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Stochastic Hydro-Financial Watershed Modeling for Environmental Impact Bonds

Matthew W. Brand[1], Napoleon Gudiño-Elizondo[1,2], Maura Allaire[3], Steven Wright[4], Waylon Matson[4], Phil Saksa[5], and Brett F. Sanders[1,3]

[1]Department of Civil and Environmental Engineering, University of California, Irvine, CA, USA, [2]Instituto de Investigaciones Oceanológicas, Universidad Autónoma de Baja California, Ensenada, México, [3]Department of Urban Planning and Public Policy, University of California, Irvine, CA, USA, [4]4Walls International, National City, CA, USA, [5]Blue Forest Conservation, Lake Oswego, OR, USA

Key Points:
- A stochastic watershed modeling framework is developed to support the development of an environmental impact bond
- Bond period and interest rates are linked to distributions of costs that account for aleatory and epistemic uncertainty
- The feasibility of financing interventions to address watershed erosion problems at the U.S.-Mexico border is shown

Supporting Information:
- Table S1
- Figure S1

Correspondence to:
M. W. Brand,
mbrand1@uci.edu

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Abstract Soil erosion, poor water quality, and degraded ecosystems impose major cost burdens and challenges for stormwater managers. We present a stochastic hydro-financial watershed modeling framework for designing an Environmental Impact Bond (EIB)—a new form of financing for comprehensive, watershed scale interventions. EIBs provide capital for interventions that is repaid over time with interest by stakeholders who experience reduced costs (savings). The EIB is also structured so stakeholders and investors share the reward of cost savings. The framework estimates cost savings from interventions and accounts for aleatory and epistemic uncertainty in costs, which in turn impacts the financial terms of the EIB. In particular, we show a method to reward investors for taking on the risk that interventions fail. The framework is applied to a transnational pollution and sedimentation problem on the U.S.-Mexico border and has broad applicability for a wide range of environmental problems.

Plain Language Summary Soil erosion, poor water quality, and degraded ecosystems pose significant management challenges. Oftentimes, the key issue is not a lack of understanding about what is needed to address these problems but the inability to finance solutions at the scale that is needed to be effective. Financial barriers may be cash flow limitations, political constraints, legal constraints, or other factors. Environmental impact bonds (EIBs) are a new form of financing capable of overcoming institutional and cash flow barriers: Investors provide the capital required for comprehensive watershed interventions, which is repaid over time with interest by stakeholders who experience a reduction in management costs or savings. This paper describes a modeling method for determining a fair interest rate and return period to reward investors for the risk that interventions fail. After presenting a formulation of the method, it is applied to a sediment management problem at the U.S.-Mexico border and the feasibility of an EIB is for several possible interventions is shown. General strategies for making EIBs feasible are also reported.

1. Introduction

Watershed models describe environmental system states and fluxes (e.g., soil moisture and streamflow) in response to initial conditions and forcing (Singh & Frevert, 2005) and have been widely used to understand watershed dynamics (Clark et al., 2015; Freeze & Harlan, 1969; Sorooshian et al., 2008), improve environmental and water resources management (Matthies et al., 2007; Stedinger et al., 1984), and develop solutions to complex environmental problems (Hirsch, 1981; Lant et al., 2005). Uncertainties in watershed model simulations arise from several sources including imperfect model structure, parameters, and forcing (Liu & Gupta, 2007) and can be quantified using stochastic methods (Beven & Binley, 1992; Daniel et al., 2011; Vogel, 2017; Vrugt, 2016). Stochastic watershed models introduce and propagate a degree of randomness to account for uncertain parameters, forcing, and model structure and give system states and fluxes in the form of probability distributions. This is especially important in the context of watershed management, where modeling is relied upon to assess the relative advantages and drawbacks of different interventions. Application of a deterministic watershed model will typically show that the outcomes from two contrasting interventions are different, but whether these differences are significant (in a statistical sense) and the possible range of these differences will not be readily apparent. Conversely, stochastic modeling approaches can readily assess the statistical significance of differences between interventions by comparison of probability distributions. Additionally, stochastic modeling can quantify the likelihood that any particular intervention achieves desired goals—important information for watershed stakeholders confronting management challenges.

Today, one of the major impediments to solving watershed management challenges is not a lack of knowledge about watershed dynamics, that is, how the system is behaving, but rather a lack of funding to implement proven interventions. This is particularly true for stormwater management challenges (Roy et al., 2008; WEF, Stormwater Institute, 2019) and for environmental management in low resource settings (Arrossi et al., 2014). Unlike water supply infrastructure and wastewater infrastructure where the cost of interventions can be passed on to customers who pay a service fee, the financial burdens of stormwater management typically fall on local and/or state governments whose resources are already stretched thin to address a wide range of social and environmental needs (WEF, Stormwater Institute, 2019). Moreover, as a result of institutional and legal constraints, governments may not be in a position to implement proven and cost-effective interventions such as land use changes and source control measures. This conundrum can leave governments saddled with high management costs despite knowledge of more cost-effective management approaches developed through watershed modeling.

A promising funding mechanism that has recently emerged is an Environmental Impact Bond (EIB), a financial instrument whereby investors provide capital for watershed interventions that is repaid with interest by watershed stakeholders who experience reductions in management costs (savings) (Geobey et al., 2012). An EIB is typically administered by a third party responsible for attracting investors, implementing interventions, evaluating achievement of goals, and coordinating debt service among watershed stakeholders. Hence, parties involved in EIB financing include investors, stakeholders, and a third party coordinator or evaluator. Like traditional bond financing, EIB financing is attractive for stakeholders burdened with high management costs, since no upfront capital is required, and can overcome legal and institutional restrictions associated with the expenditure of stakeholders funds on interventions. However, EIBs differ from traditional bonds in two important ways: (1) EIBs tie the financial return on investment to the success of the intervention, which aligns financial returns to environmental outcomes (Hall et al., 2017; Nicola, 2013), and (2) EIBs can meet portfolio allocation requirements for Socially Responsible Investing (SRI) (Saha & d'Almeida, 2017), for which there is presently lack of adequate supply to meet high demand (Hamrick, 2016). Examples of EIBs in practice are few and include the DC Water Bond (Gonella, 2017) and the Forest Resilience Bond (Madeira & Gartner, 2018), but closely related Social Impact Bonds (SIBs) have exponentially grown in popularity since their introduction nearly 10 years ago, with 74 projects globally worth $278 million (Guter-Sandu, 2018). SIBs have focused on improving health outcomes (Clarke et al., 2018), lowering recidivism rates (Butler et al., 2013), and supporting watershed forest conservation (Nicola, 2013). We also note that the financial structure of EIBs and SIBs may not necessarily match that of a traditional bond, such as zero-coupon bond whereby the Face Value of the bond, the sum of the Principal and interest, is paid at some future date conditioned on the success of the interventions. For example, loan and/or pay-for-success contract structures have been used for the Forest Resilience Bond, DC Water Bond, and Atlanta Flood Bond (Balboa, 2016; Blue Forest Conservation, 2017; Goldman Sachs, 2016; Hallauer et al., 2019; Nicola, 2013; Olson et al., 2013).

To date, the adoption and implementation of EIBs have faced several challenges. Perhaps most significant is the need to know future savings in management costs based on the funded interventions—demonstrating to investors the potential for a financial return on investment (Jackson, 2013). As noted earlier, the financial return on investment generated by the EIB is conditioned on whether the funded interventions generate stakeholder cost-savings. Another major challenge has been accounting for uncertainty in future system dynamics (and stakeholder costs), which arises from uncertainty in understanding and modeling of watershed processes (epistemic uncertainty) and uncertainty in the environmental conditions (aleatory uncertainty) that influence watershed processes, such as the amount of rainfall (Brandstetter & Lehner, 2015). Uncertainty does not necessarily harm investors or stakeholders, but it needs to be quantified as a risk. Brandstetter and Lehner (2015) note "institutional investors are bound by their fiduciary duties and are committed to asset class specific benchmarks for expected financial risk and return" and "institutional investors apply conventional portfolio allocation frameworks built on the evaluation of financial risk and returns in order to make rational investment decisions." In other words, appropriately modeling and accounting for risk within EIBs, especially risk due to environmental uncertainty, is critical for their acceptance in the wider financial community.

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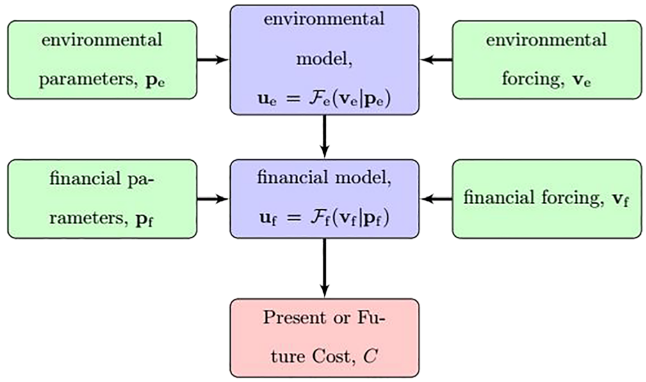

Figure 1. The stochastic hydro-financial watershed model couples environmental and financial models to estimate financial costs, C, using Monte Carlo methods, with $\mathbf{v}$, $\mathbf{u}$, and $\mathbf{p}$ representing input, output, and parameters, respectively, $\mathscr{F}$ representing the model transformation, and the subscripts e and f indicating *environmental* and *financial*, respectively.

The objective of this paper is to present a stochastic hydro-financial modeling framework that addresses the challenges mentioned above, in particular linking (1) watershed interventions to cost savings and (2) environmental risks to the financial returns of investments. Stochastic watershed modeling has a long history in water resources research addressing hydrologic risks (Vogel, 2017), and stochastic modeling with Monte Carlo methods is widely used in finance to quantify risks (Glasserman, 2013; Korn et al., 2010). Hence, this paper seeks to bridge the gap between stochastic watershed modeling and the financial risk assessment needs of EIBs described above, including a systematic approach for aleatory and epistemic uncertainty. The paper is presented in two parts. First, we begin with development of basic theory linking uncertainty in watershed model simulations to financial parameters that affect the variables of the EIB, namely, interest rates and repayment period. We also address the feasibility of an EIB as a funding model based on the relative magnitude of intervention costs, reductions in management costs (savings), and tolerances for risk. Secondly, we present an application of the framework to an institutionally complex stormwater erosion and sediment management challenge in a binational watershed on the U.S.-Mexico border. Here, we demonstrate the ability of the hydro-financial framework to quantitatively evaluate the feasibility of proposed interventions, and we demonstrate attractive financial terms for investors and a stakeholder with high sediment management costs. We close with discussion and conclusions.

2. Hydro-Financial Modeling Framework

The hydro-financial modeling framework is developed here to support an EIB structured as a zero-coupon bond, where Principal for watershed interventions is provided by investors in return for a future repayment of Principal and interest (Risk Premium). As mentioned previously, EIBs can adopt several types of payment structures, yet our goal of (1) linking investments to cost savings and (2) accounting for uncertainties is achieved parsimoniously with a focus on a zero-coupon bond. The hydro-financial modeling framework is configured as a sequence of environmental and financial modeling, as shown in Figure 1. The environmental model accounts for a set of processes that influence outcomes relevant to the environmental challenge that is the focus of the EIB (e.g., flooding, erosion, ecological degradation, water quality, and wildfires) and responds to forcing prescribed by a set of inputs and environmental parameters. The financial model combines outcomes of the environmental model with financial model inputs and parameters (e.g., interest rates, cost of interventions, and variability in goods/service prices) to estimate costs, C, which can be expressed as present or future value or as an annuity. Uncertainty can be addressed in numerous ways with stochastic models. Generally, environmental (e.g., rainfall, streamflow, temperature, dew points, vegetation indices, and channel roughness) and financial model (e.g., interest rates, inflation, and management costs) forcing and parameters are randomly sampled from distributions taken from available data (or other models), and Monte Carlo Markov Chain (MCMC) methods are used to propagate uncertainty through the coupled modeling system to yield a probability distribution of outcomes that informs the calculation of risk. However, in a specific application, modeling may proceed with only a limited number of these uncertain

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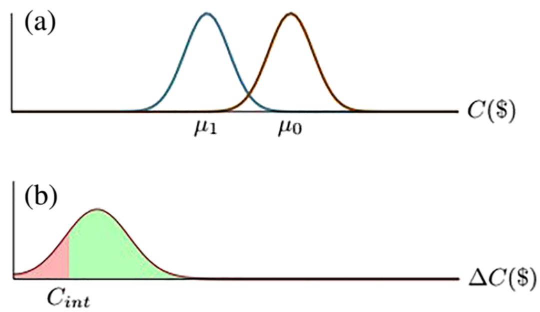

Figure 2. Probability distribution functions for (a) the baseline scenario costs ($f_0(x)$, brown curve with mean value μ_0) and intervention scenario costs ($f_1(x)$, blue curve with mean value μ_1) summed over the lifespan of the bond, (b) cost savings summed over the lifespan of the bond, $f_{\Delta C}(x)$. The area shaded red is the probability of underperformance, P_{u}, and the area shaded green is the probability of overperformance, P_{o}.

parameters relevant to the problem. Figure 2a illustrates probability density functions for the nondiscounted cumulative cost over an n year period for an intervention scenario, $f_1(x)$, and a baseline scenario, $f_0(x)$. Here, costs are presented as Gaussian distributions with mean μ and standard deviation σ, but in practical applications with environmental models, costs distributions are generated empirically with MCMC trials. The difference between $f_1(x)$ and $f_0(x)$, shown in Figure 2b, is described by the probability density function, $f_{\Delta C}(x)$, and represents the sum of n-year nondiscounted cost savings from the intervention with a cumulative distribution function (cdf) given by

$$F_{\Delta C}(x) = \int_{-\infty}^{x} f_{\Delta C}(u)\, du \tag{1}$$

In the presentation that follows, the subscript ΔC is dropped, and thus $f(x)$ and $F(x)$ are taken to represent the probability density and cumulative probability of cost savings over bond time period n from a particular intervention or set of interventions. The cost savings are compared against the cost of implementing the interventions, C_{int}, to assess the feasibility of an EIB. Interventions with low to moderate capital costs compared to cost savings are likely to be viable candidates for implementation, subject to further deliberation among stakeholders. Moreover, many interventions can be considered and modeled to work toward the most cost-effective and fair approach for addressing the environmental challenge at hand. This requires a process of dialogue and deliberation which is beyond the scope of the paper. Here, we develop the link between output and uncertainty in watershed models, namely, the probability distribution of cost savings, to the financial parameters of the EIB. Emphasis here is on formulating the relationship between the the project period, n, and interest rate, i, intervention costs, C_{int}, and cost savings, $F(x)$, as described in the following sections. Importantly, we note that to accurately estimate benefits and uncertainties, the modeling framework must have the necessary skill to resolve the processes and effects relevant to the baseline scenario and the intervention.

2.1. EIB Financial Terms

With a zero-coupon structure, a bond with a particular Face Value (amount paid out at maturity) is issued at a discounted amount representing Principal (value at initial time) to cover the cost of interventions, C_{int}. Principal associated with a particular Face Value can be linked to an annual interest rate i and bond duration (in years) n as follows (Chance, 1990; Halley, 1861; Rubinstein, 2003),

$$\text{Principal} = \frac{1}{(1+i)^n} \times \text{Face Value} \tag{2}$$

In the case of an EIB, repayment of Principal is conditioned on the success of the interventions at generating cost savings, which precipitates a need to incentivize investors for taking on the risk of no repayment. This is achieved with a Risk Premium, which is an amount paid on the condition that cost savings are generated for stakeholders (and thus can be shared with investors). Interpreting financial risk as a potential loss times the probability of occurrence, the Risk Premium is given as follows:

$$\text{Risk Premium} = P_{\mathrm{u}} \times \text{Principal} \tag{3}$$

where P_u is defined as the probability of underperformance or the probability of default (Featherstone et al., 2006; Caouette et al., 2011). Adding the Risk Premium to the Principal yields what we term the Environmental Face Value (EFV) as follows:

$$\text{EFV} = \text{Principal} + \text{Risk Premium} = (1 + P_{\mathrm{u}}) \times \text{Principal} \tag{4}$$

The EFV is useful for interpreting the overall cost of financing as a conventional interest rate. In particular, by substituting EFV for Face Value in Equation 2 and rearranging for the interest rate i, we obtain an expression for a so-called environmental interest rate i_{env} as follows:

$$i_{\mathrm{env}} = (1 + P_{\mathrm{u}})^{(1/n)} - 1 \tag{5}$$

The environmental interest rate is an indicator of risk that stakeholders are unable to pay back the bond due to unrealized project benefits. This stems from uncertainty in the environmental and financial conditions that could occur over the life of a bond (aleatoric uncertainty), as well as uncertainty in the predictive skill of models (epistemic uncertainty). Equation 5shows that the environmental interest rate depends on a combination of the probability of underperformance and the project duration. However, it should be noted that the probability of underperformance may also depend on the duration of the project. Hence, the influence of project duration on the environmental interest rate in Equation 5 is both explicit (through n) and implicit (through greater cost savings accumulated over time resulting a lower P_{u}).

The risk reflected by the environmental interest rate is separate from participant credit risk or risk that the agencies and stakeholders participating in the EIB are unable to meet their contractual obligations due to forces outside of those explicitly defined in environmental risk. Examples include, but are not limited to, a financial crisis, theft, fraud, reduced tax revenues, and/or contractual risks. Participant credit risk is based on credit ratings and interest rates on recently issued bonds, determined by an independent third party. Participant credit risk also rewards investors for the time value of money.

In the case of a zero-coupon bond structure, the Face Value of the EIB paid at maturity on the condition of stakeholder savings is inclusive of the costs of Principal, Risk Premium, and Interest. Development of a hydro-financial modeling framework for determining the Risk Premium, and environmental interest rate, is the main focus here to provide a tool for designing affordable and beneficial intervention strategies. However, we note that the credit risk interest rate, which is a consideration for setting the total Face Value of the EIB, could be tied to any number of financial instruments depending on the issuing agency. For instance, if a state utility or agency is the fiscally responsible payer of the bond, their credit rating could be used to determine the credit risk interest rate.

The probability of default, P_u, represents the likelihood that stakeholder cost savings are insufficient for repayment of Principal when the EIB matures and is shown graphically as the red shaded area in Figure 2. Mathematically, the probability of default represents the cdf of the cost savings distribution evaluated for the intervention costs as follows (Herrera et al., 2019):

$$P_{\mathrm{u}} = F(C_{\mathrm{int}}) \tag{6}$$

Conversely, the area shaded green in Figure 2 corresponds to the probability of overperformance which is defined by Herrera et al. (2019):

$$P_{\mathrm{o}} = 1 - F(C_{\mathrm{int}}) \tag{7}$$

By combining Equations 6 and 5, we arrive at an expression for the environmental interest rate as a function of the intervention costs, bond duration, and the cost savings cdf as follows:

$$i_{\mathrm{env}} = [1 + F(C_{\mathrm{int}})]^{(1/n)} - 1 \tag{8}$$

Moreover, application of the stochastic hydro-financial modeling framework yields an empirical cdf of cost savings, $F(x)$. The Risk Premium is then computed and expressed as an environmental interest rate—an indicator of the affordability of the EIB. Note that the Risk Premium scales with the probability that stakeholder savings are insufficient for repayment of the Principal. The greater the risk of failure, the greater the Risk Premium delivered to investors.

The final element we consider here for the formulation of an EIB is the measurement of cost savings. How cost savings are defined bears on the probability of default, and in turn, the Risk Premium. Two options for cost savings are considered here assuming a preintervention and postintervention cdf of n-year management costs, C_0 and C_1, respectively. The first option estimates the cost savings cdf as the difference between the two cost cdfs over the bond duration:

$$F^{(1)}(x) = C_0(x) - C_1(x) \tag{9}$$

The second option estimates the cost savings as the difference between costs incurred before and after the project was implemented, that is, two different windows of time, as follows:

$$F^{(2)}(x) = n\bar{C}_0 - C_1(x) \tag{10}$$

where $\bar{C}_0$ represents the average annual costs prior to intervention. Conceptually, the key difference between these two options is that the latter reflects actual costs before and after the intervention, whereas the former controls for differences in environmental conditions between the preintervention and postintervention periods which are likely to skew the cost savings. Conceptually, these two options can be considered as contemporaneous ($F^{(1)}(x)$) and sequential ($F^{(2)}(x)$) differences in costs.

We note that the above definitions of cost savings also bear on evaluation of the EIB at the time of the maturity and the repayment of investors. At maturity, the actual cost savings realized in the project need to be quantified. With cost savings defined by Equation 10, actual cost savings follow simply as the difference between preintervention and postintervention management costs. And with cost savings instead given by Equation 9, the hydro-financial modeling system would need to be rerun based on actual environmental and financial conditions experienced during the course of the project to estimate costs that would have been incurred had the intervention not been implemented.

2.2. EIB Feasibility

Whether an EIB is a feasible solution for funding environmental problems will depend on the cost of interventions, the savings in management costs, and tolerances for risk for stakeholders and investors. Clearly, with increasing intervention costs relative to management cost savings, an EIB becomes less feasible since funding to service debt becomes insufficient. However, consideration of a wide range of interventions and project periods is likely to yield financial options deserving of careful consideration and deliberation. Environmental interest rates given by Equation 5 are presented in Figure 3 based on the duration (in years, n) and probability of default, P_u, and shows that a longer duration and smaller default probability result in lower i_{env} rates and thus greater feasibility for EIB implementation. The key takeaway from Figure 3 is that if a project has a high P_u (say greater than 10^{-1}), managers could extend the number of years for EIB repayment to improve the EIB financial feasibility for the project. Furthermore, a longer project period would also reduce P_u considering accumulation of savings. A second takeaway is that shorter EIB periods demand increasingly smaller values of P_u for stakeholders to avoid excessively high interest rates.

2.3. Decision-Support Process

The hydro-financial modeling framework described herein is a decision-support tool for supporting watershed management. Moreover, the framework is suited to an iterative process of stakeholder engagement for the coproduction of useful and actionable knowledge (DeLorme et al., 2016; Dilling & Lemos, 2011; Luke et al., 2018; Sanders et al., 2020). The design, implementation, and outcome of a coproduction process is beyond the scope of the paper, but for the purpose of future work coordinating the iteration of hydro-financial modeling and stakeholder engagement (e.g., Sanders et al., 2020), the main steps of hydro-financial modeling are envisioned as follows:

1. Identification of watershed problem with potential for cost savings and the factors that deserve consideration for the assessment of costs.
2. Identification of potential interventions with cost estimates, C_{int}.

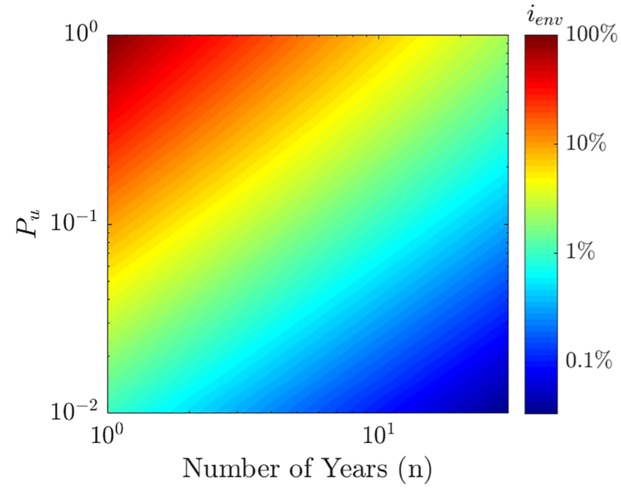

Figure 3. Filled contour plot of EIB interest rate as a function of probability of underperformance (P_u) and number of years of bond issue (n).

3. Development and calibration of a watershed model, $\mathscr{F}_e$, that resolves the system dynamic of interest and its sensitivity to interventions under consideration over multiyear time scales comparable to the duration of bonds (loans).
4. Development of a financial model, $\mathscr{F}_f$, to transform watershed model outputs into costs, C.
5. Monte Carlo and/or MCMC simulations of system dynamics (and costs) to yield EIB parameters and feasibility for each intervention and project duration, n, under consideration: C_{int}, $F(x)$, P_u, i_{env}, and i. Note that a baseline scenario is needed for cost savings analysis.
6. Dialogue, deliberation, and iteration toward a comprehensive management plan.
7. Implementation and evaluation of interventions, including calculation of cost savings.
8. Bond fulfillment, namely, repayment of Face Value conditioned on project success.

The hydro-financial modeling framework is now applied to demonstrate Steps 1–5 listed above for a cross-border sediment and debris management issues in the Tijuana River Valley.

3. Sediment Management at the US-Mexico Border

3.1. Problem Description

The Los Laureles Canyon Watershed (LLCW, Figure 4) is a small watershed (11.6 km^2) on the U.S.-Mexico border with relatively high population density (6,700 habitants/km^2, Al-Delaimy et al., 2014) and significant sediment management challenges (Goodrich et al., 2020; Safran et al., 2017; Webber, 2010). The LLCW lies on the San Diego formation, which includes deposits of fluvial and marine loosely packed sediments, with steep slopes (average of 15°) and terraced hillsides (Gudino-Elizondo, Biggs, Castillo, et al., 2018). Soil and gully erosion is magnified by vegetation loss and drainage over unpaved roads, affecting quality of life and flood hazards in Tijuana (Goodrich et al., 2020; Grover, 2011), and ecosystems within the Tijuana River Valley especially on the U.S. side of the border (Weis et al., 2001). Excessive sedimentation buries salt marsh habitat and spreads pollutants and trash throughout the Tijuana River Estuary (Weis et al., 2001). As a result, two sedimentation basins were constructed in the U.S. just downstream (North) of the U.S.-Mexico Border. The sediment basins are designed to protect salt marsh and estuarine habitat from excessive sedimentation, trash, and debris including plastics. The basins have a combined capacity of 185,804 to 234,830 tons of sediment and are cleaned out on a yearly basis (Biggs et al., 2010; CA State Parks, personal communication) at considerable expense to California State Parks, approximately $1.236 million per year (in 2018 dollars). Costs can vary substantially from year to year based on the amount of sediment and debris (which is linked to seasonal rainfall) and disposal costs (Biggs et al., 2018). A sediment basin is also on the Mexican side of the border, but this basin is entirely managed by Mexico with the costs not borne by the U.S. stakeholders, so it was not included in the analysis.

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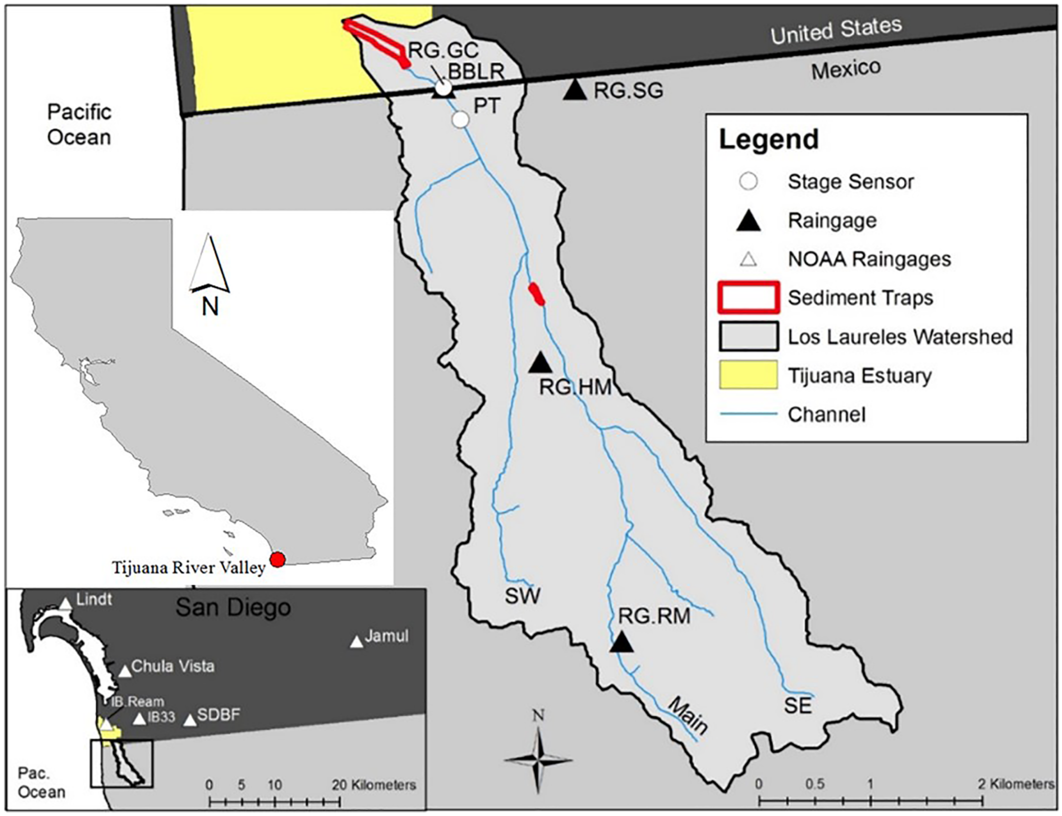

Figure 4. Los Laureles Canyon Watershed (LLCW) location, flowpaths, and raingauge. Inset shows the geographic locations of nearby rain gauges and location within the Southern California/Baja California Border region. Modified from Gudino-Elizondo et al. (2019).

The causes of excessive sediment generation in LLCW include sheet and rill erosion of hillslopes following loss of vegetative cover, gully erosion, especially along unpaved roads, and channel erosion. Unpaved roads often follow depressions in topography leading to the concentration of high velocity runoff during storms and formation of gullies within the roadway (Gudino-Elizondo, Biggs, Bingner, et al., 2018; Gudino-Elizondo, Biggs, Castillo, et al. 2018). Additionally, changes in land cover increase flood peaks and, in turn, channel erosion (Taniguchi et al., 2018). Presently, there is a mix of paved and unpaved roads across the watershed as well as a mix of hard-bottom and soft-bottom drainage channels. The interface between hard-bottom and soft-bottom channels has have been termed *hard points* (Taniguchi et al., 2018) and are a focal point of channel erosion as shown in Figure 5.

Stabilization of hillslopes (e.g., with vegetation or other erosion control methods), armoring of channels, and paving of roadways are presently viewed as possible source control measures. Furthermore, there is shared understanding among stakeholders on both sides of the border that improved watershed infrastructure and reduced sediment loads would be mutually beneficial. However, the U.S.-Mexico border acts as a major impediment for collaboration (Ingram & Laney, 1995). In particular, the stakeholders facing high management costs on the U.S. side of the border do not have the freedom or authority to make infrastructure investments on the Mexico side of the border. An EIB will allow downstream stakeholders to address the upstream erosion issues without having to make direct investments within Mexico itself and will use only the sum of the yearly cost savings to pay back the Principal of the bond, and many interventions will yield continual cost savings which will extend beyond the lifespan of the bond. Secondly, there is weak governmental support on both sides of the border for addressing infrastructure issues (Grover, 2011). Lacking funding for source control measures and given the complex trans-border setting, an EIB is a promising financial instrument that is under consideration by stakeholders.

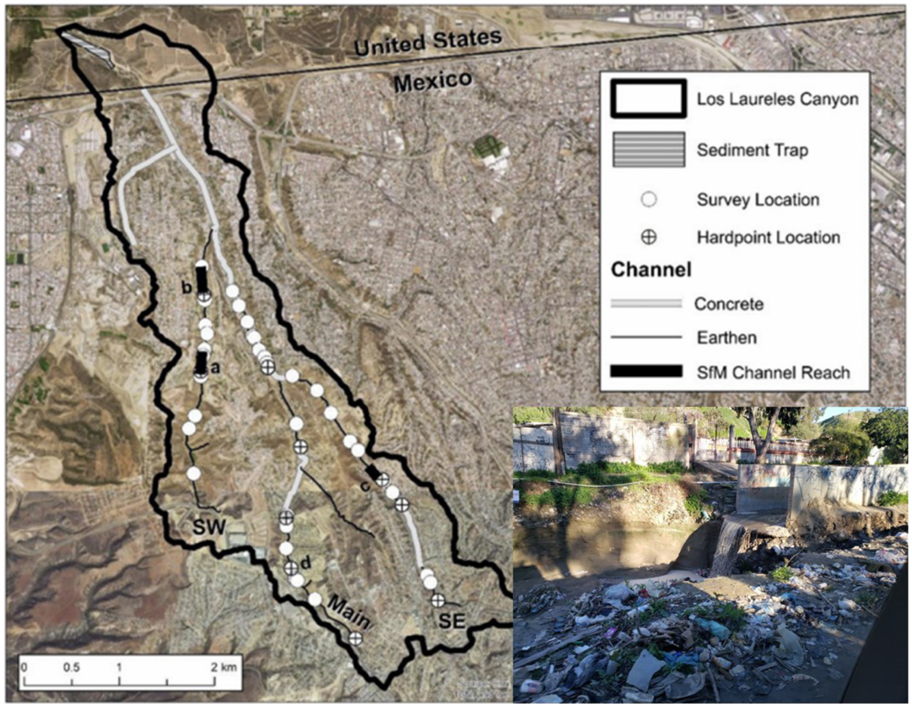

Figure 5. Drainage channel configuration in LLCW and location of hardpoints where channel erosion is magnified (adapted from Taniguchi et al., 2018), as shown in the inset photograph.

3.2. Potential Interventions and C_{int}

Four intervention options are considered for hydro-financial modeling and analysis of EIB feasibility, as shown in Table 1. These cost estimates are meant to be a first estimate for demonstrating feasibility of the bond and not for official planning purposes. Following from the discussion above, armoring channels (AC) are considered because the unlined channel in LLCW contributes a significant percentage (25% to 40%, per Taniguchi et al., 2018) of the total yield and presents a major hazard for housing. The cost estimate for armoring the channel comes from a nearby example, the channelization of the nearby Rio Tecate, which cost an inflation adjusted 450,000 USD/km (para America Latina y el Caribe, 1998). There is approximately 2.25 km of channel armoring required in the LLCW, yielding a total cost of roughly $1.01 million.

Paving roads (PR) are considered because unpaved roads contribute a significant proportion of overall sediment load (Biggs et al., 2010) and are considered a priority of the local community (Grover, 2011; Gudino-Elizondo et al., 2019). The C_{int} of PR was estimated by assuming paving costs of $\$60/m^2$ (City of Tijuana, personal communication) and assuming average road widths of 10 m, this yields an estimate of 600,000 USD/km for road paving. The length of unpaved roads within hot spots identified from the AnnAGNPS model were then measured using satellite imagery available in Google Earth (Google, Mountain View, California), yielding a total length of 12.0 km of needed paving, resulting in $7.20 million for C_{int}.

Table 1
Potential LLCW Interventions for Sediment Management

Abbreviation	Description	Cost (10^6 2018 dollar)
AC	Armor/line main channel	$1.01
PR	Pave critical roads	$7.20
HV	Hillslope revegetation	$0.71
LD	Low-cost disposal	$3.38

Note. LD assumes a 10-year total timeframe.

Hillslope revegetation is considered because hillslopes contribute 60–75% of sediment to the channel (Taniguchi et al., 2018), and hillslope failures are a considerable hazard to the local community. As recently as 2018, 19 homes were recently lost within LLCW due to hillslope failure (Proteccion Civil Tijuana, personal communication). Reduced hillslope erosion and surface runoff was modeled within AnnAGNPS through revegetating barren hillslopes with native vegetation. The cost estimate for revegetating barren hillslopes (HV) is estimated by 4Walls International based on the price of 150 pesos/plant and labor budgets estimated from the SEMARINAT PET programs (de Medio Ambiente y Recursos Naturales & de Proteccion al Ambiente, 2015). The total cost of HV is estimated at $708,000.

Finally, the last intervention described as Low-Cost Disposal (LD) reflects the potential to reduce disposal costs if measures are taken to improve sediment quality and dispose of the clean sediment locally instead of the current practice of trucking to landfills. Presently, sediment quality is poor due to contamination with tires, plastic, and other wastes (CA State Parks, personal communication; 4Walls International, personal communication). These contaminants must be removed from the sediment and then trucked to a hazardous waste landfill, resulting in significantly higher disposal costs compared to clean sediment alone. Reducing sediment contamination through incentivized community waste management programming will cost around $262,500 annually (4Walls International, personal communication), and locally disposing of the cleaner sediment will reduce the 2018 dollar cost of sediment disposal from $32.56–46.87/ton to $18.07/ton (Lee & O'Callahan, 2016). In addition to disposal costs, there are about $758,000 in one-time costs for local disposal for environmental permitting and planning (Lee & O'Callahan, 2016).

3.3. Watershed Model

Sediment loads are simulated with a daily time step in response to daily rainfall using the watershed model AnnAGNPS developed by the USDA (Young et al., 1989), which was previously calibrated for LLCW (Gudino-Elizondo et al., 2019; Gudino-Elizondo, Biggs, Bingner, et al., 2018) and has been widely used for studies of watershed erosion and sediment loading (Borah & Bera, 2004; Bosch et al., 1998; Li et al., 2015). AnnAGNPS simulates ephemeral gully, sheet, and rill erosion as a function of daily rainfall and provides downstream routing (Young et al., 1989). AnnAGNPS does not explicitly estimate channel erosion, but previous applications at LLCW have shown it can be estimated as fraction (25–40%) of sheet, rill, and gully erosion (Gudino-Elizondo et al., 2019; Taniguchi et al., 2018). Sediment routed into downstream basins is accumulated with a daily time step until the storage capacity is reached, and the volume of accumulated sediment scales the annual management cost (for dredging and disposal, as described in the financial modeling section). Fluxes that exceed the capacity of the basins are routed downstream and discharged to the environment. The errors in annual sediment yield from sheet, rill, gully and channel erosion over a decadal time scale were previously reported by Gudino-Elizondo et al. (2019) as approximately 10%, with an RMSE equal to 48%.

3.4. Financial Model

The focus of the financial model is to identify sediment management costs and savings that could be used to make EIB payments. Sediment management costs are presently dominated by the cost of excavation and dredging, which depends on the annual volume of disposal and the disposal cost per volume which, in turn, scales with the availability of disposal sites and sediment characteristics. For example, contaminated sediments (e.g., with plastic, sewage, and/or chemicals) are more expensive to dispose than clean sediments.

The unit cost of excavating the basin (in $/ton) was taken from 7 years of historical excavation data from sediment disposal contracts provided by CA State Parks (2009, 2012, 2015–2018, supporting information Table S1 and Figure S7). These costs were adjusted for inflation and brought into 2018 dollars to account for the significant changes in excavation costs over time ($10.88/ton in 2009 to $43.23/ton in 2018). Sediment disposal costs are negatively correlated with total volumes of sediment excavated due to economies of scale. This correlation was incorporated within the financial model and is shown in Figure S9. The uncertainty from this correlation was implemented within the financial model by fitting a normal distribution to the errors and sampling from that distribution within the financial model. Future cost increases were estimated using Caltrans "Roadway Excavation Cost" data from 1972 to 2018, converted from nominal to real dollars using the same years CA CPI data. The inflation data were then fit to a Generalized Extreme Value distribution (see Figure S8) and randomly sampled to accurately estimate yearly cost increases.

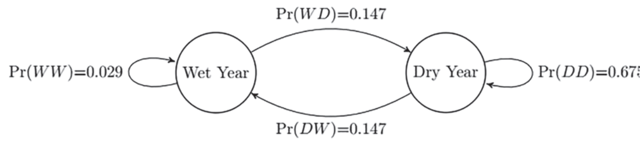

Figure 6. Yearly Markov Chain parameters describing empirical system probabilities of going from a wet-dry [P(WD)], dry-wet [P(DW)], dry-dry [P(DD)], and wet-wet [P(WW)] years. Probabilities do not add to unity due to rounding.

We do not estimate costs related to hazardous conditions in the watershed (e.g., from unsafe roads and hillslopes) or the costs associated with environmental damage, since the aim here is to understand whether and to what extent relief of debris basin management costs could support an EIB. Additional modeling could be done in the future to address the costs burdened by other stakeholders and additional environmental benefits.

The yearly cost of managing the basin (in 2018 $USD) follows from total sediment captured in the Goat Canyon sedimentation basins (tons), predicted by AnnAGNPS, multiplied by the unit disposal costs ($USD/metric ton). The model assumes the Goat Canyon sediment traps are completely emptied every year, regardless of the amount of rainfall and sediment entering the basins. In addition, the current version of the model assumes that all sediment and trash entering the basins is captured up until the basin is filled, at which point the excess sediment is discharged to the environment.

3.5. Simulations

3.5.1. MCMC Simulation of Future Sediment Loads

Following Richardson (1981), a MCMC rainfall simulator was developed for input to AnnAGNPS to simulate daily sediment fluxes under baseline and intervention scenarios as follows: First, the long-term ($N = 78$ years) Lindbergh airfield (Lindt, inset of Figure 4) data set was correlated to the short term ($N = 4$ years) RG.HM ($R^2 = 0.5685$, Figure S1) using rainfall events for the overlapping time period from 2014 to 2017 to extend the time-period of available rainfall data beyond the limited timespan of RG.HM (Brand, 2020). The data set was extended by using the logarithmic regression in Figure S1 to convert rainfall in Lindt to RG.HM. The extended RG.HM data set was then used to develop yearly Markov Chain parameters for characterizing the probability of going from a wet-dry, wet-wet, dry-dry, and dry-wet years. Wet years were defined as the mean plus one standard deviation, with dry years below that threshold. The probability of going from a wet-dry, dry-dry, wet-wet, and dry-wet period year was determined by counting the number of transitions from each period and dividing by the total time period to find the probability of each transition (represented in Figure 6).

The data set was then divided into two periods: one data set for dry years ($N = 57$) and one for wet years ($N = 12$). These data were then used to fit a Weibull distribution to both rainfall data sets for driving the dry/wet years in the MCMC simulations (Figures S4 and S5).

The MCMC simulations of rainfall were propagated into the future as follows. First, a random number was generated to seed the initial simulations to determine if the first simulation is a wet or dry year. Then, a full year simulation is generated from the corresponding daily wet or dry year Markov Chain parameters, which are used to determine if rain falls that day (Figures S2 and S3). Specifically, a random number is first drawn from a uniform random distribution for each day. This number is then compared to the Markov Chain parameter for that day. If the random number is higher than the P01 (dry to wet day) Markov Chain parameter (Figures S2 and S3), then the simulation draws from the appropriate Weibull distribution to simulate rainfall for that day (Figures S4 and S5).

After a wet day, a random number is drawn again, and compared to the probability of the wet to wet Markov Chain parameter (P11, Figures S2 and S3). If the probability is lower than the Markov Chain parameter, then the simulation draws again from the same wet or dry year Weibull distribution to simulate rainfall for that day. Otherwise, the simulation reverts back to a dry state, and no rainfall is generated. These simulations are repeated for the entire year, at which point a random number is generated and compared to the Markov Chain parameter describing the probability of transferring from a wet-dry, wet-wet, dry-wet, or dry-dry year (Figure 6). The random draws are then used to determine if the following year's simulation draws from a wet year or dry year Weibull distribution.

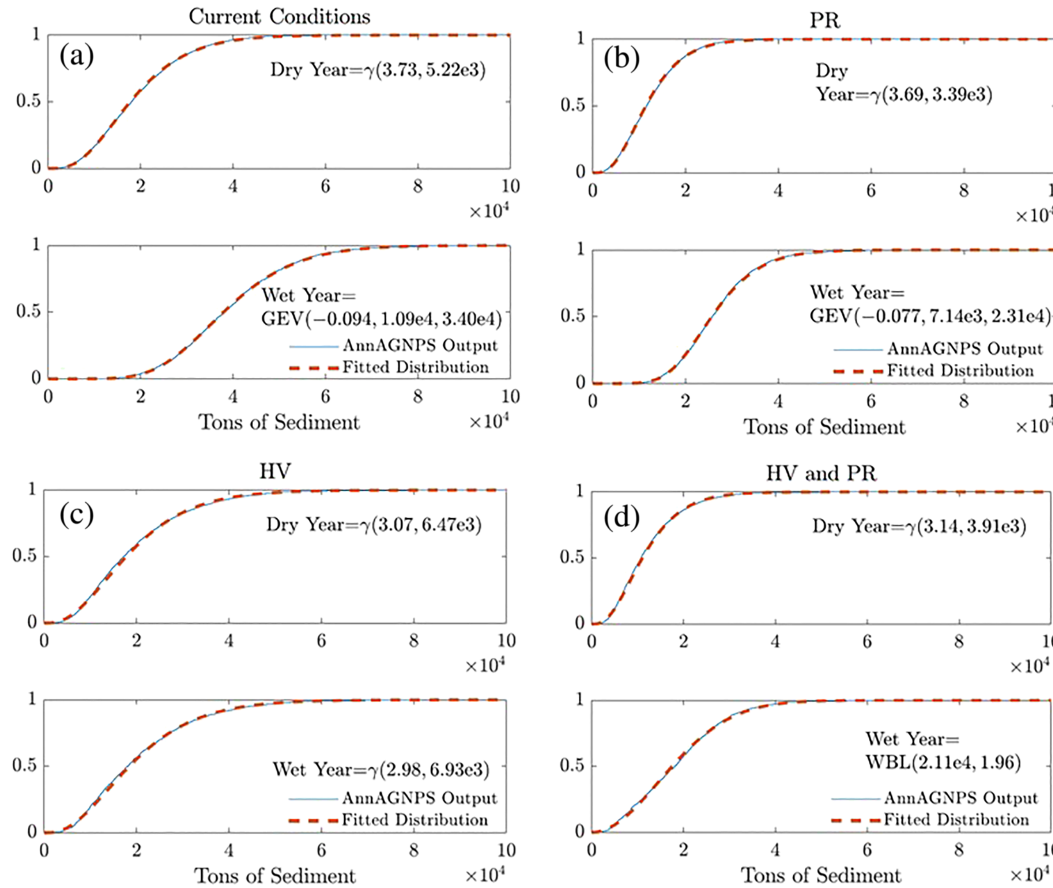

Figure 7. Analytical distribution fit (dashed red line) to MCMC model output (solid blue line) of sheet, rill, and gully erosion sediment yield for LLCW for (a) current conditions, (b) paving roads (PR), (c) hillslope revegetation (HV), and (d) a combination of hillslope revegatation and paving roads (PR and HV).

For each intervention outlined in Table 1, the AnnAGNPS model was run with 1,000 simulations lasting a total of 10 years. This yielded 10,000 year-long simulations of AnnAGNPS model output, per intervention, that was subsequently separated by wet and dry years (using the index from the rainfall generator) and fitted to statistical distributions (Figure 7). These distributions served as a surrogate model for AnnAGNPS for use

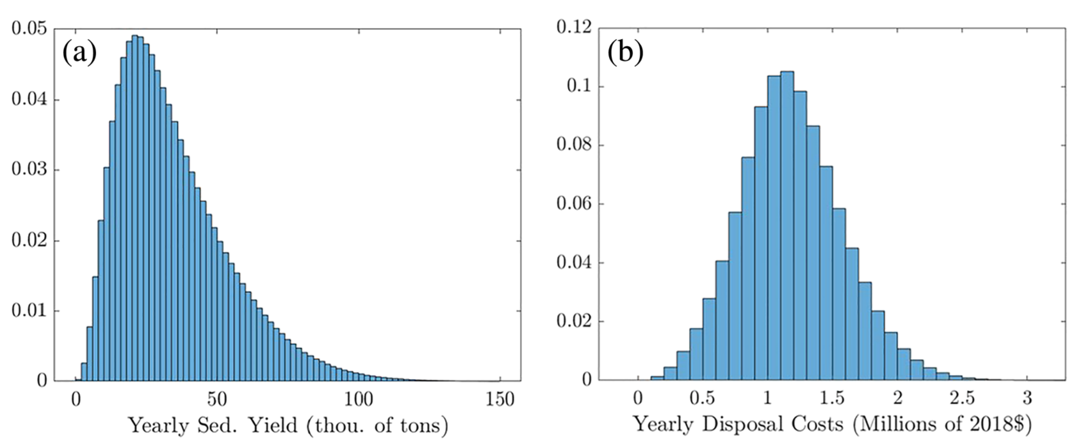

Figure 8. Baseline scenario of yearly sediment yield from the watershed in tons (a) and associated yearly disposal costs (b).

Table 2
List of Uncertainties, Their Type, and Treatment

Uncertainty	Type	Treatment
Channel erosion	Epistemic	Uniform random distribution
Sheet, rill, and gully erosion	Epistemic	Not treated
Cost of disposal	Aleatoric	Weighted random distribution
Inflation	Aleatoric	Generalized extreme value distribution
Rainfall variability	Aleatoric	MCMC modeling
Land use changes	Aleatoric	Not treated
Financial crisis	Aleatoric	Not treated

in coupled hydro-financial simulations, because direct simulation of AnnAGNPS was found to be prohibitively expensive from a computational perspective. We note that the number of simulations required for stochastic modeling increases with the number of random variables, which expand with the consideration of financial factors on top of hydrological factors. Hence, the MCMC model was applied using the same Markov Chain wet/dry probabilities from Figure 6 for the coupled hydro-financial framework, and a total of 500,000 MCMC simulations were applied for both a 5- and 10-year bond periods to account for the number of random variables considered. The coupled hydro-financial modeling system used the statistical distribution of AnnAGNPS output (Figure 7), a uniform distribution describing channel contributions, a financial model to describe the unit cost of disposal ($/yd^3) as a function of yearly sediment yield (Figure S9) and a Generalized Extreme Value Distribution to simulate cost increases (Figure S8).

3.5.2. Baseline Model Validation

The MCMC rainfall simulator was applied with AnnAGNPS and the financial model to generate sediment loads and managements costs for a given year. The hydro-financial modeling frame predicts an average sediment load of 34,712 tons/year (bottom 25% = 19,000 tons/year, upper 75% = 45,500 tons/year), costing on average (in 2018 dollars) $1.19 million/year (bottom 25% = $0.919 million/year, upper 75% = $1.44 million/year) in disposal costs (Figure 8). By comparison, data available from State Parks indicates that the measured mean annual sediment mass was 39,368 tons costing on average $1.236 million/year (Table S1).

3.5.3. Uncertainty Treatment

Both aleatoric and epistemic uncertainties are important for any investor considering a financial instrument, and major sources of uncertainty were considered for this study. Aleatoric uncertainties considered in the modeling included rainfall, cost of disposal, and inflation. Aleatoric uncertainties not explicitly modeled include financial crises, land use changes, or wildfires. Epistemic uncertainties included in the modeling were sediment loads from channel contributions. Uncertainty in estimates of sheet, rill, and gully erosion were not explicitly modeled. A summary of the different types of uncertainty and how they were treated are shown in Table 2.

The model was calibrated using data from the downstream sediment basin which lumped sheet, rill, gully, and channel erosion yields. While Taniguchi et al. (2018) was able to provide uncertainty bounds for the channel contributions 25–40% of sheet, gully, and rill erosion, there is no site-specific estimate of sheet, channel, and rill erosion uncertainty. The largest uncertainty in the model is from precipitation. Precipitation is by far the largest driver of sediment generation within the watershed and is highly variable in the Southern/Baja California region.

3.5.4. Simulation of Future Sediment Loads Under Baseline and Intervention Scenarios

The MCMC rainfall simulator was next applied to simulate baseline and intervention scenarios for $n = 5$ and 10 year project durations. AnnAGNPS parameters were adjusted to account for scenarios AC, PR, and HV, while financial parameters were adjusted to account for scenario LD. Combinations of scenarios were also considered with further adjustments to model parameters. AC was simulated through reducing the channel contributions from 25–40% to 0%. PR was simulated by modifying the unpaved road parameters within AnnAGNPS for critical roads identified in Gudino-Elizondo et al. (2019). HV was similarly modified through modifying the vegetation index parameters within AnnAGNPS for barren land. LD was modified using cost estimates for the medium-choice local disposal restoration plan (1,000,000 yd^3, 2018 cost of disposal = $18.07/ton) (Lee & O'Callahan, 2016). Following each simulation, the nondiscounted total cost savings from each project was computed by subtracting costs from current conditions compared to modified conditions to

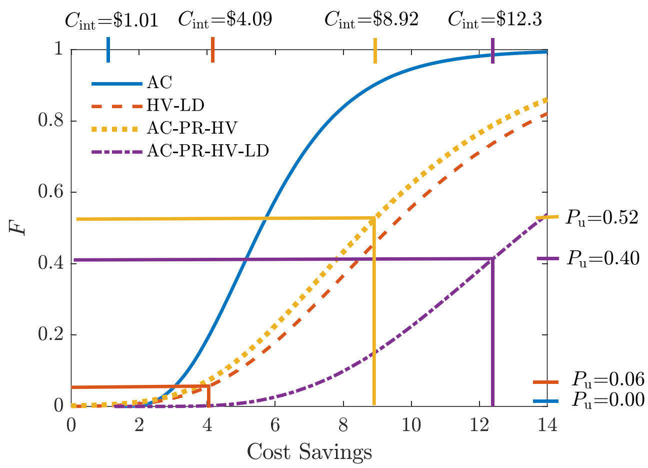

Figure 9. Empirically derived F (using Equation 9 for cost savings) for LLCW with different interventions, C_{int}, and P_{u} highlighted.

yield the cost savings cdf, F. These cdfs were then compared with the costs of implementing each intervention (from Table 1) to determine P_{u} and corresponding environmental interest rate (i_{env}). Note that cost increases due to trash and plastic were not explicitly modeled but are incorporated into the sediment disposal calculations.

4. Results and Discussion

The empirical cost saving cdf, F, is shown in Figure 9 for selected interventions using Equation 9 to calculate cost savings and a 10-year project duration. Empirical F curves for all combinations of interventions and methodologies are given in Figures S10–S16. In Figure 9, the C_{int} for each intervention is highlighted with a color-coded line drawn from C_{int} (x-axis) to the corresponding P_{u} (y-axis), which was then used to compute the environmental interest rate using Equation 5. The financial parameters for each intervention alternative are thus summarized in Table 3. We note that a 5-year bond analysis (Table S2) was also performed, but due to nearly all 5-year bonds having unacceptably high P_{u} and i_{env}, this analysis is not presented in the main

Table 3
Capital Costs (C_{int}), Default Probability (P_u), and Environmental Interest Rate (i_{env}) for Watershed Interventions Financed by a 10-year EIB

Intervention	C_{int} (10^6 2018)	$P_{\text{u}}^{(1)}$	$i_{\text{env}}^{(1)}$	$P_{\text{u}}^{(2)}$	$i_{\text{env}}^{(2)}$
AC	1.01	0.00	0.00%	0.13	1.22%
PR	7.20	0.83	6.22%	0.68	5.32%
HV	0.71	0.61	4.90%	0.51	4.20%
LD	3.38	0.06	0.54%	0.07	0.68%
AC-HV	1.72	0.17	1.59%	0.21	1.98%
AC-LD	4.39	0.02	0.19%	0.01	0.09%
AC-PR	8.21	0.55	4.50%	0.41	3.48%
HV-LD	4.09	0.06	0.57%	0.04	0.42%
PR-HV	7.91	0.77	5.92%	0.64	5.06%
PR-LD	10.58	0.45	3.76%	0.22	1.97%
AC-HV-LD	5.10	0.03	0.30%	0.01	0.05%
AC-PR-HV	8.92	0.53	4.31%	0.37	3.21%
PR-HV-LD	11.3	0.46	3.83%	0.21	1.88%
PR-LD-AC	11.6	0.38	3.27%	0.07	0.69%
AC-PR-HV-LD	12.3	0.41	3.46%	0.07	0.70%

Note. Superscripts (1) and (2) denote two different ways of estimating cost savings defined by Equations 9 and 10, respectively.

body of the results and discussion. This result demonstrates that for this situation that a 5-year duration is not long enough time to accumulate cost savings to pay back the bond Principal.

4.1. Watershed Changes, Environmental Interest Rates, and Bond Rating

The capital costs (C_{int}), default probability (P_{u}), and environmental interest rate (i_{env}) for watershed interventions financed by a 10-year EIB are presented in Table 3. Two different sets of P_{u} and i_{env} are presented corresponding to the two methods of estimating cost savings. The superscripts (1) and (2) refer to Equations 9 and 10, respectively, and conceptually represent a contemporaneous and sequential difference in costs, respectively.

From Table 3, it is immediately apparent that AC is the fiscally optimal intervention based on contemporaneous cost savings determination as it yields the lowest P_{u} and i_{env}, with a model predicted guaranteed payoff of Principal and 0% i_{env}. This finding is consistent with the work of Taniguchi et al. (2018) and Trimble (1997) which found that channel erosion is a major contributor of sediment loading within the Southern/Baja California region. In addition, the relatively low cost of armoring the channel results in a low P_{u} and i_{env}. On the other hand, PR is the least fiscally optimal scenario. While AnnAGNPS simulations indicate that PR will significantly reduce sediment loading (Gudino-Elizondo et al., 2019), the high cost of the intervention ($7.20 million, more than double the cost of the next highest single intervention, LD) results in a high environmental interest rate. Combinations of scenarios do not necessarily reduce the i_{env}. For instance, the combination of AC-HV yields a higher environmental interest rate ($i_{\mathrm{env}}^{(1)} = 1.59\%$) than AC ($i_{\mathrm{env}}^{(1)} = 0.00\%$) alone. However, combinations of interventions could be used to subsidize riskier investments given stakeholder preference. For instance, if stakeholders strongly prefer PR despite its high cost, combining AC-PR reduces $i_{\mathrm{env}}^{(1)}$ by 30%.

In general, Table 3 shows that for most interventions, the sequential methodology (superscript (2)) yields a lower P_{u} and i_{env} compared to the contemporaneous method (superscript (1)). The exceptions generally occur where the probability of default is relatively small, in this application around 10% or less. Differences in P_{u} and i_{env} between the contemporaneous and sequential methods are due to differences in the shape of cost savings distributions $F^{(1)}(x)$ and $F^{(2)}(x)$. Generally, $F^{(2)}(x)$ is characterized by a smaller variance than $F^{(1)}(x)$ since the former is obtained by subtracting a scalar from a distribution, while the latter is obtained by taking the difference between two distributions. In some cases, these differences are substantial (e.g., PR-LD-AC and AC-PR-HV-LD) which may make the choice of methods an important point for dialogue and deliberation among investors and stakeholders when designing an EIB.

4.2. Potential Risk Reduction Techniques

If the P_{u} and i_{env} are too high to be palatable to stakeholders and investors, a number of different strategies could be used to reduce them to more manageable levels. One of the simplest methods for reducing P_{u} and i_{env} is to extend the issue length of the bond to allow more time for cost savings to accrue. This result is supported by comparing the 10-year versus 5-year bond for LLCW, where all the 5-year bonds have significantly higher i_{env} rates compared to 10-year bonds. This result is also supported by the theoretical results in Figure 3 which show longer bond issue lengths yield a lower i_{env} if P_{u} is held constant.

Another strategy for reducing risks to investors is using bond guarantees. Bond guarantees are contracts where interested parties who stand to benefit from the bond provide insurance against losses for investors. This methodology has precedent, as it was used in the SIB for Riker's Island prison in NYC. Bloomberg Philanthropies provided grant funding as a guarantee on a SIB from Goldman Sachs for an SIB to reduce recidivism rates (Olson et al., 2013). In the case of LLCW, the cities of San Diego, Tijuana, and Imperial Beach would benefit from less marine bound debris, which would improve the cleanliness and recreational value of their beaches. Less sediment delivery to the estuary also results in less habitat destruction, which provides additional value not explicitly modeled.

Another methodology which could be used to reduce P_{u} is through cost sharing among multiple stakeholders. This could be accomplished by more rigorously accounting for environmental and social benefits (or even costs) of the proposed interventions. For example, paving the roads is considered a priority of the community as it reduces dust and allows community members to travel to work poststorm more easily (Grover, 2011). In addition, road paving reduces gully erosion and does not significantly impact peak discharge, as reported by Gudino-Elizondo, Biggs, Bingner, et al. (2018). Similarly, revegetating hillslopes increases safety and reduces the risk of financial damages by reducing the probability of hillslope failure and may also add urban amenity through vegetative cooling effects and access to green spaces. The effects of channel hardening are more complex but worthy of consideration. For example, hard bottom channels are effective at managing the risks of flooding and erosion for events that fall within the design capacity of the system but increase the risk of major losses for events beyond the design capacity and create so-called "legacy risks" such as degraded water quality, negative impacts to ecosystems, and unrealized urban amenities (Sanders & Grant, 2020). Given the central role of LLCW channel erosion in downstream ecosystem degradation, this points to a difficult tradeoff between within-channel and downstream ecosystem impacts.

While not investigated in this study, another strategy for potentially reducing the Risk Premium paid to investors is using collateral for the bondholders to recover Principal in case of default. Examples of collateral include landholdings, equipment, and facilities. Another possibility is using future cost savings from the environmental work which extend beyond the lifespan of the bond. More research is needed to explore all of these risk reduction options further.

5. Summary and Conclusions

Herein, we present a stochastic hydro-financial watershed modeling framework for development of an environmental impact bond—a mechanism whereby investors provide funding for comprehensive watershed interventions that is repaid with interest by stakeholders who experience reductions in management costs (savings). Hence, stochastic hydro-financial modeling can be viewed as a decision-support tool that delivers the following information to stakeholders and investors contemplating use of an environmental impact bond,

1. The probability distribution of cost savings from proposed interventions, F.
2. The probability of failure (or default) based on intervention costs relative to cost savings, P_u.
3. A Risk Premium for rewarding investors for accepting the risk of default due to unrealized cost savings.
4. An environmental interest rate that serves as an indicator for the cost-effectiveness of the EIB financing and can be adjusted by varying the length of the EIB term.
5. Evaluation and certification of cost savings to support terms of the EIB agreement.

We find that a stochastic modeling approach is ideal for propagating the impacts of aleatory and epistemic uncertainties (both hydrologic and financial) onto the probability distribution of cost savings, which in turn impacts the risk of failure, interest rates, and repayment periods. In this case, major sources of uncertainty include the interannual variability in rainfall, which drives sediment production and interannual variability in sediment disposal costs. Additionally, interannual and seasonal variability in daily rainfall, which drives sediment production, was captured using a MCMC rainfall simulator which, in turn, was input into a mechanistic sediment production model to yield annual probability distributions of sediment production. These distributions capture the major differences in sediment yield that occur in wet years versus dry years, which is a major consideration for the probability of underperformance.

Results show that increasing the repayment period (or duration) of a bond is an effective means of improving its feasibility. Not only do greater savings accrue over time to pay back principal, but the bond is less likely to be affected by the possibility that bond duration overlaps with a wet year (or years) that would otherwise reduce savings compared to the average year. Note, however, that this phenomenon is only an issue when using the sequential methodology, as the contemporaneous methodology for calculating cost savings would account for the additional rainfall. At the Tijuana site, analysis of bond length finds that 5-year bonds are likely not feasible due to high probability of failure which leads to high i_{env} rates for nearly all interventions. On the other hand, a 10-year bond length finds a menu of feasible possible options with reasonable i_{env}.

The effects of P_u and repayment period (n) on i_{env} were investigated through a sensitivity analysis. This analysis revealed that increasing the number of years (n) for repayment was an effective way of reducing i_{env}. This method is effective because it gives the stakeholders more time to repay the Principal of the bond using accumulated cost savings, reducing P_u. The second method to lower i_{env} is through reducing P_u using different interventions. The effectiveness and cost of the implemented intervention (C_{int}) are the controlling factors of P_{u}.

EIBs are relatively new financial instruments for which a common financial structure has yet to emerge, and the approach developed here is based on a relatively simple zero-coupon bond structure. More research is therefore needed to examine stochastic hydro-financial modeling support for development and implementation of EIBs with alternative financial structures, and this should be a priority based on high interest in socially responsible investing and the potential for EIBs to overcome vexing financial barriers to more sustainable watershed management.

Conflict of Interest

The authors declare no financial conflicts of interest with this research.

Data Availability Statement

Data used within in this study are available in the open repository DRYAD (https://doi.org/10.7280/D1M38Z).

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