1}\left(\vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t\right), \\ t = 1 : n-1 \end{cases} \tag{3}$$

where $f_{t+1}(\vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t) = \underbrace{\min}_{\overline{\Delta X}_{t+1}} F_{t+1}(\overline{\Delta X}_{t+1}, \vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t)e^{-r_{t+1}}$ and the overall objective is $Min\ F_1(\overline{\Delta X}_1, \vec{X}_1)$. The cost $C_t(\overline{\Delta X}_t, \vec{X}_t)$ at time t depends on the flow frequency distributions. Assuming no more maintenance or improvement after the end of the planning period, the present value (cost) at the last planning stage $t = n$ for an infinite horizon problem is:

$$C_n\left(\overline{\Delta X}_n, \vec{X}_n\right)\frac{e^{r_n}}{e^{r_n}-1} \tag{4}$$

The scenario-based cost $c_t(\overline{\Delta X}_t, \vec{X}_t, A_t^s)$ in this DDP approach depends on the flow frequency distributions and the probability distribution of hydrology scenarios at each time step t, and the cost $C_t(\overline{\Delta X}_t, \vec{X}_t)$

at each time step t is the expected cost weighted by the hydrology scenario probabilities $P(A^s)$. Similar to the probabilistic recursive function, the expected cost at each time t is:

$$C_t\left(\overline{\Delta X}_t,\ \vec{X}_t\right) = \sum_{s=1}^{m} P(A^s)\ c_t\left(\overline{\Delta X}_t,\ \vec{X}_t, A_t^s\right),\ t = 1 : n \tag{5}$$

The ultimate probability of a hydrology scenario is not necessarily equal to the initially projected probability of that hydrology scenario - uncertainty exists in the nonstationary hydrology. A stochastic dynamic programming model with a Markov Process (SDP) is developed to solve such uncertain nonstationarity by including the conditional probability $P_t(A_t^s|\bar{A}_{t-1})$ that a hydrology scenario A_t^s is "true" at current stage given an observed hydrology scenario state $\bar{A}_{t-1}$ at the previous stage (Vicuna et al., 2010). The decision stage, decision variables and objective function are the same as the DDP model. State variables include, in addition to the infrastructure's state vector $\vec{X}_t$ at the current stage, the observed hydrology scenario at the previous stage $\bar{A}_{t-1}(\bar{\mu}_{t-1}, \bar{\sigma}_{t-1})$ represented by observed mean $\bar{\mu}_{t-1}$ and standard deviation $\bar{\sigma}_{t-1}$ of annual peak flood flows.

The backward recursive function for this SDP model becomes:

$$F_t\left(\overline{\Delta X}_t, \vec{X}_t, \overline{A}_{t-1}\right) = \begin{cases} C_n\left(\overline{\Delta X}_n, \vec{X}_n\right)\dfrac{e^{r_n}}{e^{r_n}-1}, t = n \\ C_t\left(\overline{\Delta X}_t, \vec{X}_t\right) + \displaystyle\sum_{s=1}^{m} P_t\left(A_t^s|\overline{A}_{t-1}\right) \\ f_{t+1}\left(\vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t, A_t^s\right), t = 1 : n-1 \end{cases} \tag{6}$$

The Markov uncertainty $P_t(A_t^s|\bar{A}_{t-1})$ adds the state variable $\bar{A}_{t-1}$ to the formulation, compared to the DDP with constant hydrology scenario probabilities. Because the present hydrology scenarios are conditioned on those of the immediate past, each possible past hydrology scenario state must be represented in the recursive function:

$$f_{t+1}\left(\vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t,\ A_t^s\right) = \underbrace{min}_{\overline{\Delta X}_{t+1}} F_{t+1}\left(\overline{\Delta X}_{t+1},\ \vec{X}_{t+1} = \vec{X}_t + \overline{\Delta X}_t,\ A_t^s\right) e^{-r_{t+1}} \tag{7}$$

The observed hydrology scenario state at previous stage $\bar{A}_{t-1}(\bar{\mu}_{t-1}, \bar{\sigma}_{t-1})$ affects the conditional probability $P_t(A_t^s|\bar{A}_{t-1})$ of each hydrology scenrio A_t^s at the current stage. Using Bayes' Theorem, the probability that hydrology scenario A_t^s is "true" at current stage t, given the observed scenario $\bar{A}_{t-1}$ at time $t-1$ is:

$$P_t\left(A_t^s|\bar{A}_{t-1}\right) = \frac{P(A^s)P_{t-1}\left(\bar{A}_{t-1}|A_t^s\right)}{P\left(\bar{A}_{t-1}\right)} = \frac{P(A^s)P_{t-1}\left(\bar{A}_{t-1}|A_t^s\right)}{\sum_{s=1}^{m}\left[P(A^s)P_{t-1}\left(\bar{A}_{t-1}|A_t^s\right)\right]} \tag{8}$$

The cost function $C_t(\overline{\Delta X}_t,\ \vec{X}_t)$ in this SDP model involving the Bayes' conditional probability is:

$$C_t\left(\overline{\Delta X}_t,\ \vec{X}_t\right) = \sum_{s=1}^{m} P_t\left(A_t^s|\bar{A}_{t-1}\right)c_t\left(\overline{\Delta X}_t,\ \vec{X}_t, A_t^s\right),\ t = 1 : n \tag{9}$$

Assuming no upgrades after the end of the planning horizon, the present value (cost) at the last planning stage $t=n$ for an infinite horizon problem is the same as in Eq. (5).

The optimal infrastructure design decisions and the estimated investment and cost are conditioned on both infrastructure state and the most recent observed hydrology scenario state. By comparing the optimal results from the SDP formula Eq. (6) with uncertain nonstationarity, and from the DDP formula Eq. (3) with known nonstationarity, we can analyze the influence of uncertainty in hydrologic nonstationarity on long-term infrastructure planning.

4. Application to risk-based levee system planning

As a numerical example, a levee system planning problem is used to illustrate the application of the proposed models for different hydrologic situations (Fig. 2). H is levee height, B_C is levee crown width, α is land-side slope angle and β is water-side slope angle. B is channel width, W is total channel width to the toe of the levee, D is channel depth below the levee toe, τ is floodplain slope. Y is water depth, calculated from river flow using Manning's Equation.

4.1. Model formulation for levee system planning

For this problem, levee height is the only decision variable and the levee cannot be degraded. Decision variables $\overline{\Delta X}_t$ are the levee height increment ΔH_t at each stage (in this example stage is the year in planning period). State variables in the DDP model are the existing levee height at the beginning of the current stage, H_t, while in the SDP model also include the observed hydrology scenario $\bar{A}_{t-1}$ represented by log-normal distributed annual flood flow at the previous stage. Levee height increment, existing levee height and the observed hydrology scenario are all discretized. The overall objective is to minimize the summed discounted costs over the lifetime of the levee system.

The state cost function $C_t(\overline{\Delta X}_t,\ \vec{X}_t)$ differs in the two models (Eqs. (5) and (9)). For a known nonstationary hydrology, the cost function in the DDP includes averaged expected annual residual flood damage costs $EAD_t(\Delta H_t, H_t, A_s)$ and levee building or upgrade costs $CC_t(\Delta H_t, H_t)$ under different hydrology scenarios with probabilities of each hydrology scenario $P(A_s)$ (Eq. (10a)). For an uncertain nonstationary hydrology, the cost function in the SDP includes $EAD_t(\Delta H_t,\ H_t, A_t^s)$ and $CC_t(\Delta H_t, H_t)$ averaged by the conditional probability $P_t(A_t^s|\bar{A}_{t-1})$ (Eq. (10b)). When the levee system is upgraded, $\Delta H_t > 0$, a fixed levee alteration cost is added to $CC_t(\Delta H_t, H_t)$ representing costs for regulating, design, consulting, and organizing construction, etc.

$$C_t\left(\Delta H_t, H_t\right) = \begin{cases} \left\{\displaystyle\sum_{s=1}^{m} P(A^s)\left[EAD_t\left(\Delta H_t, H_t, A^s\right) + CC_t\left(\Delta H_t, H_t\right)\right]\right\} e^{-r_t} (a) \\ \left\{\displaystyle\sum_{s=1}^{m} P_t\left(A_t^s|\overline{A}_{t-1}\right)\left[EAD_t\left(\Delta H_t, H_t, A_t^s\right) + CC_t\left(\Delta H_t, H_t\right)\right]\right\} e^{-r_t} (b) \end{cases} \tag{10}$$

Levee flood failure could occur by overtopping when peak flow overtops the levee, or by intermediate geotechnical non-overtopping failure when peak flow rises between the toe and top of the levee such as through-seepage levee failure (Hui et al., 2016a). The expected annual residual flood damage cost considering both overtopping and geotechnical non-overtopping failures, for known and uncertain nonstationarity is:

$$\begin{aligned} EAD_t\left(\Delta H_t, H_t, A^s\right) = EAD_t\left(\Delta H_t, H_t, A_t^s\right) &= \int \left[P\left(Q_t^s\right)D_t\left(Q_t^s\right)\right] \\ &= \int_{QC_{\min}}^{QC_{\max}(\Delta H_t, H_t)} \left[P\left(Q_t^s\right)D_t\left(Q_t^s\right)\right] \\ &\quad + \int_{QC_{\max}(\Delta H_t, H_t)}^{\infty} \left[P\left(Q_t^s\right)D_t\left(Q_t^s\right)\right] \end{aligned} \tag{11}$$

Levee quality and performance are assumed constant over its lifetime. Levee deterioration affects the levee fragility curve and therefore the intermediate geotechnical non-overtopping failure probability, which can be addressed in a future study. We assume that the intermediate geotechnical levee failure probability is a linear function of channeled water height in this example; failure probability increases linearly from 0 at the toe to 1 at the top (Wolff 1997; Perlea and Ketchum 2011).

Levee building or upgrade costs include the materials, management and purchasing land at every construction or upgrade stage:

$$\begin{aligned} CC_t\left(\Delta H_t, H_t\right) &= 2 \times \left(V_t C_{adjust} C_{soil} + LC_t\right), for\ t \\ &= 1, T+1, 2T+1, 3T+1 \ldots \end{aligned} \tag{12}$$

C_{adjust} is the soft cost multiplier for construction management and C_{soil} is construction cost per unit material. The total volume (trapezoidal) of upgrading levees along the entire length (L) of the river reach

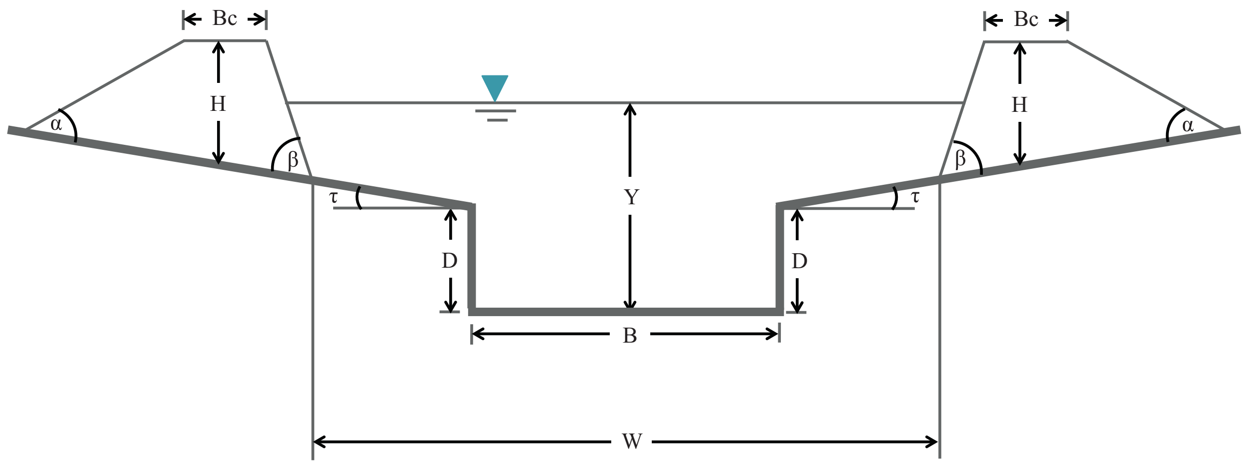

Fig. 2. A simple levee system with identical levees on opposite riverbanks.

Table 1
Examined levee system planning strategies.

Planning strategy	Adaptation year interval T	Number of intervals N_T	Adaptations
One-time building	200	1	0
100 year adaptive building	100	2	1
50 year adaptive building	50	4	3
25 year adaptive building	25	8	7
5 year adaptive building	5	40	39
Annual adaptive building	1	200	199

is $V_t = L\{Bc\,\Delta H_t + \frac{1}{2}(\frac{1}{tan\alpha} + \frac{1}{tan\beta})[(H_t + \Delta H_t)^2 - H_t^2]\}$. The cost for purchasing land on floodplains to upgrade the levees, with a unit land cost UC, the additional area of land occupied by a levee base A_{base} is $LC_{base} = UC\ A_{base} = UC\ L[Bc + (\frac{1}{tan\alpha} + \frac{1}{tan\beta})\Delta H_t]$.

Assuming no more upgrades after the end of the planning period, the present value (cost) at the last planning stage $t=n$ for an infinite horizon problem is $C_n(\Delta H_n,\ H_n)\frac{e^{rn}}{e^{rn}-1}$.

4.2. Model input and examined cases

The decision horizon of the illustrative levee system plan is assumed to be $n=200$ years. Two types of planning strategies are analyzed and compared: one-time building planning, and adaptive building and improvement planning. For the latter type, we analyze cases with shorter or longer planned adaptation year interval (more or fewer adaptations allowed) during the lifetime of the levee system after initial construction (Table 1). With the one-time building strategy where $T=200yr$ and $N_T=1$, the levee system is built to an economically optimal height at the beginning and retains this height over its lifetime. The adaptive planning strategy allows the levee system to be upgraded every T years after its first construction. The number of adaptations/upgrades refers only to upgrades after initial construction. The input parameters for the example are roughly based on the Cosumnes River in California (Table 2). We use a constant discount rate for simplification and ignore the uncertainty in this time-dependent variable, which is more uncertain in the long-term. Degradation of the levee system over time is not considered.

Six illustrative hydrology scenarios ($m=6$) are used here for modeling long-term plans, and are assumed to cover the full range of possible scenarios. Since climate projections vary significantly with different climate model and input parameters, we examined four hypothetical projected climate cases with different annual changing rates of mean μ^{1s} and standard deviation σ^{1s} of flood flow in each hydrology scenario and in each uncertainty case (Eq. (1)). The annual change rates of mean and standard deviation of flood flow in a corresponding normal distribution in climate Case 1 are $\mu^{1s}=0\%,\ 0.2\%,\ 0.4\%,\ 0.6\%,\ 0.8\%,\ 1\%$ and $\sigma^{1s}=0\%,\ 0.2\%,\ 0.4\%,\ 0.6\%,\ 0.8\%,\ 1\%$ for each hydrology scenario, respectively. Climate Case 2 has the same μ^{1s} as in Case 1 but higher σ^{1s} ($\sigma^{1s}=0\%,\ 0.5\%,\ 1.0\%,\ 1.5\%,\ 2.0\%,\ 2.5\%$). Climate Case 3 has higher μ^{1s} and σ^{1s} that are $\mu^{1s}=0\%,\ 0.5\%,\ 1.0\%,\ 1.5\%,\ 2.0\%,\ 2.5\%$ and $\sigma^{1s}=0\%,\ 0.5\%,\ 1.0\%,\ 1.5\%,\ 2.0\%,\ 2.5\%$. Climate Case 4 has the same μ^{1s} as in Case 3, but higher σ^{1s} ($\sigma^{1s}=\ 0\%,\ 1.0\%,\ 2.0\%,\ 3.0\%,\ 4.0\%,\ 5.0\%$). Fig. 1(c) illustrates the variations of annual peak flow distributions over 200 years for climate Case 1. Because the log values of annual flood flow follow a normal distribution, the corresponding log-normal distributions change slightly over time with the hypothetical changing means and standard deviations in the four climate cases. Fig. 3 plots the annual peak flow distributions in 200 year for each forecasted hydrology scenario in each hypothetical climate case. In climate Case 1 and Case 2, the mean of the annual flood flow's natural logarithm is increasing from hydrology scenario 1 to 6, and it increases more in climate Case 3 and Case 4. The standard deviation of the annual flood flow's natural logarithm is the same for each hydrology scenario in climate Case 1 and Case 3 as the annual changing rates of mean and standard deviation in the corresponding normal distribution are the same, while it is increasing from hydrology scenario 1 to 6 in climate Case 2 and Case 4 as the changing rate of standard deviation in the normal distribution exceeds that of the mean. The long-term levee system plan is modeled and compared for the four hypothetical nonstationary climate cases.

The initial probabilities of the six hydrology scenarios are equally 1/6. Such probabilities will be constant during the entire planning period in the assumed known nonstationary hydrology. The Bayes' conditional "true" probability of each hydrology scenario in the assumed uncertain nonstationary hydrology is updated in each following stage, based on the observed previous hydrology scenario represented by the mean and standard deviation of annual flood flow distribution. The Bayesian probabilities at stage 50, 100, 150, and 200 for the 6 hydrology scenarios in climate Case 1 are plotted in Fig. 4. Early stages have fewer variations of hydrology scenario probabilities for observed previ-

Table 2
Input parameters of the example case.

Variable symbol	Parameter name	Value
L	Levee system length	2000 m
W	Leveed channel total width till the toe of the levee	90 m
B	Leveed channel width	60 m
D	Channel depth	1 m
$tan\alpha$	Land-side slope	1/4
$tan\beta$	Water-side slope	1/2
τ	Floodplain slope	0.01
S_C	Longitudinal slope of the channel	0.0005
N_C	Manning's coefficient	0.05
B_C	Levee crown width	10 m
μ^{0s}	Initial mean of annual flood flow*	100 m^3/s
σ^{0s}	Initial standard deviation of annual flood flow*	66 m^3/s
DC	Flood damage cost for each failure	$10 million
UC	Land price for purchasing a unit land	$1/m^2
C_{soil}	Construction cost per unit material	30 $/m^3
C_{adjust}	Soft cost multiplier for construction management	1.3
r_t	Inflation-adjusted discount rate assumed constant	3.5%
H_0	Initial levee height is 0m	0 m
discretized ΔH	Discretized height increment	0.1 m
H_{max}	Maximum levee height	15 m
ΔH_{max}	Maximum upgrading levee height	10 m
OM	Annual levee maintenance unit cost**	$74,000/km
$FLAC$	Fixed levee alteration/upgrade cost	$0.5 million

* These are values at the beginning of the planning period, which are changing differently among the projected hydrology scenarios. For the assumed log-normal distributed annual peak flood flow, the mean or location parameter for the normally distributed logarithm is about 4.42, and the standard deviation or scale parameter is about 0.60.
** Annual levee maintenance cost is $46,000/mile or $74,000/km considering levee operation and maintenance (DWR, 2016).

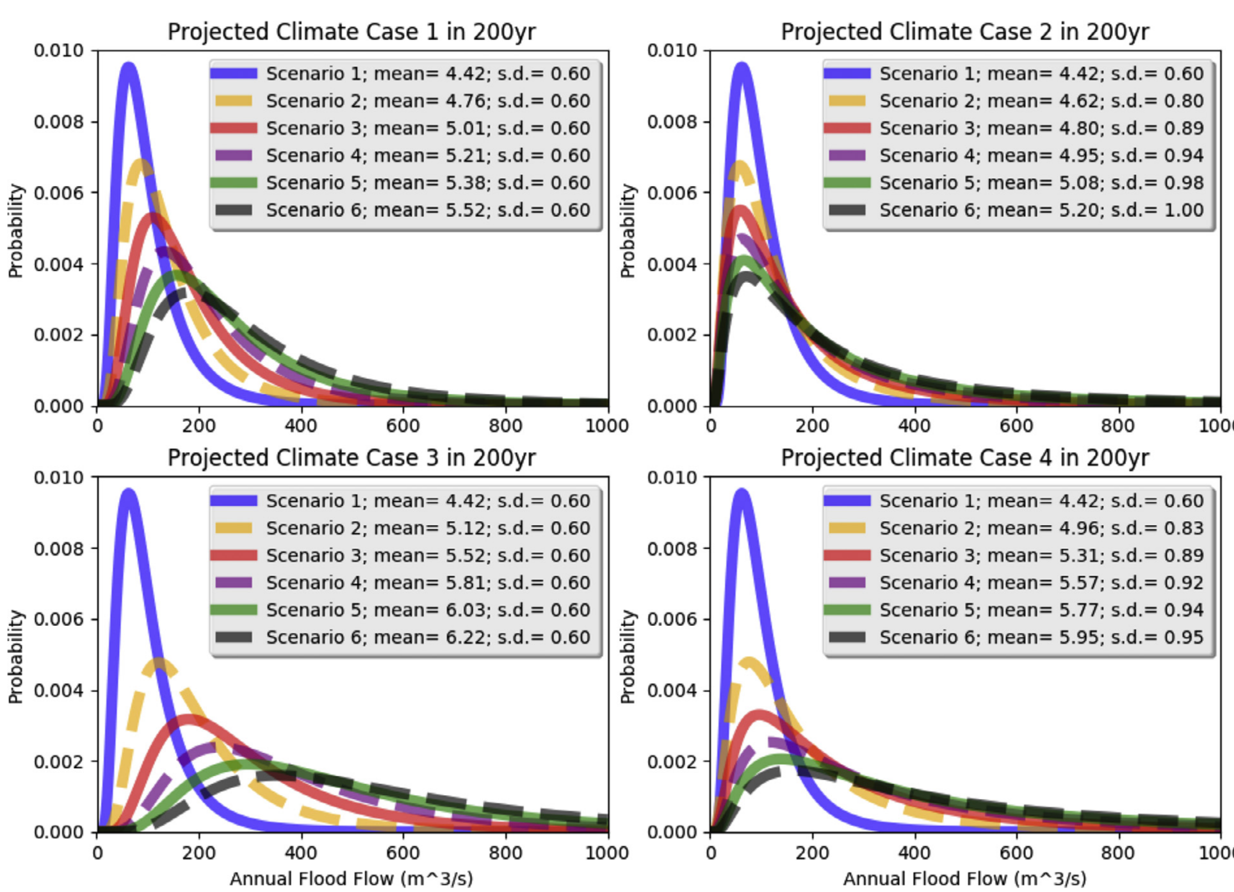

Fig. 3. Annual flood flow distributions for each projected hydrology scenario in 200 year in four hypothetical climate cases with different changing rates of mean and standard deviation.

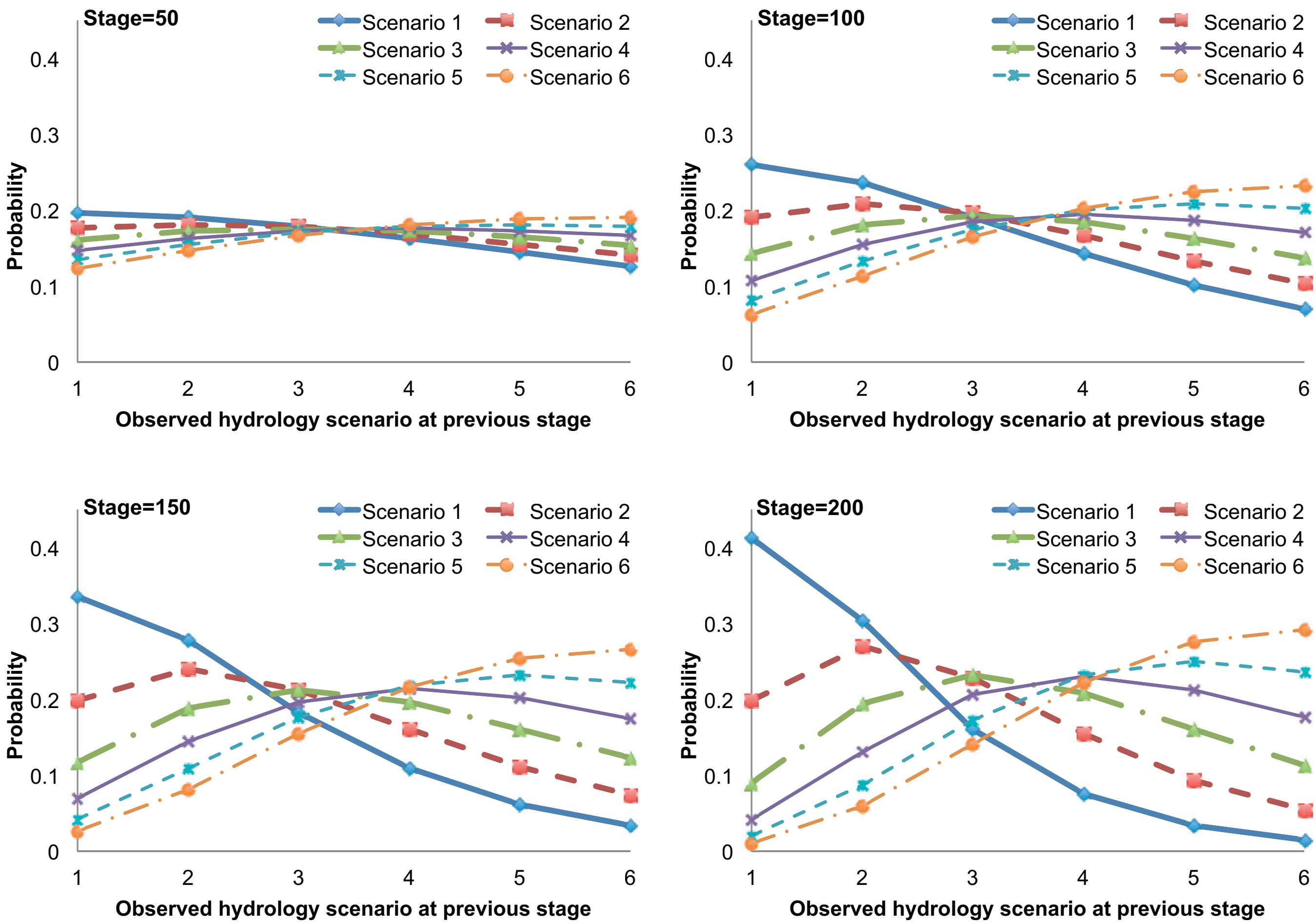

Fig. 4. Variations of Bayes' conditional probabilities of hydrology scenarios given the observed previous stage hydrology scenario at different planning stages.

ous scenarios. As time goes on, the probability of a hydrology scenario when observing a similar scenario at previous stage is much higher than when the previous observed scenario is rather different. At stage 200, the probability of a current hydrology scenario 1 when observing scenario 1 at previous stage is almost 30 times more than observing scenario 6, and is reciprocal for a current hydrology scenario 6. The probability of a current hydrology scenario 3 or 4 when observing scenario 1 or 6 is smaller than observing other scenarios. Over time, observed hydrology improves estimation of future hydrology with nonstationarity, given the assumption that long-term hydrology conditions are probabilistic.

5. Results and discussion

This section presents and discusses results insightful for three comparative situations:

(1) One-time versus annual adaptive building planning for the four hypothetical climate cases with the DDP and the SDP model, respectively.
(2) Detailed discussion of results for climate case 1, including comparison of levee system planning with the DDP and the SDP models for annual adaptive building planning strategy, the advantages of adaptive plan illustrated by various planning strategies with the DDP model, and impacts from a fixed cost for levee upgrades.
(3) Comparison of results from the DDP and the SDP models and applying the DDP results to the SDP model, to show the advantage of planning for an uncertain nonstationary hydrology.

5.1. Optimal levee system planning summary

Different frequencies of planned levee upgrades/adaptations with the four climate cases for a known nonstationary hydrology were modeled using the DDP and for an uncertain nonstationary hydrology using the SDP. Table 3 summarizes the main results from model runs with a one-time building planning strategy and an annual adaptive building planning strategy that allows levee system upgrades every year during the 200 year planning horizon. Resulting levee heights from the SDP in later stage can differ for existing levee height and observed previous hydrology scenario, so with adaptive building strategy there exists a range of possible final levee height at stage 200. The optimized present value cost for the SDP method $Min\ F_1(\overline{\Delta X_1}, \vec{X}_1)$ is the weighted-average cost added up through the backward recursion, which does not differ for varying possible levee heights at later stages.

With the one-time building plan, the levee is built to an optimized height at the first stage, and remains at that height for the entire planning horizon. With the annual adaptive building plan, the levee is built slightly lower at the first stage compared to the one-time building plan, but is upgraded continuously to a much higher height at the ending 200-year stage. Allowing annual adaptation is always less costly than not allowing adaptation, for every climate case and either method. The DDP approach weights each projected hydrology scenario with a constant probability, while the SDP approach weighs each scenario with an updated probability as more hydrologic observations are available. Since the expected cost (weighted average cost of all possible hydrology scenarios) of the SDP and the DDP depends on the time-varying Bayes' conditional probability and scenario-based cost, the overall present value

Table 3
Results summary of four climate cases.

Climate case	Planning strategy	Method	Optimized present value cost (million $)	Initial Levee height at Stage 1 (m)	Final Levee height at Stage 200 (m)
Stationary climate	Any	Dynamic program	98.65	7.4	7.4
Case 1	One-time building	SDP	109.89	7.8	7.8
		DDP	**109.81**	7.8	7.8
	Annual adaptive building	SDP	109.81	7.7	8.6 – 10*
		DDP	**109.74**	7.7	9.4
Case 2	One-time building	**SDP**	**108.40**	7.7	7.7
		DDP	108.44	7.7	7.7
	Annual adaptive building	**SDP**	**108.40**	7.7	8.3 – 8.5*
		DDP	108.44	7.7	8.3
Case 3	One-time building	SDP	124.93	8.3	8.3
		DDP	**124.15**	8.3	8.3
	Annual adaptive building	SDP	124.55	8.0	8.0 – 11.1*
		DDP	**123.86**	8.0	10.0
Case 4	One-time building	**SDP**	**120.74**	8.0	8.0
		DDP	121.02	8.0	8.0
	Annual adaptive building	**SDP**	**120.66**	7.9	8.7 – 8.9*
		DDP	120.98	7.9	8.7

* The range of possible resulting levee height at stage 200.

(cost) of the SDP solution differs slightly from using the DDP in each climate case with any planning strategy. The SDP solution has slightly lower overall cost in climate Case 2 and Case 4 where both mean and standard deviation of the log-transformed annual flood flow increase faster over time. The DDP solution has slightly lower overall cost in climate Case 1 and Case 3, where standard deviation of the annual flood flow is constant and the mean is increasing (lower overall cost for each comparison case is bolded in Table 3). Compared to planning in the assumed stationary climate case, optimal present value cost and initial and final levee heights all increase for assumed nonstationary climate cases as climates possibly become severe. Later discussion shows the economic disadvantage of applying planning decisions from assumed known nonstationary DDP models to an actual uncertain nonstationary hydrology modeled by the SDP.

For this study example with any climate case, model results show that annual adaptive building slightly reduces the overall present value cost, but more substantially alters the planning decisions especially in future years (Table 3), and the results are similar for the other planning horizon intervals as well. Overall costs vary little with adaptation frequency. Adaptive planning has little advantage compared to one-time building planning from an economic (present value) perspective, but becomes more reliable given the similar economically optimal present value and much higher levees in the future. The adaptive system levees are lower when flood events are less extreme and rise gradually with increased extreme floods.

5.2. Optimal levee system planning for climate Case 1

5.2.1. DDP and SDP comparison for annual adaptive building strategy

To illustrate the detailed levee system planning decisions, Fig. 5 plots the optimal SDP model results in climate Case 1 over a 200-year planning horizon for observed hydrology scenario 1, 3 and 6 at previous stage *t-1*, given different existing levee heights with annual adaptation allowed. The mean and standard deviation of annual flood flow in the stationary hydrology scenario 1 are constant over the planning horizon. The small annual change in the rates of mean and standard deviation of flood flow in hydrology scenario 3 indicate an increasing chance of larger annual peak flood flows over time. The more extreme hydrology scenario 6 has even higher annual change rates of mean and standard deviation of flood flow, representing a significantly increasing chance of extremely larger annual peak flood flows compared to hydrology scenario 3. The blue line on each graph in Fig. 5 is the optimal levee system planning strategy from the DDP model results for comparison. Each marker point on the graphs represents a resulting upgraded height at a stage given the possible existing heights, for an observed hydrology scenario at the previous stage. For instance, the upper graph in Fig. 5 presents all possible resulting upgraded levee heights at each stage *t* if observing hydrology scenario 1 at previous stage *t-1*, given possible existing heights. Different existing levee heights at a stage may correspond to a same upgraded height, shown as one marker point on the graphs. At early stages, levee height upgrades are the same for any observed hydrology scenario. At later stages, upgraded levee heights often differ with observed hydrology scenarios. The range of possible levee heights expands with time, as more hydrologic observations are obtained.

The optimal levee system planning strategy from the DDP model results with known nonstationary hydrology is to build the levee system at 7.7 m at the beginning stage 1, and increase the levees to 8.6 m at stage 63 and again to 9.4 m at stage 153 (blue line in Fig. 5). Initial levee height at stage 1 with the SDP model is the same at 7.7 m, while the first upgrade/adaptation to 8.6 m occurs earlier at stage 60 when observing hydrology scenario 6, and a wide range of upgrade options become available later. In later upgrade stages, the SDP results with uncertain nonstationary hydrology have more levee height planning options given different hydrologic observations and different existing levee heights; and the SDP results have higher levees than those averaged from the DDP by frequencies of upgraded heights (Fig. 5). The maximum optimal levee heights with the SDP are driven by observation of the more severe hydrology scenarios and are much higher than that with the DDP at the ending stages. Observation of more extreme peak flow conditions brings higher levee upgrades. For instance, observing hydrology scenario 6 leads to higher levee upgrades than observing hydrology scenario 1. If the stationary hydrology scenario 1 continues to be observed, levee heights remain at initial levels. However, levees are raised from existing heights in some stages if hydrology scenarios 3 or 6 are observed.

The range of differences among forecasted hydrology scenarios and the economic discount rate both affect optimal planning decisions given observed hydrology scenarios. Optimal levee height is usually the same across diverse observed scenarios in the early planning stages (Fig. 5), especially when hydrology scenarios differ slightly and discounting homogenizes effects of future changes. As time goes on, the mean and standard deviation of annual flood flows diverge progressively, leading optimal levee heights to diverge in later planning stages. The optimal levee height for observed hydrology scenario 6 starts to differ from other hydrology scenarios at stage 60, and differences across hydrology sce-

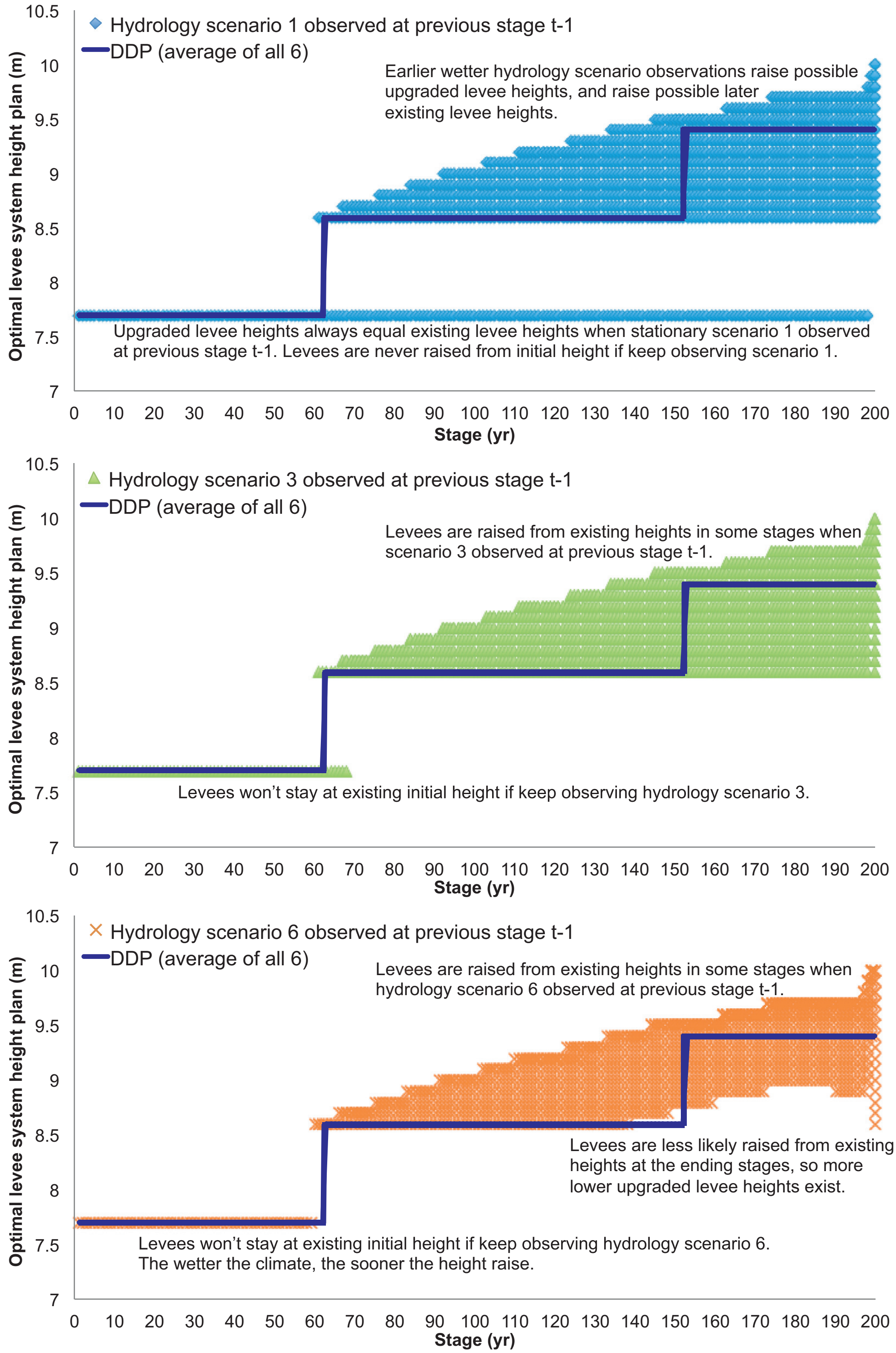

Fig. 5. Adaptive Levee system height planning decisions with the SDP for different observed hydrology scenarios and with the DDP, for annual adaptive building.

narios grow in later stages. The minimum optimal levee height with the observed hydrology scenario 1 is less than that with the observed more severe hydrology scenario 6 at any stage. The optimal upgraded heights at later stages change with observed previous hydrology scenarios (Fig. 5). Economically optimal planning balances the cost from annual expected residual damage and construction at each stage and over the entire planning period. In later upgrade stages, the more frequent and severe floods increase the expected annual damage cost, and then have less indirect impacts on construction cost due to balancing of costs

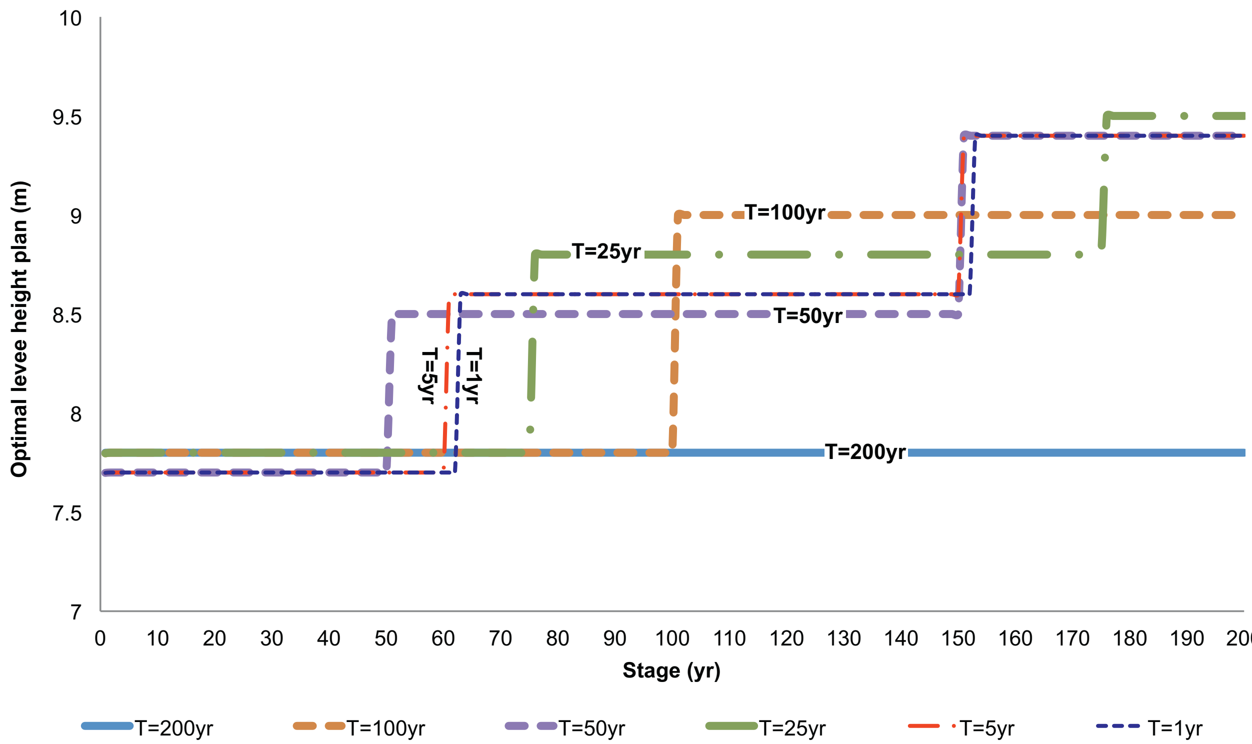

Fig. 6. Levee height planning decisions with the DDP model for different adaptation year intervals.

overall. Differences in damage costs for various hydrology scenarios are partially offset by the discount rate.

5.2.2. Advantages of adaptive planning

Adaptive planning allows adjustments to a changing and uncertain climate, as more hydrologic observations are available. With any adaptive planning strategy, the levee will be built and upgraded periodically to a greater height than the one-time building plan (here 7.8 m). For example, with one adaptation, the levee system is built to 7.8 m at the first stage, then raised to 9.0 m with observed hydrology scenarios 1, 2, or 3 and to 9.1 m with the observed hydrology scenarios 4, 5, or 6 at the upgrading stage (100 year). Variations of optimal levee system heights for different observed hydrology scenarios increase with the opportunities for adaptions. As more adaptations are planned, the maximum eventual upgraded height increases and the range of eventual upgraded heights widens.

Fig. 6 shows the adaptive levee system planning strategies assuming a known nonstationary hydrology for different adaption year intervals with the DDP model. Planning cases with more adaptions allowed having a lower initial levee height and a higher final levee height. Optimal levee height decisions cross for different planning cases over intermediate stages due to varying hydrology scenarios and discount rate. With a changing climate, levees are upgraded economically with every opportunity, unless fixed costs are large. Fewer upgrading opportunities increases individual upgrade heights. More frequent upgrades allow the levee system to adapt to the changing nonstationary hydrology gradually and economically, as the planning cases with shorter upgrade intervals show.

5.2.3. Fixed levee upgrade cost effects

The fixed cost for upgrading the levee also affects optimal levee planning decisions. Levee upgrades occur only when the expected reduced flood damage cost exceeds the upgrade cost, which is the construction cost including a fixed levee upgrade cost. For the annual adaptive plan (levee can be upgraded every year), optimal levee heights from the SDP model with a \$0.5 million fixed levee alteration cost start to diverge from stage 60 given different observed hydrology scenarios. If the fixed levee alteration cost is doubled to \$1 million, optimal levee heights are the same for different observed hydrology scenarios until stage 86. The overall present value cost increases slightly with doubled fixed levee alteration cost (\$110.35 million compared to \$109.81 million); the optimal initial levee height also rises slightly (7.8 m compared to 7.7 m), and the final upgraded levee heights both end at 10 m.

5.3. Advantages of modeling for uncertain nonstationary hydrology

The SDP considering uncertainty in a nonstationary hydrology has little overall cost advantage compared to the DDP, as the cost in each hydrology scenario contributes to the averaged overall cost (Table 3). The overall present value cost with the SDP model is less than that with the DDP model when mean and standard deviation of the log-transformed annual flood flow increase from hydrology scenario 1 to 6 over time. The SDP uses an increasingly reliable projected climate updated over time with the available hydrologic observations. The probability of future severe hydrology scenarios in the SDP model would increase based on the observed more severe hydrology scenarios, leading to a higher expected annual residual damage cost. The SDP model provides a different levee height trajectory for each observed hydrology scenario in the long-term. The DDP model provides only one levee height trajectory. The final levee heights from the SDP model are no lower than the final levee height from the DDP model in all planning cases.

Optimal levee plans made with a known nonstationary hydrology may not be economically efficient for the more likely uncertain nonstationary hydrology. Implementing the known nonstationary hydrology plan under the alternative uncertain nonstationary hydrology may under-design or over-design with additional regret costs (Kang and Lansey, 2012). Table 4 compares the overall present costs from the SDP model, the DDP model, and applying the optimal levee heights plan from the DDP model assuming known nonstationary hydrology to the SDP model in an uncertain nonstationary hydrology, for each climate case with different planning strategies. When applying the DDP optimal levee heights to the SDP model for each case, the optimal levee system

Table 4
Overall present value costs of the SDP model, the DDP model, and applying optimal planning decisions from the DDP model to the SDP model with uncertain nonstationary hydrology.

Planning strategy	Climate case 1			Climate Case 2			Climate Case 3			Climate Case 4		
	SDP	DDP	DDP in SDP*	SDP	DDP	DDP in SDP*	SDP	DDP	DDP in SDP*	SDP	DDP	DDP in SDP*
One-time building	109.9	**109.8**	123.93	**108.4**	**108.4**	122.44	124.9	124.2	138.97	**120.7**	**121.0**	134.78
100 year adaptive building	**109.8**	**109.8**	123.86	**108.4**	**108.4**	122.44	124.8	124.1	138.83	**120.7**	**121.0**	134.75
50 year adaptive building	**109.8**	**109.8**	123.77	**108.4**	**108.4**	122.43	**124.6**	**123.9**	138.54	**120.7**	**121.0**	134.66
25 year adaptive building	**109.8**	**109.7**	123.82	**108.4**	**108.4**	122.43	**124.6**	**123.9**	138.54	**120.7**	**121.0**	134.66
5 year adaptive building	**109.8**	**109.7**	123.79	**108.4**	**108.4**	122.43	**124.6**	**123.9**	138.47	**120.7**	**121.0**	134.67
Annual adaptive building	**109.8**	**109.7**	123.79	**108.4**	**108.4**	122.43	**124.5**	**123.9**	138.46	**120.7**	**121.0**	134.68

* The DDP model solution evaluated under the SDP model, applying optimal levee heights plan from the DDP model assuming known nonstationary hydrology to the SDP model with uncertain nonstationary hydrology.

planning decisions assuming known nonstationary hydrology has poorer economic performance in the uncertain nonstationary hydrology with updated conditional probabilities of hydrology scenarios (Table 4).

For any climate case with each planning strategy, the overall present value cost of applying the optimal levee planning decisions from the DDP model to the SDP model exceeds that of the DDP or the SDP by 11–13% (Table 4). Similar to the overall cost from the SDP and the DDP models, such an overall cost decreases slightly with the increase in adaption frequency. And in some cases the differences of overall present values among various planning strategies are too insignificant to determine (bolded numbers in Table 4), particularly in climate Case 2 and Case 4 where both mean and standard deviation of the annual flood flow increase. In the most severe hydrology scenario 6, applying the optimal DDP model plan to the SDP model results in a significantly higher overall cost. Plans from the SDP model have better performance for severe hydrology scenarios, and overall better reflect the long-term climate change projections.

6. Conclusions

A risk-based stochastic dynamic programming model with a Markov process can incorporate uncertain nonstationary hydrology explicitly into long-term water infrastructure planning. This study developed an explicit risk-based stochastic dynamic programming model with a Markov process for long-term water infrastructure planning affected by uncertainty in nonstationary hydrology. Uncertain nonstationary hydrology is represented by several projected hydrology scenarios with time-varying statistical properties, and the probability of each projected hydrology scenario is updated by Bayes' theorem based on ongoing hydrologic observations. The approach can support adaptive planning to improve reliability and economic performance.

The SDP model that accounts for uncertainty in nonstationary hydrology shows little economic advantage compared to the DDP model with known nonstationarity. However, the SDP better represents reality and provides different height options, especially in later years when the SDP performs better than the DDP for more severe hydrology scenarios. For the studied numerical example of a levee system planning problem, the economic advantage of the SDP model compared to the DDP model depends on the changing rates of peak flow distribution parameters in a projected climate. The SDP model generally provides more flood protection reliability with little increase in the overall present cost. The optimal levee planning strategy resulted from the DDP model, assuming a known nonstationary hydrology, has much poorer economic performance in the SDP model that assumes uncertain nonstationary hydrology with updated conditional probabilities of hydrology scenarios. The changing climate extremes, inflation-adjusted discounting, fixed levee upgrade cost, and balances between expected annual residual damage cost and construction cost affect the differences in optimal levee heights for observed hydrology scenarios.

Adaptive water infrastructure plans with nonstationary hydrology have advantages for long-term planning. In light of the various plausible future hydrology conditions, a long-term water infrastructure plan should be able to adapt to changes as new information becomes available. Adaptive planning with more upgrade opportunities is preferable to one-time construction planning or adaptive planning with few upgrade opportunities in terms of cost and reliability under known or uncertain nonstationary hydrologies. Although adaptive plans have little advantage with respect to the net present overall economic cost, the strategies are valuable for financial planning, especially in the long-term when severe hydrology scenarios could require additional investments. Lower levee heights at early stages result in less construction and total annualized cost that alleviate the near-term financial burden. Higher levee heights at later stages add little to the overall present value costs, but provide better protection for severe floods.

The importance of considering nonstationarity and the uncertainty of nonstationarity depends on the magnitude of uncertainty in the nonstationary hydrology. With less variation and uncertainty in the future climate projections, long-term infrastructure planning for uncertain nonstationary hydrology may not be worthwhile for capital investment. Assuming deterministic nonstationarity might be sufficient if future climate conditions remain close to historical conditions. Discount rate, damage potential uncertainty, and hydraulic uncertainty such as Manning's coefficient could have larger impacts. Yet, it is substantially better to model uncertain nonstationarity for capital investment and infrastructure planning when the future climate has great uncertainty. The reliability of infrastructure can be heavily affected by uncertainty in nonstationary hydrology.

This study has limitations in the simplified hydrology scenarios represented by varying mean and standard deviation of annual flow distribution, and the linear changing trends in the mean and standard deviation. Streamflow ensembles generated by a general circulation model combined with a Representative Concentration Pathway (Van Vuuren et al. 2011; Stocker 2014) could be used to refine plausible ranges of future hydrology scenarios. Future work can examine changes in the levee system, levee setback decisions (Zhu and Lund 2009), and levee deterioration in the long-term. A theoretical study can examine how the changing rates of peak flow distribution parameters in a projected climate affect the DDP and the SDP model results, as guidance for choosing between these models. The proposed model in this study only analyzes uncertainty in hydrology, while economic uncertainty also has large impacts for planning (Zhu et al., 2007). Uncertainty in the development of the adjacent floodplain, such as urbanization, can also be analyzed in future studies.

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