# Risk-Based Characterization for Vapour Intrusion at a Conceptual Brownfields Site: Part 2. Pricing the Risk Capital

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*Abstract*-The focus of this paper is to price the guarantee period of a brownfields redevelopment project, which is the present value of the sum of the cost of failure plus the cost of data collection. The cost of failure is essentially a contingency fee that the developers must reserve from the sale of each residential house to cover the risk of repurchasing it and maintaining the development at a future date. Its price is largely dependent on prediction uncertainty associated with three metrics evaluated in a companion paper. Two methods were adapted from Yu et al. (2012) to estimate the risk capital portion of the contingency fee to cover the developers' preference for risk aversion. These methods were modified to accommodate the worth of hydrogeological data in reducing prediction uncertainty. The first method is denoted as the "actuarial" premium calculation principle because it follows classical P&C insurance policies. This method uses the standard deviation of the cost of failure as a safety loading factor. The second method is denoted as the "financial" premium calculation principle, which expresses the safety loading term as an interest rate surcharge in excess of the risk free (nominal) interest rate. The advantage of this approach is that it provides an unambiguous link between market information and the worth of hydrogeological data in reducing prediction uncertainty.

Keywords- Risk-Cost-Benefit Analysis; Optimization; Probability of Failure; Risk Capital; Real Option

## I. INTRODUCTION

Brownfields are defined as "abandoned, idled, or under-used industrial and commercial facilities where expansion or redevelopment is complicated by real or perceived environmental contamination" by the U.S. Environmental Protection Agency (US EPA). Brownfields are usually unintended by-products of industrial practices of the last several decades in which measures were not taken to prevent industrial operations from damaging the natural environment. In brownfields, there exist known and potential contaminants, such as volatile organic compounds (VOCs) or semi-volatile organic compounds (SVOCs) which over time, may migrate to neighbouring lands through groundwater or surface runoff and may be exposed to the air and potentially threaten public health and have negative impacts on the environment. Redevelopment of brownfields is beneficial to the environment as well as communities. It is an efficient, effective, and environmentally-friendly way to encourage development using existing infrastructures, services, and resources. Redeveloping brownfields can also generate great economic benefits if appropriate and reasonable methodologies were designed. There are strong environmental, social, and economic grounds to redevelop and utilize brownfields. Redevelopment provides a means of creating jobs, increasing the federal and local tax base, increasing the attractiveness of neighbourhoods, and protecting natural ecosystems [1-3].

Since the 1980's, both North America and Europe have recognized the social, environmental, and economic benefits of fostering the redevelopment of brownfields sites. The USA enacted the Superfund Liability Act to reclaim 1,410 heavily contaminated sites across the nation. However, the complex and uncertain nature of the subsurface hydrogeology and its impact on financial liabilities, benefits and risks inherent in the redevelopment project often serve to stifle any redevelopment plans. Reference [4] identifies two obstacles that the developer would face prior to making the capital investment decision of a brownfields redevelopment. First, it is likely that the cost of the initial investment may surpass its returns. Second, there are potential public health concerns for the building occupants due to contaminated vapor intrusion causing indoor air quality degradation. If it occurs, the developer may confront unexpected punitive damages in compliance with government regulations. This latter issue is the focus of [5], and [6] who explore the impact of multiple hydrogeological factors on the fate and transport of Trichloroethylene (TCE) from a Dense non-aqueous phase liquid (DNAPL) source zone located below the water table, with dissolution into the groundwater and vaporization into the indoor air of a residential dwelling located above the groundwater plume. Health impacts are assumed to arise should the indoor air concentration exceed a regulatory limit [7, 8].

A typical brownfields project undergoes numerous stages before development is complete [9, 10]. They are aggregated here into five stages as depicted in Fig. 1. Stage 1 involves site purchase at time  $t_0$ . Stage 2 follows with environmental site assessment, evaluation and planning starting at time  $t_1$ . Stage 3 includes site remediation and additional risk assessment at time  $t_{II}$ . Stage 4 begins the process of construction which involves a residential development and the sale of the houses at time  $t_{III}$ . Stage 5 operates until the termination of the project and involves site operation and monitoring until time  $t_{IV} = T$ . The worth of the project to the developer can be valued by discounting cash flows arising from the above five stages to present value [11], expressed as:

$$PV(\mathcal{C}_{total}) = PV(\mathcal{C}_0) + PV(\mathcal{C}_{I}) + PV(\mathcal{C}_{II}) + PV(\mathcal{C}_{III}) + PV(\mathcal{C}_{IV})$$
(1)

where *PV* denotes present value,  $C_{total}$  is the total cost of the project, and  $C_0$ ,  $C_I$ ,  $C_{II}$ ,  $C_{II}$  and  $C_{IV}$  are the costs of each of the five stages.



Fig. 1 The five phases of a brownfields redevelopment project

Following [4], this paper focuses on Stage 5 otherwise known as the guarantee period. This stage arises because hydrogeological site complexities often prevent complete remediation of legacy DNAPL source zones in Stage 3, providing the potential for future degradation of the indoor air quality of residential houses within the development. The interpretation of the guarantee for this paper is as follows. To appeal to buyers, the developer guarantees that when vapor intrusion occurs and the public health becomes a concern, they will immediately buy out any resident occupying an affected house, with the purchase price of the house appreciated by the US national home price index. Indoor air concentrations are monitored every  $\Delta t_{monitor}$  days, and the guarantee lasts from time  $t_{IV}$  until time T. Thereafter, the developer is compensated by the government for any additional costs [12, 13]. In exchange for the repurchase agreement and the developer's due diligence for continuous monitoring, the residents agree not to pursue any legal action against the developer for any health issues emerging from potential long-term exposure to contaminated indoor air. To sustain the development, the developer undertakes remediation efforts to restore the contaminated subsurface. The affected houses are either demolished, and rebuilt, or renovated, and then resold. While this description of the guarantee period is identical to that of [4], central questions regarding its implementation by the developer in the context of this study are substantially different and are outlined below.

Reference [6] explored the impact of various hydrogeological factors when defining an exclusion zone for indoor air contamination around the lateral edges of a groundwater plume. This same problem geometry is directly amenable to exploring questions related to the guarantee period in this study (see Fig. 2). To review the conceptual model, the assumption is that the developer has already repurchased the two houses located directly over the plume (houses 2 and 5) as part of their due diligence and is faced with dilemma of assessing their liability with regards to the houses adjacent (houses 1, 3, 4 and 6) to those directly over the plume. The dilemma arises from the fact that although they have liability should the indoor air concentrations in these houses exceed the regulatory limit, they do not necessarily have access to monitor the indoor air quality without purchasing the houses a priori.

In the companion paper, the authors explored the worth of collecting permeability and soil gas concentration data for reducing the prediction uncertainty of whether the TCE concentration within the indoor air of the laterally offset houses will exceed a regulatory limit. Without direct access, the authors presume the developer conducts their due diligence by using the data to simultaneously reduce prediction uncertainty while minimizing costs associated with the guarantee period and in effect promoting sustainable development. A specific objective of the companion paper was to quantify predication uncertainty using three metrics: first, the ability to correctly estimate the actual indoor air concentrations at unmonitored locations (i.e. within

houses 1, 3, 4 and 6) at any point in time; second, the ability to use available soil gas concentration data to reduce the standard deviation in indoor air concentration at unmonitored locations; and third, to accurately forecast the probability that indoor air concentrations will exceed a regulatory exposure level at unmonitored locations. The third metric is in fact the probability of failure. The three metrics were evaluated based upon the sampling strategy regarding various combinations of permeability and soil gas concentration data as shown on Table 1. The design of the sampling strategies was to reflect common practice, ranged from the least to the greatest reasonable effort that one would pursue when characterizing and monitoring a site.



Fig. 2 The three-dimensional problem geometry: a) top view, and b) vertical cross section

TARIE 1 PE	RMEABILITY AND	CONCENTRATION	DATA LOCATIONS FO	OR ALTERNATIVE SAMPLE	NG STRATEGIES
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	Sampling Strategies														
Locations	1K 2C	1K 4C	1K 7C	3K 2C	3K 4C	3K 7C	5K 2C	5K 4C	5K 7C	7K 2C	7K 4C	7K 7C	80K 2C	80K 4C	80K 7C
House 1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
House 2	С	С	С	С	С	С	С	С	С	С	С	С	С	С	С
House 3	-	-	_	_	-	-	_	-	_	-	-	_	-	_	_
House 4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
House 5	-	-	С	-	-	С	-	-	С	-	-	С	-	-	С
House 6	-	-	-	_	-	-	_	-	_	-	_	_	-	_	_
BH 1	-	-	-	_	-	-	_	-	_	Κ	Κ	Κ	Κ	Κ	Κ
BH 2	-	-	С	-	-	С	Κ	Κ	K, C	Κ	Κ	K, C	Κ	Κ	K, C
BH 3	-	С	С	Κ	K, C	К, С	Κ	K, C	К, С	Κ	К, С	К, С	Κ	K, C	К, С
BH 4	K, C	K, C	K,C	K, C	K, C	К, С	K, C	К, С	K, C	K, C	K, C				
BH 5	-	С	С	Κ	K, C	К, С	Κ	К, С	K, C	Κ	K, C	K, C	Κ	K, C	K, C

BH 6	-	-	С	_	-	С	Κ	K	K, C	K	Κ	K, C	Κ	K	K, C
BH 7	-	-	-	-	-	_	-	-	_	Κ	Κ	Κ	Κ	Κ	Κ
÷	-	-	-	-	-	-	-	_	_	-	-	-	:	:	:
BH 80	-	-	-	-	-	-	-	-	-	-	-	-	Κ	Κ	Κ
-	denote	es no sar	nple dat	ta at the	location	1									

K denotes permeability measurements obtained from boreholes (BH)

C denotes soil gas concentration sample obtained from either boreholes or residential houses

The objectives of this paper are: to present a methodology to price the guarantee period of a brownfields redevelopment project, to evaluate the worth of the data collection and eventually to obtain an optimal sampling strategy based on minimizing the cost during the guarantee period. In this paper, costs associated with the guarantee period  $C_{IV}$  are assumed to arise from two categories: the cost of the monitoring data  $C_{data}$ , and the cost of failure arising from the need to repurchase and eventually resell an affected house  $C_{failure}$ . This is expressed as:

$$PV(\mathcal{C}_{IV}) = PV(\mathcal{C}_{failure}) + PV(\mathcal{C}_{data}).$$
<sup>(2)</sup>

Reference [4] focused entirely on the cost of failure term as the main challenge facing the developer. They state that the cost of failure is essentially a contingency fee that the developer must reserve to cover the "risk" that they potentially need to repurchase the affected house and enable a sustainable development. Alternatively, the contingency fee could be considered as an upfront payment of an insurance premium providing the means to transfer the "risk" to an insurance company. Reference [4] further clarified their definition of "risk" as "risk capital", which includes a surcharge supplementary to the expected present value of the probability of failure multiplied by the cost of failure. Specifically, this surcharge represents how much a risk-averse developer would accept to invest in a brownfield redevelopment project given large inherent uncertainties and the potential loss of investment principal.

Some authors proposed and applied a general cost-benefit-risk framework applicable to the brownfields redevelopment project in that it estimates the value of a project by incorporating both hydrogeological and economic information [14-16]. Reference [17] used the same framework for the design of soil vapor extraction systems. Reference [18] developed a cost-benefit uncertainty analysis for solving a contaminated aquifer management problem focusing on the relationship between increased management costs and the desired level of protection. Additional cost-benefit analyses have been used to examine risk assessment strategies for human health due to chemical exposure arising from hydrogeological projects [19, 20], and to make remedial action decisions in an optimization framework [21]. Reference [22] used the same cost-benefit-risk framework for decision analysis of problems related to groundwater remediation. A central principle in the above cost-benefit-risk analyses is that all risks within an engineering project can be defined as the product of the probability that the engineered system will fail to meet the intended goal (probability of failure) and the cost of not reaching that goal [23-27] assessed the economic worth of hydrogeological information obtained through sampling in an optimization problem uncertainty using stochastic programming.

Reference [4] indicated that a common element in the [15, 16, 17, 28] cost-benefit-risk framework is the application of the classical economic utility function which takes into account the level of risk aversion that a decision maker has to accept. The utility function is an abstract measure of risk-averse tendencies capturing the subjective perception of risk based on prevailing social and economic factors. It is difficult to both conceptualize and define. However, empirical studies by [29] and [30] indicate that common practice by contractors is to surcharge their bid on a project by a factor of 1%-3% to accommodate construction risk. Reference [31] further indicated that this surcharge is then expressed as an interest rate spread over and above the consumer price index, and in fact can be inferred from appreciation of the stock of construction companies trading on the market.

A novel contribution of this paper is to adapt two risk capital valuation methods from [4] to unambiguously parameterize and value the risk capital problem at hand. As such, the authors seek to minimize an objective function based largely upon Eq. (2) that balances the trade-offs between collecting progressively more data to reduce project uncertainty and hence the cost of failure, but at an ever increasing site characterization cost. Specifically, the authors show how the hydrogeological and financial (market) data can be used to form two approaches: a classical P&C insurance valuation involving safety loading which is termed an "actuarial" approach; and a risk-neutral valuation that is based on implied loss distributions from market prices which is termed a "financial" approach. By equating, comparing and contrasting these two risk capital valuation approaches, both hydrogeological and financial uncertainties are related to the developer's needs to minimize the objective function.

#### II. MODEL PARAMETERS DURING THE GUARANTEE PERIOD

## A. Probability of Failure

The probability of failure follows directly from the companion paper, and is reviewed briefly here for completeness. The key issue in this work is the assumption that although the developer has the liability for indoor air impacts to houses 1, 3, 4 and 6, the developer does not have access to these properties which is often the case at the real sites. To constrain the prediction uncertainty for indoor impacts on these houses, the developer uses knowledge of the subsurface permeability structure obtained from the soil cores in combination with TCE soil gas concentration measurements within these same boreholes, as well as TCE soil gas concentration measurements from beneath the foundation slab of house 2. The third metric associated with prediction uncertainty is directly related to the first and second moments of  $\hat{c}_{IA_{i,j}}^{+}$  which represent indoor air concentrations conditioned using kriging and the static Kalman filter to assimilate the permeability and soil gas data.

The probability of failure during the guarantee period can be calculated under the assumption that the developer guarantees to monitor the indoor air quality every  $\Delta t_{monitor} = 100$  days during the guarantee period that lasts for  $T - t_{IV} = 1800$  days (5 years). Within a monitoring interval  $(t_{i-1}, t_i]$  where  $t_i = i \times \Delta t_{monitor}$  with  $i = \{1, 2, ..., n_{times}\}$  and  $n_{times} = (T - t_{IV})/\Delta t_{monitor}$ , the probability of exceedance  $P_{i,j}$  for the *j*th location (i.e. one of houses 1, 3, 4 and 6) in one of two methods is calculated. First, it can be estimated as the ratio of the sum of the number of Monte Carlo realizations where for the first time the indoor air concentration exceeds the regulatory limit  $n_{c_{IA_{i,j}} > c_{regu}}$  to the total number of Monte Carlo realizations

n<sub>realizations</sub>:

$$P_{i,j} = \frac{n_{c_{IA_{i,j}} > c_{regu}}}{n_{realizations}} .$$
(3)

The probability of failure is independent within each monitoring interval and not based on prior values. For a given house within a monitoring interval, the probability of failure is in the range of  $0 \le P_{i,j} \le 1$ . However, for the same house, the sum of the probability of failure over all time steps may exceed unity. Therefore, this approach provides a conservative estimate of the probability of failure over the entire monitoring period. Second, a log-normal as well as a beta distribution is fitted to  $c_{IA_{i,j}}^{+}$  in order to better capture the tail of the distribution with the limited number of Monte Carlo simulations. Both the log-normal and beta distributions make use of the first two moments of  $\hat{c}_{IA_{i,j}}^{+}$  given by  $\mu_{IA_{i,j}}^{+}$  and  $\sigma_{IA_{i,j}}^{+}$ . All values of  $P_{i,j}$  are shown in Figs. 7, 9 and 10 of the companion paper.

## B. Cost of Failure

The cost of failure is largely adapted and abbreviated from [4] with modifications to accommodate the optimization problem need to value  $PV(C_{IV})$  as expressed by Eq. (2). The cost itself follows from the developer's guarantee, and its value  $C_{failure_i}(t_i)$  at time  $t_i$  in the time interval  $(t_{i-1}, t_i]$  is:

$$\mathcal{C}_{failure_i}(t_i) = \eta \, S_i \tag{4}$$

where  $S_i$  is the value of one of the lateral houses offset from the groundwater plume (i.e. houses 1, 3, 4 and 6) at time  $t_i$  appreciated by the US national home price index, and  $\eta$  is a scalar  $0 < \eta < 1$  and is used to represent the lost revenue arising from the purchase, remediation, demolition, rebuilding and stigma associated with the resale value of the house. The present value of the cost of failure within time interval  $(t_{i-1}, t_i]$  is:

$$\mathcal{C}_{failure_i}(t_0) = \eta \, S_i \exp\left\{\int_{t_0}^{t_i} -\rho \, dt\right\}$$
(5)

where  $\rho$  is the discount rate for a brownfields redevelopment project.

Following from [4], the US national home price index *S* released by Standard & Poor's (see Fig. 1a of [4]) is assumed to follow a stochastic Geometric Brownian Motion (GBM) path with a drift given by:

$$dS = \alpha_s S \, dt + \sigma_s S \, dZ_s \tag{6}$$

where  $\alpha_s$  is the annual rate of appreciation in the US housing market,  $\sigma_s$  is the volatility, and  $dZ_s$  is a Wiener process. Estimates of  $\alpha_s$  and  $\sigma_s$  calculated using the maximum likelihood estimation methodology is provided on Table 2. A sample realization of  $C_{failure_i}(t_i)$  based on market movements in  $S_i$  follows as:

$$C_{failure_i}(t_i) = \eta \, S_0 \exp\left\{ \left( \alpha_s - \frac{\sigma_s^2}{2} \right) t_i + \sigma_s Z_s(t_i) \right\} \,. \tag{7}$$

The notation  $C_{failure_i}(t_i)$  will be simplified as  $C_{failure_i}$  in this work due to its frequent occurrence. Eq. (7) provides an estimate of the expected value of  $C_{failure_i}$ :

 $\mathbb{E}[\mathcal{C}_{failure_i}] = \eta \, S_0 \exp\{\alpha_S \, t_i\}$ 

and variance:

$$\operatorname{Var}[\mathcal{C}_{failure_i}] = \eta^2 S_0^2 \exp\{2 \alpha_S t_i\} (\exp\{\sigma_S^2 t_i\} - 1).$$

(8)

(9)

TABLE 2 RISK CAPITAL PARAMETER VALUES

	Parameter	Value
General		
$t_0$	start date for brownfields project	March 2008
$\Delta t_{monitor}$	indoor air monitoring interval	100 days
Т	guarantee period for brownfields project	2000 days
η	house value reduction after resold	0.2
US national housing	ng index parameters for S	
S <sub>0</sub>	unit price of house at time $t_0$	\$200,000
$\alpha_S$	annual rate of appreciation	0.0456 per annum
$\sigma_{S}$	volatility	0.0375
$\hat{q}_S$	market price of risk	0.0316
Annual rate of infl	lation $r_{f}$	
$\kappa_{\mathcal{I}}$	speed of adjustment	5.83
$ heta_{\mathcal{I}}$	reversion level	3.12 per annum
$\sigma_{\mathcal{I}}$	Volatility	6.19
$\widehat{q}_{\mathcal{I}}$	market price of risk	-0.1 to 0.1
Annual discount r	ate $ ho$	
ρ	discount rate $\rho = r_{\mathcal{N}} + \hat{q}_s \sigma_s$	0.0612
Nominal annual in	terest rate $r_{\mathcal{N}}$	
$\kappa_{\mathcal{N}}$	speed of adjustment	0.2
$ heta_{\mathcal{N}}$	reversion level	0.06 per annum
$\sigma_{\mathcal{N}}$	Volatility	0.07
$\widehat{q}_{\mathcal{N}}$	market price of risk	-0.1
S&P 500 paramete	ers for <i>M</i>	
$\alpha_M$	annual rate of appreciation	0.0662 per annum
$\sigma_M$	volatility	0.1537
$\mathrm{E}[\mu_M]$	expected return on the market portfolio M	0.12 per annum
$\beta_S$	correlation between $\mu_S$ and $\mu_M$	0.0197
Safety loading par	ameters	
$b_{(ac)1}, b_{(f)1}$	weighting parameter for coefficient of variation	0.6
$b_{(ac)2}, b_{(f)2}$	weighting parameter for relative accuracy	0.4
$a_{(f)h}$	hydrogeological coefficient in financial method	0.7210
$a_{(ac)h}$	hydrogeological coefficient in actuarial method	0.7916

Note: modified from Table 4.2. of [36] and based on  $\bar{a}_{(f)} = 0.1$  per annum.

## C. Cost of Data

Within Eq. (2), the present value of the cost of data is expressed as  $PV(\mathcal{C}_{data})$  and is further defined as:

$$\mathcal{C}_{data}(t_0) = \sum_{i=1}^{n_{times}} n_C \mathcal{C}_C \exp\left\{\int_{t_0}^{t_i} r_J dt\right\} \exp\{-\rho t_i\} + n_K \mathcal{C}_K$$
(10)

where  $C_c$  is the cost of obtaining a single concentration sample and  $C_K$  is the cost of obtaining a single permeability measurement, while  $n_c$  and  $n_K$  denote the number of concentration (i.e. 0C, 2C, 4C and 7C) and permeability data (i.e. 1K, 3K, 5K, 7K and 80K) collected according to the sampling strategies outlined on Table 1. The cost of individual concentration and permeability measurements is provided here on Table 3. Reference [32] reviewed numerous factors governing a borehole drilling strategy, including depth, cost, reliability for obtaining samples, availability of drilling equipment, site accessibility, well installation and development time, and minimizing damage to the site and the subsurface. Auger drilling was chosen to obtain the samples at 10 cm spacing throughout the 8 m aquifer thickness. The main itemized cost for obtaining the permeability data includes: operation of the drill rig, mobilization and demobilization, and sample analysis [33, 34]. Soil gas concentration sampling strategies are either passive or active. Here, passive soil gas sampling via a buried collector was chosen at an overall cost of \$250 per sample [35]. While all permeability data are collected at time  $t_0$ , the concentration data are collected in the time interval  $(t_{i-1}, t_i]$ . The cost of all data is discounted from their collection time at  $t_i$  to present value at the inflation rate  $r_1$ .

TABLE 3 SAMPLING COST	'S FOR SOIL GAS	CONCENTRATION A	ND PERMEABILITY DATA

Cost of sampling	concentration (\$)	Cost of permeability data (\$)			
Type of method	Buried collector	Type of method	Auger drilling		
Equipment		Drill	430.71		
Mobilization		Equipment	100		
Operation		Mobilization	400		
Per sample	250	Sampling per borehole	7800		
Total	$250n_C$	Total	$930.71 + 7800n_k$		

Note:  $n_C$  and  $n_K$  are the number of concentration and permeability data.

The annual rate of inflation  $r_7$  represented by the Consumer Price Index (see Fig. 1b of [4]) is often observed to follow a mean-reverting stochastic process described by the Ornstein-Uhlenbeck model:

$$dr_{g} = \kappa_{g} \left(\theta_{g} - r_{g}\right) dt + \sigma_{g} dZ_{g}$$
(11)

where  $\kappa_{\mathcal{I}}$  represents the speed of adjustment,  $\theta_{\mathcal{I}}$  is the reversion level,  $\sigma_{\mathcal{I}}$  is the volatility, and  $dZ_{\mathcal{I}}$  is a Weiner process. Estimates of  $\kappa_{\mathcal{I}}$ ,  $\theta_{\mathcal{I}}$ , and  $\sigma_{\mathcal{I}}$  obtained using the maximum likelihood estimation method are provided on Table 2. The following equation provides an estimate of the expected cost of the data  $E[\mathcal{C}_{data}]$  given as:

$$E[\mathcal{C}_{data}] = \sum_{i=1}^{n_{times}} n_C \mathcal{C}_C E\left[\exp\left\{\int_{t_0}^{t_i} r_j \, dt\right\}\right] \exp\{-\rho \, t_i\} + n_K \mathcal{C}_K$$
(12)

Section 3.7 of Reference [4] provides a discussion of how to evaluate  $E\left[\exp\left\{\int_{t_0}^{t_i} r_j dt\right\}\right]$  when  $r_j$  is a stochastic process as expressed by Eq. (11).

## III. RISK CAPITAL VALUATION METHODOLOGY

During the guarantee period for this brownfields problem involving houses 1, 3, 4 and 6, *H* is the total claim or risk at time  $t_0$  and is calculated as the product of the probability and cost of failure within a time interval  $(t_{i-1}, t_i]$ :

$$H = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} H_{i,j}(t_0) = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \mathcal{C}_{failure_i} \exp(-\rho t_i) \mathbf{1}_{c_{IA_{i,j}} > c_{regu}}$$
(13)

where:  $n_{houses} \in \{1,3,4,6\}$  so that  $n_{houses} = 4$ ; and  $\mathbf{1}_{c_{IA_{i,j}} > c_{regu}}$  is a Bernoulli random variable which takes a value of 1 with the probability of failure  $P_{i,j}$  in the time interval  $(t_{i-1}, t_i]$  for the *j*th house when the indoor air concentration  $c_{IA_{i,j}}$  exceeds the regulatory limit  $c_{regu}$ , and a value of 0 with the probability of  $1 - P_{i,j}$ . The Bernoulli probability distribution of variable **1** is formulated as

$$f(\mathbf{1},p) = \begin{cases} P_{i,j}, & \text{if } \mathbf{1} = 1 \text{ when } c_{IA_{i,j}} > c_{regu} \\ 1 - P_{i,j}, & \text{if } \mathbf{1} = 0 \text{ otherwise }. \end{cases}$$
(14)

At this point, the value of *H* does not completely represent the risk capital because it does not cover the developers' preference for risk aversion. Reference [4] then adapted five methodologies to price the risk capital in the guarantee period that directly take into consideration the developer's risk aversion based on the actuarial and financial practices. In this study, the authors further adapt two of these methodologies to account for the worth of hydrogeological data in reducing prediction uncertainty as to whether the indoor air concentrations within houses 1, 3, 4 and 6 exceed the regulatory limit. First, the authors focus on method 2 as described in Section 3.1 of Reference [4] that follows classical P&C insurance policies and uses the standard deviation of the cost of failure as a safety loading factor [37, 38]. The worth of the hydrogeological data is to reduce the standard deviation in the cost of failure and hence minimize the safety loading factor. Here, this methodology is denoted as the "actuarial" premium calculation principle. Second, the authors focus on method 5 as described in Section 3.5 of Reference [4] which adopted the strategy of seeking implied loss distributions from market prices based on the empirical studies [39-42]. Reference [4] demonstrated that the safety loading factor can be expressed as an interest rate surcharge in excess of the risk free rate. Once again, the worth of the hydrogeological data is to reduce this interest rate surcharge. Here, this methodology is

denoted as the "financial" premium calculation principle. The adaptations of these two methodologies to pricing the risk capital for the guarantee period will be presented below with the intent of incorporating the worth of hydrogeological data.

### A. The Actuarial Premium Calculation Principle

Within the actuarial literature, one of the non-life insurance premium calculation principles involves charging a premium based on the expected value of the claim enhanced by a safety loading term. In the context of the guarantee period, this principle is described as:

$$V(H) = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \{ E^{\mathbb{P}} [H_{i,j}] + A(H_{i,j}) \}$$
(15)

where V(H) denotes the risk capital arising from the guarantee period for houses 1, 3, 4 and 6;  $E^{\mathbb{P}}$  is the expectation of claim  $H_{i,j}$  under the physical measure  $\mathbb{P}$ ; and  $A(H_{i,j})$  is the safety loading term.

The expectation of the claim  $\mathbb{E}^{\mathbb{P}}[H]$  is adapted from [4] as:

$$\mathbb{E}^{\mathbb{P}}[H] = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \mathbb{E}^{\mathbb{P}}[H_{i,j}] = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \eta S_0 \exp(\alpha_S t_i) \exp(-\rho t_i) P_{i,j}$$
(16)

which is the present value of the probability of failure multiplied by the cost of failure. In the companion paper, the authors explore the worth of data to reduce prediction uncertainty on the probability of exceedance term  $P_{i,j}$ . Results for the brownfields redevelopment problem used in this work show that the actual probability of failure  $P_{i,j} = 0 \forall i, j$  which may not be true in general. Furthermore, the root mean square error between the predicted and actual probability of exceedance diminishes as the number of permeability and concentration measurements increases. Therefore, this same progression of data is expected to minimize  $E^{\mathbb{P}}[H]$  for this particular guarantee period.

The risk loading term  $A(H_{i,j})$  is evaluated using the standard deviation principle [43], and is adapted here for the guarantee period as:

$$A(H_{i,j}) = a_{(ac)_{i,j}} \sqrt{\operatorname{Var}[H_{i,j}]}$$

$$A = a_{(ac)_{i,j}} \sqrt{\exp\{-2\rho t_i\} \left\{ \operatorname{Var}[\mathcal{C}_{failure_i}] P_{i,j} + \operatorname{E}[\mathcal{C}_{failure_i}]^2 P_{i,j} (1 - P_{i,j}) \right\}}$$
(17)

where  $a_{(ac)_{i,j}}$  is a data informed scalar for the safety loading factor under the actuarial principle (denoted here by the subscript " $(ac)_{i,j}$ ") in the time interval  $(t_{i-1}, t_i]$  for the *j*th house, and the expansion for  $Var[H_{i,j}]$  follows from [4] and [44]. While  $A(H_{i,j})$  is informed by the probability of failure in an identical manner to  $E^{\mathbb{P}}[H]$ , intuitively one would expect that it would also have some dependence on the first two metrics used to quantify predication uncertainty. Therefore, these terms are introduced into a parameter  $a_{(ac)_{i,j}}$  as:

$$a_{(ac)_{i,j}} = \min\left[a_{(ac)h} \min\left(b_{(ac)1}\omega_{1_{i,j}} + b_{(ac)2}\omega_{2_{i,j}}, 1.0\right), 1.0\right]$$
(18)

with:

$$\omega_{1_{i,j}} = \left| \frac{\sigma_{IA_{i,j}}}{\mu_{IA_{i,j}}} \right|$$

$$\omega_{2_{i,j}} = \left| \frac{\hat{c}_{IA,reality_{i,j}}}{\hat{c}_{IA,reality_{i,j}}} \right| .$$
(19)

Eq. (18) represents hydrogeological uncertainty as scaled by the parameter  $a_{(ac)h}$ . Parameterization of the scalars  $a_{(ac)i,j}$ ,  $a_{(ac)h}$ ,  $b_{(ac)1}$ , and  $b_{(ac)2}$  will be discussed later. Eq. (19) indicates that  $\omega_{1i,j}$  is the expression of the coefficient of variation in an absolute form, which is a measure of variability associated with uncertainty and is dimensionless and independent of scale. In statistics, it is a normalized measure of dispersion of a probability distribution and is known as the relative standard deviation. Reference [45] used the coefficient of variation as a criterion to select target sampling locations. The parameter  $\omega_{2i,j}$  is a measure of relative accuracy and it is defined as a ratio of the absolute error of a measurement to the accepted value of the measurement. In combination,  $\omega_{1i,j}$  and  $\omega_{2i,j}$  address the first two prediction uncertainty metrics, and are illustrated in Fig. 3



for each house during the guarantee period using the progression of permeability and soil gas concentration sampling strategies itemized as 1K2C, 1K4C, 7K4C and 7K7C.

Fig. 3 Values of  $\omega_1$  and  $\omega_2$  in time interval  $(t_{i-1}, t_i]$  under sampling strategies 1K2C, 1K4C, 7K4C and 7K7C in (a) house 1, (b) house 2, (c) house 3, (d) house 4, (e) house 5, and (f) house 6

Finally, a closed-form expression of the risk capital during the guarantee period is presented as:

$$V(H) = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \left( \underbrace{\eta S_0 \exp\{\alpha_S t_i\} \exp\{-\rho t_i\} P_{i,j}}_{\mathbb{E}^{\mathbb{P}}[H_{i,j}]} + \underbrace{a_{(ac)_{i,j}} \sqrt{\exp\{-\rho t_i\} \left[\eta^2 S_0^2 \exp\{2\alpha_S t_i\} \left[\exp\{\sigma_S^2 t_i\} - 1\right] P_{i,j} + \eta^2 S_0^2 \exp\{2\alpha_S t_i\} P_{j,i} (1 - P_{i,j})\right]}_{A(H_{i,j})} \right).$$
(20)

For projects with a non-zero  $P_{i,j}$  in reality, Eq. (20) shows that as progressively more hydrogeological data are collected then  $\omega_{1_{i,j}}$  and  $\omega_{2_{i,j}}$  in  $a_{(ac)_{i,j}}$  are driven to "zero" (along with  $a_{(ac)_{i,j}}$  in Eq. (18)) leaving only the financial risk in the housing market to surcharge the expected cost of failure via the project discount rate  $\rho$  as shown in Eq. (A.2).

#### B. The Martingale Premium Calculation Principle in a Financial Market

In the previous section, the premium for a risky asset is defined as the expectation of the total claim amount to be paid in a given time interval surcharged by a safety loading factor. In the financial markets, observed prices for insurance premiums on risky assets are never equal to the mathematical expectations of the underlying assets under the  $\mathbb{P}$  measure because they do not take into account the risk averseness of investors. Reference [38] introduced a method for evaluating the insurance premium in an arbitrage free market by taking a risk-neutral probability distribution under the  $\mathbb{Q}$  measure. Reference [46] applied this principle to a process with a compound Poisson probability distribution. This principle will also be adopted for the risk capital valuation of a risk-based brownfields redevelopment project under the risk-neutral  $\mathbb{Q}$  measure in this paper. For clarity and completeness of notation, the method 5 of [4] with application to pricing the risk capital for this guarantee period will be reviewed.

To begin with, the authors no longer focus on the probability of failure of each individual house, but rather expand it to the number of occurrences of failure within a residential area using a compound Poisson distribution. Suppose that:

$$\{N(t_i), t_i \ge 0\} \sim Poisson(\lambda_{i,i}) \tag{21}$$

which is a counting process using  $N(t_i)$  as a random variable in time interval  $(t_{i-1}, t_i]$  with a Poisson distribution. The probability of obtaining  $k_{i,j}$  occurrences of failure in the time interval  $(t_{i-1}, t_i]$  for the *j*th house (which can alternatively be expressed as the number of houses  $k_{i,j}$  being affected by the TCE gas concentration in exceedance of the regulatory limit) can be formulated as:

$$P(N(t_i) = k_{i,j}) = f(k_{i,j}, \lambda_{i,j}\Delta t_i) = \frac{(\lambda_{i,j}\Delta t_i)^{k_{i,j}}}{k_{i,j}!} e^{-\lambda_{i,j}\Delta t_i}$$
(22)

where  $\lambda_{i,j}$  is the rate of the Poisson process and is equal to the expected number of occurrences during the given time interval  $(t_{i-1}, t_i]$  for the *j*th house,

$$A_{i,j} = \frac{n_{c_{IA_{i,j}} > c_{regu}}}{\Delta t_i} \quad ; \tag{23}$$

and  $n_{c_{IA_{i,j}} > c_{regu}}$  is the number of realizations where the indoor air concentration of TCE exceeds the regulatory limit over the time period  $(t_{i-1}, t_i]$ . The choice of  $\lambda_{i,i}$  is made to ensure that

$$\frac{\lambda_{i,j}\Delta t_i}{n_{realizations}} = P_{i,j} \,. \tag{24}$$

The expected value and the variance of variable  $k_{i,i}$  are:

$$E[k_{i,j}] = Var[k_{i,j}] = \lambda_{i,j}\Delta t_i .$$
<sup>(25)</sup>

The present value of cost of failure within the time interval  $(t_{i-1}, t_i)$  for the *j*th house can be derived from Eq. (13) as:

$$H_{i,j}(t_0) = \exp\{-\rho t_i\} \sum_{z=1}^{k_{i,j}} (\mathcal{C}_{failure_i})_j^z$$
(26)

and implies that the cost of failure for any single house within the development is the same. The expected cost of failure can then be evaluated under the physical  $\mathbb{P}$  measure as:

$$\mathbb{E}^{\mathbb{P}}[H_{i,j}] = \exp\{-\rho t_i\} \mathbb{E}^{\mathbb{P}}\left[\sum_{z=1}^{k_{i,j}} (\mathcal{C}_{failure_i})_j^z\right] = \exp\{-\rho t_i\} \mathbb{E}^{\mathbb{P}}[k_{i,j}] \mathbb{E}^{\mathbb{P}}[(\mathcal{C}_{failure_i})_j^1]$$
(27)

which now involves the loss on a "unit" house  $(C_{failure_i})_j^1$  during the time interval  $(t_{i-1}, t_i]$ . In terms of the problem at hand, the unit house implies that each of houses 1, 3, 4 and 6 has the same value in terms of their contribution to the "cost" of failure.

The probability distribution defining the cost of failure under the  $\mathbb{P}$  measure can be converted into a probability distribution under the  $\mathbb{Q}$  measure, which is also a compound Poisson process. Furthermore, these distributions are progressively equivalent. Under  $\mathbb{Q}$ , the price process becomes a Martingale. The probability under  $\mathbb{Q}$  tends to assign more weight to less favourable events in a risk-averse environment. The expected cost of failure under the  $\mathbb{Q}$  measure can be defined as:

$$\mathbb{E}^{\mathbb{Q}}\left[H_{i,j}\right] = \exp(-r_{\mathcal{N}}t_{i}) \mathbb{E}^{\mathbb{Q}}\left[\sum_{z=1}^{k_{i,j}} (\mathcal{C}_{failure_{i}})_{j}^{z}\right] = \exp(-r_{\mathcal{N}}t_{i}) \mathbb{E}^{\mathbb{Q}}\left[k_{i,j}\right] \mathbb{E}^{\mathbb{Q}}\left[(\mathcal{C}_{failure_{i}})_{j}^{1}\right]$$
(28)

where the discount rate  $\rho$  in Eq. (27) is replaced with the risk-free rate  $r_{\mathcal{N}}$ . Having established the notation for  $\mathbb{E}^{\mathbb{Q}}[H_{i,j}]$  for the guarantee period, the next step is to relate  $\mathbb{E}^{\mathbb{Q}}[k_{i,j}] \mathbb{E}^{\mathbb{Q}}[(\mathcal{C}_{failure_i})_j^1]$  in Eq. (28) to their same expectations under the physical  $\mathbb{P}$  measure which can then be evaluated using the available hydrogeological data. The premise of this transformation is that the  $\mathbb{Q}$  measure achieves its risk loading via an interest rate surcharge in excess of  $\alpha_s$ , which is the expected appreciation rate of the brownfields project arising from the sale of the houses. This interest rate surcharge varies within time interval  $(t_{i-1}, t_i]$  as well as for houses  $j \in \{1,3,4,6\}$  and is expressed as:

$$a_{(f)_{i,j}} = \underbrace{\min\left[a_{(f)h} \min\left(b_{(f)1}\omega_{1_{i,j}} + b_{(f)2}\omega_{2_{i,j}}, 1.0\right), 1.0\right]}_{hydrogeological risk} - \underbrace{\hat{q}_{S}\sigma_{S}}_{financial}_{risk}.$$
(29)

The transformation is accomplished using Proposition 2.1 of [46] combined with  $\beta$  defined as  $a_{(f)_{i,j}} \times t_i$ .

Finally, the total value of the risk capital can be expressed as:

$$V(H) = \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \exp\{-r_{\mathcal{N}} t_i\} \operatorname{E}^{\mathbb{P}}[k_{j,i}] \operatorname{E}^{\mathbb{P}}[\mathcal{C}_{failure_i}] \exp\{a_{(f)_{i,j}} t_i\}$$

$$= \sum_{i=1}^{n_{times}} \sum_{j=1}^{n_{houses}} \eta S_0 \exp\{\left(\alpha_S + a_{(f)_{i,j}} - r_{\mathcal{N}}\right) t_i\} \lambda_{i,j} \Delta t_i .$$
(30)

The estimation of parameters  $a_{(f)h}$ ,  $b_{(f)1}$  and  $b_{(f)2}$  will be discussed in the next section. Once again for projects with a non-zero  $P_{i,j}$  in reality, Eqs. (29) and (30) show that as progressively more hydrogeological data are collected then  $\omega_{1_{i,j}}$  and  $\omega_{2_{i,j}}$  in Eq. (29) are driven to "zero" leaving only the financial risk in the housing market  $\hat{q}_S \sigma_S$  within  $a_{(f)i,j}$  to surcharge the risk capital. This financial risk term can be combined with  $r_N$  to yield the project discount rate  $\rho$  as shown in Eq. (A.2).

#### C. Optimization and Parameter Estimation

Eqs. (20) and (30) both provide closed-form expressions of the risk capital during the guarantee period that involve hydrogeological and financial (market) data. Differences between these expressions arise because the former is based on a classical P&C insurance valuation involving safety loading which is termed an "actuarial" approach; while the latter is a risk-neutral valuation that is based on implied loss distributions from market prices which is termed a "financial" approach. As part of the optimization and parameter estimation approach in this section, comparing, contrasting, and equating these two risk capital valuation approaches will be involved.

The optimization and parameterization problem that embodies this work is best expressed by Eq. (2), and involves the attempt to find the least cost strategy for the guarantee period. The premise here is that one can assess the financially sustainable market rate for companies specializing in this type of activity by observing the interest rate spread that shares in these companies trade at in excess of appreciation in the US housing market  $\alpha_s$ . Insurance policies for the guarantee period are likely to be quoted in an over-the-counter market (as with insurance policies in general), and cannot be directly observed. In the companion paper, the authors alluded to the idea that 7K4C and 7K7C appeared to be optimal sampling strategies in that they provided the "best" estimates of the three statistical metrics quantifying the worth of the hydrogeological data with a reasonable (i.e. not excessive as with 80K) amount of data. In this section, the authors build upon this idea and demonstrate that the interest rate spread can be used to price the worth of the hydrogeological data in terms of minimizing the risk capital for the guarantee period.

It begins by recasting  $PV(\mathcal{C}_{IV})$  in Eq. (2) as the value of an objective function Obj, and then  $PV(\mathcal{C}_{failure})$  using V(H) from either Eq. (20) or (30). The objective function is now stated as:

$$Obj = V(H) + \mathbb{E}[\mathcal{C}_{data}] \quad \text{subject to} \quad 0 \le Obj \le S_0 \, n_{house} \, (1 - \eta) \tag{31}$$

where  $n_{houses} \in \{1,3,4,6\}, S_0 = \$200,000$ , and  $\eta = 0.2$ . Therefore, the expected value of the risk capital cannot exceed \$640,000 otherwise the developer should never attempt to resell any house should it become impacted by indoor air quality issues. The following optimization and parameterization effort is built upon the idea that the minimum value of the objective function is located within the vicinity of the 7K4C and 7K7C sampling strategies. Clearly, the objective function seeks to balance the worth of the hydrogeological data in terms of minimizing V(H), and the expense of ever increasing site characterization costs valued by  $E[C_{data}]$ .

The first step in the procedure is to simultaneously parameterize the four unknown values of  $b_{(ac)1}$ ,  $b_{(f)1}$ ,  $b_{(ac)2}$  and  $b_{(f)2}$  of both the actuarial and financial approaches using the 7K4C sampling case strategy. The idea is to balance the contributions of the first two statistical metrics that quantify prediction uncertainty, measured by  $\omega_{1i,j}^{7K4C}$  and  $\omega_{2i,j}^{7K4C}$  and  $\omega_{1i,j}^{7K4C}$  and  $\omega_{2i,j}^{7K4C}$  and  $\omega_{2i,j}^{7K4C}$  and  $\omega_{2i,j}^{7K4C}$  are provided in Fig. 3. As a result of solving Eq. (B.1), one found that the weighting coefficients  $b_{(ac)1}$  and  $b_{(f)1}$  are approximating to 0.6, and  $b_{(ac)2}$ ,  $b_{(f)2}$  are approximating to 0.4. These values are listed on Table 2. The same procedure for the 7K7C sampling strategy (i.e. by using  $\omega_{1i,j}^{7K7C}$  and  $\omega_{2i,j}^{7K7C}$ ) was repeated and found similar results.

The second step in the procedure is to parameterize  $a_{(f)h}$  within the financial approach. It begins by observing a long-term average interest rate surcharge  $\bar{a}_{(f)}$  (in excess of  $\alpha_s$ ) in the stock of companies that specialize in trading the risk associated with the guarantee period. It is anticipated that this might be difficult given that it is more likely that companies will be involved in all activities associated with the brownfields development as expressed by Eq. (1). To proceed,  $0 \le \bar{a}_{(f)} \le 0.2$  per annum with a base case value of  $\bar{a}_{(f)} = 0.1$  per annum is assumed given the anecdotal evidence that brownfields projects rarely receive funding given the multitude of other "safer" investment opportunities in the financial markets.  $\bar{a}_{(f)}$  is then used

to parameterize  $a_{(f)h}$  for the project at hand assuming the optimal solution lies somewhere between the 7K4C and 7K7C sampling strategies. This is formulated in Eq. (B.2). The value of  $a_{(f)h}$  on Table 2 is based on  $\bar{a}_{(f)} = 0.1$  per annum.

The third step in the procedure is to parameterize  $a_{(ac)h}$  within the actuarial approach. This is done by equating the risk capital V(H) from the actuarial and financial approaches as expressed by Eqs. (20) and (30), respectively. It begins by recasting the objective function expressed by Eq. (B.3) under the assumption that the minimum value lies somewhere between the 7K4C and 7K7C sampling strategies. The value of  $a_{(ac)h}$  is found by minimizing Eq. (B.3), with a value provided on Table 2 when  $\bar{a}_{(f)} = 0.1$  per annum.

# IV. RESULTS

The optimal cost of the risk capital is such, that when added to the cost of the hydrogeological data, the least cost for guarantee period is achieved. This concept is directly expressed by Eq. (31). In the Section of optimization and parameter estimation, a joint parameter estimation and optimization exercise was conducted with the understanding that the least cost for the guarantee period lies somewhere between the 7K4C and 7K7C sampling strategies based on the results in the companion paper. Beyond the 7K4C sampling strategy, there was no statistically significant reduction in the prediction uncertainty of the first two metrics at the 5% level of significance. By implementing Eq. (31), one can price all components of the risk capital, which involves evaluating the risk capital using both the actuarial and financial methodologies, for all data collection strategies. The worth of data becomes apparent by comparing and contrasting the expected cost of the guarantee period for the alternative data collection strategies.

The discussion on the optimal cost of the risk capital begins with focusing on the financial methodology. In Fig. 4, values of  $a_{(f)_{i,j}}$  in time interval  $(t_{i-1}, t_i]$  for the *j*th house when  $\bar{a}_{(f)} = 0.1$  per annum are provided. Values of  $a_{(f)_{i,j}}$  are calculated using Eq. (29) with parameters  $b_{(ac)1}$ ,  $b_{(f)1}$ ,  $b_{(ac)2}$ ,  $b_{(f)2}$  and  $a_{(f)h}$  estimated from the first two steps outlined in Appendix B. The time-varying nature of  $a_{(f)_{i,j}}$  denotes the transient risk during the guarantee period, which mimics the shape of  $\omega_{1_{i,j}}$  and  $\omega_{2_{i,j}}$  for sampling strategies 7K4C and 7K7C as shown in Fig. 3. Specifically, the interest rate surcharge  $a_{(f)_{i,j}}$  quantifying hydrogeological (and financial) risk is minimal at early time before any of the Monte Carlo permeability realization plumes arrive. Then, as the leading edge of the groundwater plume reaches the houses, the risk is the greatest because the Kalman filter is the least effective at constraining the prediction uncertainty as measured by the first two metrics. This is largely a consequence of the very low arrival-time soil gas and indoor air concentrations inflating the values of the standard deviation of soil gas concentrations and indoor air concentrations, denoted by  $\sigma_{SG_{i,j}}^{+}$  and  $\sigma_{IA_{i,j}}^{+}$ . Later,  $a_{(f)_{i,j}}$  declines and asymptotically reaches  $\bar{a}_{(f)}$ . Finally, the result shows that the contribution of the hydrogeological risk to  $a_{(f)_{i,j}}$  far exceeds that of the financial risk when  $\bar{a}_{(f)} = 0.1$  per annum.



Fig. 4 Values of  $a_{(f)_{i}}$  in time interval  $(t_{i-1}, t_i)$  for houses 1, 3, 4 and 6 under sampling strategies (a) 7K4C and (b) 7K7C

On Table 4, values of the objective function (see Eq. (31)) with the risk capital V(H) from Eq. (30), and the probability of failure  $P_{i,j}$  defined by Eq. (3) and as shown in Fig. 7 of the companion paper are provided. The value of  $a_{(f)h}$  arising from the use of the 7K4C and 7K7C sampling strategies, as discussed in the second step of the parameterization strategy of Appendix B, was applied to calculate V(H) for all remaining sampling strategies. Surprisingly, the minimum value of the objective function occurred for 1K4C. However, in the companion paper the authors recognized that while the 1K4C provided accurate estimates

of  $P_{i,j}$ , it performed poorly based on the first two performance metrics measuring prediction uncertainty. Therefore, 7K4C is accepted instead as the correct minimum. The minimum remained near 7K4C when  $\bar{a}_{(f)}$  was adjusted over the interval  $0 \le \bar{a}_{(f)} \le 0.2$  per annum.

Obj	0C	2C	4C	7C
1K – Eqn. (3)	\$640,000.00	\$640,000.00	\$51,602.64	\$521,271.29
3K – Eqn. (3)	\$493,275.59	\$454,147.37	\$170,055.57	\$129,264.35
5K – Eqn. (3)	\$631,132.02	\$524,726.16	\$261,609.59	\$151,430.53
7K – Eqn. (3)	\$326,670.09	\$149,458.83	\$91,740.90	\$97,637.68
80K – Eqn. (3)	\$626,298.71	\$634,893.85	\$640,000.00	\$640,000.00

TABLE 4 VALUES OF THE OBJECTIVE FUNCTION FOR DIFFERENT SAMPLING STRATEGIES USING THE FINANCIAL PREMIUM CALCULATION PRINCIPLE

Note: the safety loading coefficients are calculate based on  $\bar{a}_{(f)} = 0.1$  per annum.

Professional engineers, geoscientists, and actuaries involved in managing the guarantee period of the brownfields development project are more likely to envision the time-varying cost of the risk capital V(H) by decomposing it into a contribution from the first and second moment analogous to the actuarial methodology in Eq. (20). In step 3 of the parameterization strategy in Appendix B, a value of  $a_{(ac)h}$  in Eq. (18) was adjusted so that the costs of the risk capital between the financial and actuarial methodologies, and for the average of the 7K4C and 7K7C sampling strategies, were identical. This can be observed on Tables 4 and 5. Note that the cost of the objective function using either the actuarial or financial methodologies to evaluate V(H) exhibits the same trends for the various sampling strategies. Also, 1K4C still remains minimum. However, the authors use their judgement to denote 7K4C as the correct minimum.

In the first column of Fig. 5, values of various components of the objective function calculated using the probability of exceedance from Eq. (3) are shown. These components include:  $\mathbb{E}^{\mathbb{P}}[H]$  which is the expected cost of the risk capital (i.e. first moment), A[H] which is the risk loading term arising from the standard deviation in the risk capital (i.e. second moment),  $E[C_{data}]$  which is the expected cost of data, and Obj which is the cost of the objective function from Eq. (31). The value of the risk capital in Eq. (31) is  $V(H) = E^{\mathbb{P}}[H] + A[H]$ . The solid lines indicate the cost of each component while the dashed lines indicate the percentage by which they contribute to the total cost of the objective function. The expected costs of failure for both 7K4C and 7K7C are nearly identical, and almost "zero" in keeping with reality for the problem at hand in which the indoor air concentration never exceeds the regulatory limit for houses 1, 3, 4 and 6. The risk loading term for 7K4C is slightly larger than that for 7K7C due to the worth of the extra soil gas concentration data in 7K7C for reducing prediction uncertainty. However, these extra soil gas concentration measurements cause the cost of data for 7K7C to exceed that of 7K4C. The optimal sampling strategy 7K4C achieves a least cost by balancing the worth of the cost of hydrogeological data against its value in reducing the risk loading term arising from prediction uncertainty. In contrast, 7K7C places too much emphasis on data collection relative to its actual worth in reducing the cost of the risk loading term. The optimal balance achieved by 7K4C indicates that the distribution of costs for the guarantee period should be:  $\mathbb{E}^{\mathbb{P}}[H] = 10.09\%$ , A[H] = 10.53%, and  $E[C_{data}] = 79.38\%$  for a total cost of \$91,883.66. Once again, this breakdown of costs was established under the assumption that financial risk  $\bar{a}_{(f)} = 0.1$  per annum.

Sampling strategies 1K and 80K provide extreme opposite insights into the merits of Eq. (20) for evaluating the risk capital. For instance, 1K exhibits erratic behaviour with the cost of  $E^{\mathbb{P}}[H]$  and A[H] for 4C being less than 7C. This is irrational and is a consequence of Eq. (20) being strongly dependent on the probability of failure  $P_{i,j}$ . This is due to the earlier assumption in Eq. (13) that the total claim or risk *H* is the product of the probability and cost of failure. Therefore, when there is insufficient data as with 1K4C, one may erroneously underestimate  $P_{i,j}$  (as the third performance metric quantifying prediction uncertainty) yielding a low value for the total claim or risk and ultimately the risk capital. Given that the cost of data is also at a minimum, the objective function is minimized implying an optimal management strategy. The attempts to alleviate this problem by introducing the first and second performance metrics for prediction uncertainty (i.e.  $\omega_{1i,j}$  and  $\omega_{2i,j}$ ) into  $a_{(f)i,j}$  and  $a_{(ac)i,j}$  were not entirely successful. This could create a problem for optimization algorithms that do not depend on human judgement. At the opposite end of the spectrum, 80K exhibits perfectly rational behaviour in that the extensive site characterization effort yields a cost for  $E^{\mathbb{P}}[H]$  and A[H] which are effectively "zero" in keeping with reality for the problem at hand. However,  $E[\mathcal{C}_{data}]$  is exorbitantly large yielding a high total cost and hence sub-optimal management strategy.

In the second and third columns of Fig. 5, once again values of various components of the objective function except using the probability of exceedance  $P_{i,j}$  derived by fitting the log-normal and beta distributions to  $c_{IA_{i,j}}^+$  are shown. This adjustment to  $P_{i,j}$  has a direct impact on both  $E^{\mathbb{P}}[H]$  and A[H], as shown by Eq. (20). Focusing specifically on the 7K sampling strategies, one can see on Table 5 and in Fig. 5 that the beta distribution yields the lowest total cost of the objective function. This is a consequence of the fact that it yields the lowest estimates of  $P_{i,j}$  as discussed in the companion paper. Similarly, the

log-normal distribution yields the greatest total cost given higher estimates of  $P_{i,j}$ . Of particular interest is the observation that the use of the log-normal distribution to calculate  $P_{i,j}$  appears to place the most value on  $\mathbb{E}[\mathcal{C}_{data}]$  as a percentage of the total costs relative to using Eq. (3) to calculate  $P_{i,j}$ . It also inflates the percentage contribution of  $\mathbb{E}^{\mathbb{P}}[H]$  and A[H] to the total costs. In contrast, the beta distribution has the opposite effect relative to using Eq. (3) to calculate  $P_{i,j}$ , although the impact is only slight. This should be of concern to professional engineers, geoscientists and actuaries who will jointly share the wealth created by the brownfields project. As one progressively removes permeability data and transition down to the 5K, 3K and finally 1K sampling strategies, the above observations become less relevant. It can be reiterated from the companion paper that there is little value in using either the log-normal or beta distributions to extrapolate the probability distribution for extreme events when  $\mu_{IA_{i,j}}^{+}$  and  $\sigma_{IA_{i,j}}^{+}$  are poorly constrained by insufficient data.



Fig. 5 Values of the guarantee period evaluated using the actuarial premium calculation principle for alterative permeability and soil gas concentration sampling strategies. The risk capital is priced by Eq. (20) and is the sum of E[H] and A[H], the expected cost of the data is given by Eq. (12), and the total cost is the sum of the risk capital and data given by Eq. (31). The first column involves  $P_{i,j}$  estimated using Eq. (3), the second column uses a log-normal distribution, and the third column uses a beta distribution

TABLE 5 VALUES OF THE OBJECTIVE FUNCTION FOR DIFFERENT SAMPLING STRATEGIES USING THE ACTUARIAL PREMIUM CALCULATION PRINCIPLE

Obj	0C	2C	4C	7C
1K – Eqn. (3)	\$603,020.27	\$296,437.90	\$42,618.83	\$222,052.10
3K – Eqn. (3)	\$371,076.73	\$322,743.19	\$150,245.09	\$126,015.93
5K – Eqn. (3)	\$424,568.91	\$312,474.46	\$200,695.79	\$148,339.10
7K – Eqn. (3)	\$257,024.86	\$132,073.46	\$91,883.66	\$97,766.69
7K – lognormal	\$243,745.38	\$157,082.49	\$127,352.46	\$128,136.10

7K – beta	\$231,657.80	\$125,717.41	\$90,354.70	\$91,032.11
80K – Eqn. (3)	\$626,298.71	\$634,943.26	\$640,000.00	\$640,000.00

Note: the safety loading coefficients are calculate based on  $\bar{a}_{(f)} = 0.1$  per annum.

The remaining question is the sensitivity of the total cost of the guarantee period to the long-term average interest rate surcharge  $\bar{a}_{(f)}$  (in excess of  $\alpha_s$ ) on the stock of companies that specialize in trading the risk associated with the guarantee period. The motivation for this sensitivity analysis follows from the fact that one is unaware of the availability of market data to estimate  $\bar{a}_{(f)}$  and expect that it may instead come from public disclosure of over-the-counter financial products. The authors surmise that a successful brownfields project will be the one whose progress is least sensitive to potential market fluctuations in  $\bar{a}_{(f)}$ , as well as being managed at the least cost. This sensitivity analysis is conducted by adjusting  $\bar{a}_{(f)}$  over the interval  $0 \le \bar{a}_{(f)} \le 0.2$  per annum, and re-establishing steps 2 and 3 of the parameterization strategy processes discussed in Appendix B for each increment of  $\bar{a}_{(f)}$ . Each incremental value of  $\bar{a}_{(f)}$  yields a new estimate of  $a_{(ac)h}$  and ultimately the cost of the safety loading term A[H]. The costs of  $\mathbb{E}^{\mathbb{P}}[H]$  and  $\mathbb{E}[\mathcal{C}_{data}]$  in the objective function remain unaffected.

Fig. 6 provides the cost of A[H] and the objective function with  $0 \le \bar{a}_{(f)} \le 0.2$  per annum, for sampling strategies 1K2C, 1K4C, 7K4C and 7K7C. Once again, 1K4C appears optimal although it should be discarded based on the first two performance metrics quantifying prediction uncertainty. For sampling strategies 7K4C and 7K7C, the cost of the safety loading term A[H] increases monotonically with  $\bar{a}_{(f)}$ . This occurs because A[H] is proportional to  $a_{(ac)h}$ , and  $a_{(ac)h}$ , which increases with  $\bar{a}_{(f)}$ . Because A[H] for sampling strategy 7K4C is greater than that for 7K7C, the spread between their safety loading terms also increases with  $\bar{a}_{(f)}$ . In other words, as the market places a greater premium on risk during the guarantee period by increasing the average interest rate surcharge  $\bar{a}_{(f)}$ , the contribution of the safety loading term to the total cost of the safety loading term A[H]. This transition whereby 7K7C becomes the optimal least cost management strategy is shown in Fig. 6 as  $\bar{a}_{(f)}$  increases beyond 0.17 per annum when using Eq. (3) to calculate  $P_{i,j}$ . It is reassuring to note that the total cost of the objective function for both 7K4C and 7K7C does not increase appreciably with  $\bar{a}_{(f)}$  because both sampling strategies already place a significant emphasis on the worth of data as a means of reducing prediction uncertainty. Finally, the results show that the above observations are insensitive to whether Eq. (3), the log-normal, or beta distributions are used to calculate  $P_{i,j}$ .



Fig. 6 Sensitivity in the cost of the safety loading term A[H] and the total cost of the guarantee period, as priced by Eq. (31), to  $\bar{a}_{(f)}$  over the interval  $0 \le \bar{a}_{(f)} \le 0.2$  per annum. The first column involves  $P_{i,j}$  estimated using Eq. (3), the second column uses a log-normal distribution, and the third column uses a beta distribution

#### V. SUMMARY AND CONCLUSIONS

The objective of this paper is to present a methodology to price the guarantee period of a brownfields redevelopment project, which is the present value of the sum of the cost of failure plus the cost of data collection. The cost of failure is essentially a contingency fee that the developer must set aside to cover the risk of repurchasing the affected house and maintaining the development at a future date. This contingency fee is dependent on two factors: first, the expected cost of repurchasing/renovating/reselling affected homes based on the probability that their indoor air concentrations will exceed a regulatory exposure level; second, prediction uncertainty associated with assessing the probability of exceedance based on the three metrics evaluated in the companion paper.

Two methods were adapted from [4] to estimate the risk capital portion of the contingency fee to cover the developers' preference for risk aversion. These methods were modified to accommodate the worth of hydrogeological data in reducing prediction uncertainty. The first method is denoted as the "actuarial" premium calculation principle because it follows classical P&C insurance policies, and uses the standard deviation of the cost of failure as a safety loading factor. The worth of the hydrogeological data is to reduce the standard deviation and hence minimize the safety loading factor. The second method is denoted as the "financial" premium calculation principle, which expresses the safety loading term as an interest rate surcharge in excess of the risk free (nominal) interest rate. The worth of the hydrogeological data is now to reduce this interest rate spread. Parameterization of these two methods follows from empirical evidence of the financially sustainable market rate at which shares in companies specializing in brownfields redevelopment trade at in excess of appreciation in the US housing market  $\alpha_s$ , which is the expected appreciation rate of the brownfields project arising from the sale of the houses. Next, an objective function that represents the present value of the sum of the cost of failure plus the cost of data collection is formulated for each method. These two objective functions are equated because they are alternate expressions for the price of the same guarantee period. Furthermore, they are minimized within the vicinity of two sampling strategies, namely 7K4C and 7K7C. These two sampling strategies appeared to be optimal in that they provided the "best" estimates of the three statistical metrics quantifying the worth of the hydrogeological data with a reasonable amount of data.

The primary difference of risk capital valuation methods in this paper and the traditional cost-benefit-risk framework applied by [15, 16, 22] and many others is that the methods here include a surcharge supplementary to the expected presented value of the product of the probability failure and the cost of failure. This surcharge is a form of risk aversion developers use and takes prediction uncertainty into account for a risk-based engineer project, which results in a more conservative estimate of risk capital. The discounted cash flow of a brownfield redevelopment project within a guarantee period is another important factor considered in this paper. The real estate market is relatively volatile compared with common commercial goods and housing prices can vary significantly within a short period of time. It is a common practice to discount future cash flow to a present value for real estate construction projects.

Conclusions from pricing the guarantee period of the brownfields project are threefold, and have broader implications to engineering projects in general. First, insufficient data may yield an erroneously low probability of failure causing the developer to reserve a financially unsustainable amount of risk capital. This occurs under the traditional paradigm where the risk capital is expressed as the product of the cost and probability of failure. Second, the actuarial premium calculation principle is particularly effective at relating the transient hydrogeological risk profile as it evolves over the guarantee period to the overall risk inherent in the project as priced by the financial market. Third, for the guarantee period under the least cost 7K4C sampling scenario, the expected costs associated with repurchasing/renovating/reselling houses is 10.09% of the total project costs, the safety loading factor allowing the redeveloper to be risk adverse is similarly 10.53%, and the cost of data contributes to a majority of the total project costs at 79.38%. A clear benefit of this approach is that there is an unambiguous link between market information and the worth of hydrogeological data in reducing prediction uncertainty. In other words, both financial and engineering aspects of the project are aligned with a unique set of measurable parameters.

Extension of the approach discussed in this work to practical applications requires the practitioner to have a thorough understanding of the field of "real options" [47, 48], and specifically the seminal application by [49] to pricing natural resource investments. References [50-52] as well as [53] provided applications of real options to water resources management. The starting point for the practitioner is identifying that asset which is both fundamental to the projects value and has a market price. In this case, it was the price of a house appreciated by the US national home price index. Reference [4] showed the financial approach outlined in the Section of the Martingale premium calculation principle in a financial market is fundamentally the same as the real option approach, albeit with the ability to incorporate hydrogeological in addition to market uncertainty into the value of the project. Here, the authors show an actual example as it relates to a conceptual brownfields redevelopment. In the case of a natural resource investment, subsurface uncertainty may affect the quantity, quality and distribution of the commodity being produced/managed subject to available drilling/sampling or even meteorological data.

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(B.2)

#### APPENDIX A. THE RISK FREE AND PROJECT DISCOUNT RATES

The conventional approach in the engineering literature for estimating the discount rate  $\rho$  for cost-benefit-risk projects is to use a relatively broad spectrum of values accounting for the decision-makers' subjective and biased evaluation of risk. For instance, [15] use  $\rho = 0.05$  to 0.20 per annum with a base case of  $\rho = 0.1$  per annum. Reference [54] advocated an approach built upon arbitrage or equilibrium in the financial markets in order to estimate the market value of the project. Reference [55] further modify this approach with information from the Capital Asset Pricing Model (CAPM) in order to relate  $\rho$  to the risk free rate, with their approach then adopted by [4] for application to a brownfields project. Here, Reference [57] is briefly reviewed to ensure consistency and clarity of notation in this paper.

The risk free rate (in the USA) follows from movements in the price of US Treasury securities that are risk-free and represent the nominal annual interest rate  $r_N$ . Typically,  $r_N$  is assumed to follow a mean-reverting stochastic process described by the Cox-Ingersoll-Ross (CIR) model [56]:

$$dr_{\mathcal{N}} = \kappa_{\mathcal{N}}(\theta_{\mathcal{N}} - r_{\mathcal{N}}) dt + \sigma_{\mathcal{N}} dZ_{\mathcal{N}}$$
(A.1)

where  $\kappa_{\mathcal{I}}$  denotes the speed of adjustment,  $\theta_{\mathcal{I}}$  is the reversion level,  $\sigma_{\mathcal{I}}$  is the volatility, and  $dZ_{\mathcal{N}}$  is a Weiner process. Reference [57] provided estimates of  $\kappa_{\mathcal{N}}$ ,  $\theta_{\mathcal{N}}$ , and  $\sigma_{\mathcal{N}}$ , with values provided on Table 2.

Reference [55] demonstrated an approach to estimate the discount rate using a risk premium that is consistent with the CAPM. Specifically, the discount rate  $\rho$  is given as:

$$\rho = r_{\mathcal{N}} + \hat{q}_s \sigma_s \tag{A.2}$$

where  $\hat{q}_s$  is the market price of risk for a contract (i.e. the guarantee) that is dependent on the stochastic underlying variable *S* described by a linear relationship. Finally,  $\hat{q}_s$  is calculated as:

$$\hat{q}_s = \frac{(\mathrm{E}[\mu_M] - r_N)\beta_{SM}}{\sigma_S} \quad . \tag{A.3}$$

In this equation, the expected return on the market portfolio is calculated by [58] as  $E[\mu_M] = 0.12$  per annum; Reference [4] estimated  $\beta_{SM} = 0.0197$ , yielding  $\hat{q}_s = 0.03160$  and  $\rho = 0.0612$  per annum. These results are summarized on Table 2.

## APPENDIX B. PARAMETERIZATION STRATEGY

Step 1:

$$b_{(ac)1} \frac{1}{n_{houses}} \sum_{j=1}^{n_{houses}} \left( \frac{1}{n_{times}} \sum_{i=1}^{n_{times}} \omega_{1_{i,j}}^{7K4C} \right) = b_{(ac)2} \frac{1}{n_{houses}} \sum_{j=1}^{n_{houses}} \left( \frac{1}{n_{times}} \sum_{i=1}^{n_{times}} \omega_{2_{i,j}}^{7K4C} \right)$$

$$b_{(f)1} \frac{1}{n_{houses}} \sum_{j=1}^{n_{houses}} \left( \frac{1}{n_{times}} \sum_{i=1}^{n_{times}} \omega_{1_{i,j}}^{7K4C} \right) = b_{(f)2} \frac{1}{n_{houses}} \sum_{j=1}^{n_{houses}} \left( \frac{1}{n_{times}} \sum_{i=1}^{n_{times}} \omega_{2_{i,j}}^{7K4C} \right)$$

$$b_{(ac)1} + b_{(ac)2} = 1$$

$$b_{(f)1} + b_{(f)2} = 1$$
(B.1)

where  $n_{houses} \in \{1,3,4,6\}$ .

Step 2:

 $\chi^{7K4C}$ 

$$=\frac{1}{n_{houses}}\sum_{j=1}^{n_{houses}} \left(\frac{1}{n_{times}}\sum_{i=1}^{n_{times}} \left(\min\left[a_{(f)h} \min\left(b_{(f)1} \,\omega_{1_{i,j}}^{7K4C} + b_{(f)2} \,\omega_{2_{i,j}}^{7K4C}, 1.0\right), 1.0\right] - \hat{q}_{S}\sigma_{S}\right)\right)$$

χ<sup>7K7C</sup>

$$= \frac{1}{n_{houses}} \sum_{j=1}^{n_{houses}} \left( \frac{1}{n_{times}} \sum_{i=1}^{n_{times}} \left( \min\left[a_{(f)h} \min\left(b_{(f)1} \,\omega_{1_{i,j}}^{7K7C} + b_{(f)2} \,\omega_{2_{i,j}}^{7K7C}, 1.0\right), 1.0\right] - \hat{q}_S \sigma_S \right) \right)$$

$$\frac{\chi^{7K4C} + \chi^{7K7C}}{2} = \bar{a}_{(f)}$$

where  $n_{houses} \in \{1, 3, 4, 6\}$ .

Step 3:

$$Obj_{(ac)}^{7K4C} + Obj_{(ac)}^{7K7C} = Obj_{(f)}^{7K4C} + Obj_{(f)}^{7K7C}$$
(B.3)

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