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Appraisal campaign selection based on the maximum value of sequential information

André Luís Morosov[a,b,*], Reidar Brumer Bratvold[a,b]

[a] Department of Energy Resources, Faculty of Science and Technology, University of Stavanger, Norway
[b] The National IOR Centre of Norway, Norway

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ABSTRACT

Field development projects generally demand large investments which are subject to geological uncertainty, hence projects can benefit from geological information obtained from appraisal wells before large capital commitment. But "how much data is enough"? Value erosion occurs both in over-appraisal or under-appraisal of the field and the value of information rationale is ideal to determine the right amount of data. But examples from the literature are case-specific and often limited to simple assessments with a small number of alternatives and outcomes.

We propose a general method to select the appraisal campaigns based on the value that spatial geological data adds to the development plan. It regards the appraisal campaign as a sequence of wells that will acquire geological data and optimally supports the next acquisition on a well-by-well basis. This approach is compelling for replication in any case because drilling wells is part of every development project.

The method is demonstrated in a synthetic example with 8 candidates from which the appraisal campaign must be selected and is observed up to 65% improvement in the development project expected value. Its application provides a tailored solution different values of discount factor and information cost, which are grouped in a solution map. Results clearly show how much data should be acquired considering different circumstances and sensitivity analysis in the value function show value-adding robustness.

Given the potential benefits of the appraisal selection method presented here, the modeling of spatial geological dependencies through probabilities is encouraged and future work could explore the use of subsurface flow-simulations to enhance the accuracy of the estimations by considering value coupling.

1. Introduction

New hydrocarbon field-development projects generally demand large investments which are subject to geological uncertainty and consequently economical risk. These projects are considered after a successful exploration campaign confirming hydrocarbon existence but lacking geological information to resolve production uncertainties. Appraisal campaigns[1] are the next step towards de-risking the development project by acquiring geological data on different positions of the reservoir. The appraisal plan must be able to tell what kind of reservoir data to acquire, where to acquire it, and "how much data is enough". The wells are drilled with the primary objective of data acquisition to support the development plan and might be used in the production plan.

Ideally, the appraisal campaign is selected through a value of information (VoI) assessment making sure that the information acquired will be relevant, economical, and potentially able to change the development plan (material). The appraisal context and the use of the VoI to select the data acquisition plan is also described in Demirmen (1996, 2001), Haskett (2003), Shrivastava et al. (2016), Walters et al. (2016).

Treating the appraisal campaign as a sequence of data acquisitions adds more value to the project but is complex to model, and for this reason, VoI assessments are traditionally done either with few data acquisition alternatives and few possible data outcomes. There are only a few publications on the value of sequential information (Miller, 1975; Merkhofer, 1977; Eidsvik et al., 2018) and even though theoretically accurate, none of them is practical or general enough to be replicated on the selection of the appraisal campaign.

Here we propose a method that regards the appraisal campaign as a

* Corresponding author. Department of Energy Resources, Faculty of Science and Technology, University of Stavanger, Norway.
E-mail addresses: andre.morosov@gmail.com, andre.l.morosov@uis.no (A.L. Morosov).

[1] The term campaign means one or more acquisition activities performed in one or more locations of the hydrocarbon-bearing reservoir.

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sequence of wells that will acquire geological data in different locations and are the initial part of the development project. As drilling wells is part of every appraisal and development project, the method becomes a general tool to select the appraisal campaigns based on spatial geological data. It maximizes the expected economical return of the development drilling campaign by strictly following a VoI rationale as the objective function. The geological data has spatial probabilistic dependency among the different locations (Bhattacharjya et al., 2010; Eidsvik et al., 2015) and each new information acquired (i.e. appraisal well drilled) dynamically and optimally supports the next acquisition on a well-by-well basis (Bickel and Smith, 2006; Bickel et al., 2008; Brown and Smith, 2013; Martinelli et al., 2013b). The final solution dictates which are the candidate locations that should be considered for data acquisition, how the drilling should proceed, and how much expected value is added to the development plan. The detailed campaign model is presented in section 2 and the method in section 3 and is the most complete and systematic method to exploit sequential data acquisition when compared to existing appraisal-related literature (Demirmen 1996, 2001; Haskett, 2003; Ligero et al., 2005; Branco et al., 2005; Shrivastava et al., 2016; Walters et al., 2016; David et al., 2016; Asmandiyarov et al., 2017).

1.1. Literature review of field appraisal and development

Although the relevance of appraisal campaigns in improving the economics of field development plans, the number of publications involving explicitly the terms “appraisal” and “information” is surprisingly low. Demirmen (1996, 2001) and Haskett (2003) are early theoretical argumentation and present simple synthetic exemplifications as proof of concept.

Most publications are focused on uncertainty modeling and consider a single appraisal alternative or a few competing alternatives (Ligero et al., 2005; Branco et al., 2005; Walters et al., 2016; David et al., 2016). Shrivastava et al. (2016) focus on the sequential aspect of the appraisal campaign showing an example of a compartmented field where the main uncertainty is about the sealing character of the faults which determines the spatial character of the hydrocarbon presence uncertainty. Asmandiyarov et al. (2017) present a case of sequential appraisal considering re-entering two exploration wells to perform well-tests and drilling one pilot well out of three candidates.

Santos et al. (2017) propose a ranking system to identify which uncertainties are relevant and material to the production strategy decision before actually assessing the VoI. Their application shows that the discount factor and delayed production due to information acquisition can obliterate the VoI.

1.2. Literature review on general VoI

The appraisal context is just a small subdomain of the much larger VoI knowledge domain, which has a much larger number of publications throughout many different fields. Howard (1966) presents the value of information theory arguing that in order to have value, acquired information must be used in a decision context and monetary value as the decision metric is very convenient because it allows deducting the acquisition costs when applicable. Bratvold et al. (2009) present a comprehensive summary of VoI publications up to 2009, covering a good portion of the publications mentioned in the previous section. Bhattacharjya et al. (2010) present the VoI estimation when the decision metric (distinction of interest) is spatially distributed and interdependent. The book Eidsvik et al. (2015) extends the concept of VoI in spatial decision making for different fields of application including geosciences. It recognizes the complexity of sequential data acquisition and how sparse are the publications on this matter.

1.3. Literature review on the value of sequential information (VoSI)

Miller (1975) is the first work to generically approach the VoI in a sequential data acquisition context and clearly states the importance of the information acquisition. It is stated that to decide whether or not to buy one observable we must know the prices of all the observables, as it influences the acquisition sequence. Merkhofer (1977) follows the same line but focuses on the effect of flexibility, i.e. the number of alternatives the decision-maker has along the decision chain. Eidsvik et al. (2018) is a more recent work that assesses VoSI in the spatial decision-making context. It presents two applications: the first considers two data acquisitions, which can be simultaneous, or sequential and the second uses different heuristic approaches to simplify the complex sequential character of the problem. The value of sequential testing is always larger or equal to the static testing as stated in Miller (1975) and Eidsvik et al. (2018).

2. The development campaign model

This work assumes the development campaign (DC) consists of a preconceived set of potential drilling locations defined by subsurface domain experts. Fig. 1 shows generic examples of how the locations are spatially distributed within the area of interest. The geological properties in each of these locations are uncertain, and because the reward[2] obtained from the hydrocarbon production is a function of the geological properties, the reward is also uncertain.

The expected reward value, or simply expected value (EV) from each drilling location differs from one another according to the distribution of geological properties and is used to decide if the location should be drilled or not. Because some of the potential locations might not be drilled due to negative EV, all potential locations are here called candidate locations (or wells), and the collection of all candidates is called *candidate set* (CS). The left example in Fig. 1 has CS = $\{A,B,C,D,E,F,G,H\}$ and the right example has CS = $\{A,B,C,D,E\}$. The development campaign (DC) is an endeavor to drill the sequence of candidates from CS that has the maximum EV and acquiring data in some of these candidates adds value in this decision context.

2.1. Spatial information and data acquisition

If no geological information is acquired after drilling each borehole, geological properties distributions do not change and neither the EV from each candidate, meaning that only candidates with prior positive EV will be drilled and the drilling order is irrelevant.

Knowing the geological properties of one location updates[3] the geological properties distribution on other locations, which in turn might change their EVs. Some candidates might increase their EV from negative to positive and (or) the other way around. Choosing the next candidate to drill using these updated EVs adds value to the DC.

In this DC context, information can only bring value if it supports the decision of which is the next well or to stop drilling. To create value, information must be available before the decision (observable), must be relevant to the decision, and must have the potential of changing the decision depending on its content (material), as described in Bratvold et al. (2009) and Bratvold & Begg (2010).

In this paper, we are concerned about information obtained from data acquired in the wells, which has a spatial character as it represents the geological properties only in a certain location. The data sources can

[2] Net revenue due to hydrocarbon production already discounted drilling and data acquisition costs. It can also be modeled as hydrocarbon reserves or hydrocarbon-in-place.

[3] The prior distribution becomes the posterior distribution given the new knowledge. The posterior distribution might be different depending on the probabilistic interdependency modeled.

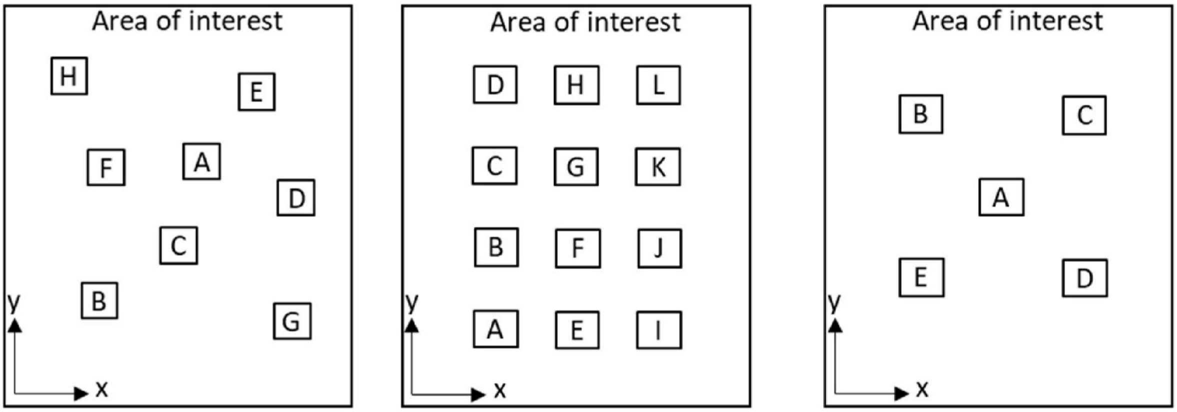


Fig. 1. Examples of candidate drilling locations within the area of interest.

be well-logs, pressure-tests, well-tests, production measurements, or any other source necessary to define the geological properties of the well for decision making. The determination of which data source is required for each candidate is done by geosciences experts. The collection of the measurements and corresponding interpretations are referenced here as a geological outcome, i.e. a summary of the geological information from the well. One simple example is to use porosity logs to classify the reservoir quality. If the average porosity found in the reservoir section is lower than 5% then the interpretation is that reservoir near the well has poor-quality, or if it is over 25% then it has high-quality. In this case, the data used is the porosity log and the geological outcome is the regional reservoir quality which impacts its reward.

Eidsvik et al. (2015) describe this context as perfect partial information. It is partial because it represents only a region of the entire area of interest and is perfect because of the accuracy of the data in the well scale. In contrast to well data, seismic surveys are regarded as total imperfect information and are not considered in this framework.

2.2. Probabilistic model (PM)

To exploit geological information to improve the DC economics there must be a probabilistic model (PM) describing the spatial dependency of the geological outcomes among the candidates. The description is done through probabilities, conditional probabilities, and (or) joint probabilities of possible geological outcomes occurrence. The PM summarizes the geological knowledge and may be presented in different forms in different contexts as detailed next.

In an exploratory context, it is common to model the probability of a well to bear hydrocarbons (also known as the chance-of-success) based on probabilities assigned to the existence of geological requisites. Murtha (1995), Wang et al. (2000), and Delfiner (2003) are examples of modeling geologic interdependency in an exploratory context where the specific location of the prospects does not matter.

Van Wees et al. (2008), Martinelli et al. (2011), Brown and Smith (2013), Martinelli et al. (2013a), and Martinelli and Eidsvik (2014) model the spatial dependency among exploration wells using Bayesian networks. Wells closely dependent share the same parent node whilst wells loosely dependent are farther away in the network, resembling their relative positions in the exploration area. The design of the network and the determination of the conditional relationships are based on geoscientists consulting.

Bickel and Smith (2006), Bickel et al. (2008), and Jafarizadeh and Bratvold (2020) generate the joint probability distribution (JPD) of the geological interdependency using the maximum entropy method described by Jaynes (1982). The principle is to numerically find the JPD closest to the joint uniform distribution (maximum entropy) that still satisfies the pairwise conditional probability assessments obtained from domain experts. The JPD completely describes the PM through explicit probabilities.

Morosov and Bratvold, 2021 present a method for building the JPD based on geostatistics, which is a tool for model uncertain spatial distributions of geological properties in the subsurface. The method allows the aggregation of different expert opinions through different concept propositions and can provide probabilistic relationships among any set of locations in the modeled area. We follow the method presented in Morosov and Bratvold, 2021 to build the JPD because it generates a relatively complex JPD using a user-friendly process.

2.3. Sequential decision model (SDM)

In our context, the DC consists of a sequential decision model (SDM) where information obtained from all past outcomes updates probabilities and expected rewards of all future alternatives. Fig. 2 presents a schematic representation of this model, where each alternative has a certain number of outcomes and each outcome is input for the next decision.

The objective of the model is to choose the alternative with the highest EV for every decision node and the solution can be found using Stochastic Dynamic Programming (SDP), originally formalized in Bellman (1957), thoroughly described in Puterman (2014), and mathematically represented by the Bellman's equation (1):

$$V_i(\boldsymbol{\omega}_i) = \max_{a\in A(i)} \left(\sum_{x\in X(a)} \left[P(x|\boldsymbol{\omega}_i)\left(r_a^x + \delta V(\boldsymbol{\omega}_i^{a,x})\right)\right]\right) \tag{1}$$

which states that the optimal expected value $V_i(\boldsymbol{\omega}_i)$ for the decision node i, with state of knowledge $\boldsymbol{\omega}_i$, is the maximum EV among its possible alternatives $A(i)$. The expected value of the uncertain outcome x of each alternative a is composed by its immediate reward r_a^x and the future expected value $V(\boldsymbol{\omega}_i^{a,x})$ when the decision sequence follows the path a, x corrected by the discount factor (DF) δ. The EV of each alternative is the average of the EV of each outcome weighted by its probability of occurrence $P(x|\boldsymbol{\omega}_i)$. Generically speaking, each decision node i can have a different set of alternatives $A(i)$ whose alternatives can have a different set of outcomes $X(a)$. The solution is obtained by recursively applying equation (1), starting in the last decision nodes where $V(\boldsymbol{\omega}_i^{a,x}) = 0$, and finishing at the root node $V_0(\boldsymbol{\omega}_0)$. For the continuous case, the summation becomes the integral of the EV probability density function of the corresponding alternative a.

The SDP method guarantees optimal solution but is limited to relatively small problems (e.g. Bickel and Smith, 2006, Bickel et al., 2008) due to the sheer combinatorial burden. It quickly becomes intractable with the increase of the sequence size, the number of decision alternatives, and the number of possible outcomes. This characteristic is known as the "curse of dimensionality" (Bellman, 1957). Solution of larger problems (e.g. Martinelli et al., 2013b; Brown and Smith, 2013; Morosov

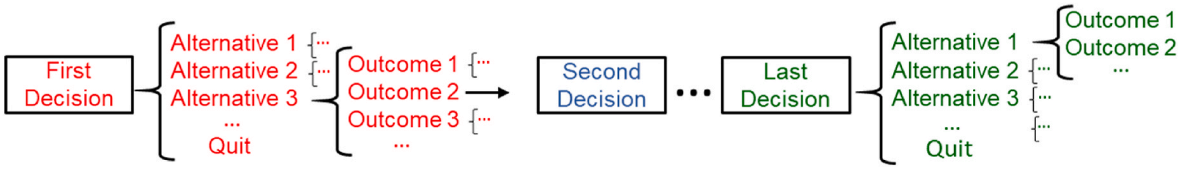


Fig. 2. Sequential decision model schematic.

& Bratvold, in press), meaning a higher number of wells and (or) possible outcomes, require heuristic approaches (see Powell, 2007) which trade accuracy of the optimal solution with performance.

In our work, $V_0(\omega_0)$ is the optimal campaign expected value (CEV) which is used in the VoI estimations. The collection of optimal alternatives in every decision node is called optimal policy and is an important part of our method. The optimal policy guides the drilling sequence of the appraisal wells according to the geological observations. A general definition of policy is present in Goodson et al. (2017).

3. Appraisal campaign selection method

We define the DC as being composed of two drilling sequences: the **appraisal campaign** and the **remaining campaign**. In the appraisal campaign, the geological information for each well is known after drilling and is used to decide which is the next well in the appraisal sequence. The remaining campaign has no geological information acquisition and starts immediately after the appraisal campaign ends. This means that the EV of the remaining wells does not change during the remaining campaign and the drilling sequence is irrelevant. Appraisal wells are drilled first as their information will be used both for the appraisal sequence optimization and for the selection of the remaining wells.

Appraisal campaign wells have the information cost (IC) discounted from their revenue, so their net rewards are lower than the rewards from the wells in remaining campaign, as presented in Table 1. IC is a function of the data acquisition operations required to know the geological outcome and because different locations might require different data sources or interpretations, IC might vary with the drilling candidate. IC is the main parameter to separate the drilling candidates into the appraisal campaign and the remaining campaign. In the hypothetical situation where there is no cost associated to the information acquisition, i.e. $IC = 0$ for every candidate, it is beneficial to collect data from every well in the sequence as it can only benefit the project. As the IC value increases, there will be a certain point where it is more advantageous to avoid acquiring data on one or more candidates as the informational value is surpassed by its cost.

The objective of the method is to maximize the development campaign expected value (CEV) by identifying which wells belong to the appraisal campaign, here called the appraisal set (AS). AS is a subset of the larger candidates set (CS) which contains all drilling candidates under consideration in the development project. The remaining set (RS) is the set of drilling candidates that belong to the remaining campaign, i.e. belongs to CS but do not belong to AS, implicating that $RS \cup AS = CS$, and RS $\cap AS$ is empty. For the occasion where is optimal to acquire geological information in every candidate, $AS = CS$ and RS is an empty set. Whilst for the occasion where is optimal not to acquire geological information in any considered candidate, $RS = CS$ and AS is an empty set. The calculation of the CEV is described in Equation (3.1)

$$CEV(CS, AS) = \sum_{s \in S} [Opt(AS, s) + EV(RS|s)] p(s) \tag{3.1}$$

with

$$\sum_{s \in S} p(s) = 1 \tag{3.2}$$

and

$$EV(RS|s) = \sum_{well \in RS} max(EV(well|s), 0) \tag{3.3}$$

where the function *Opt* is the revenue obtained from the appraisal campaign following the optimal drilling policy for AS and when the state of knowledge s is found. The state of knowledge is the collection of the geological outcomes along a certain policy path and belongs to the space S of all possible combinations of outcomes present in the optimal policy of AS.

The second term in the summation in Equation (3.1) is the expected value of the RS conditioned to the geological findings s from the appraisal campaign. Since there is no information acquisition in the remaining sequence, the choice about drilling or not any of the elements in RS depends only on their individual EV conditioned to s as in Equation (3.3). In the term $EV(RS|s)$ is implicit that only wells with individual positive EV contribute, hence. $EV(RS|s) \geq 0$.

Fig. 3 shows one numerical example of the parameters required to evaluate the CEV and assumes that the AS was submitted to a SDP optimization resulting in the optimal policy sequence partially present in the table. The policy shows that candidate E is always the first based on prior knowledge, and depending on its geological outcome, the sequence changes accordingly. When $s = \{E = \#2, H = \#5\}$, it means that if E finds outcome #2, H should be drilled second and if it finds #5, the appraisal should stop. For this s, the geological outcome of all other candidates are unknown and only C has positive EV. When $s = \{E = \#1, A = \#0, H = \#3, F = \#3\}$ the optimal appraisal sequence has four wells and for this combination of results the remaining sequence has none.

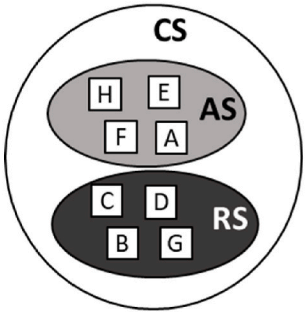
If the assessment considers discounting (i.e. $DF < 1$), it is assumed that the time-period between wells in the sequence is always the same, implicating that the same factor is applied. The discounting is applied to the rewards obtained from the second well in the sequence and onwards. If AS is empty, the first discounting happens in the second well of the remaining sequence.

3.1. Value of sequential information (VoSI) definition

The VoI can be defined as the difference of the decision process EV with additional information and the EV without additional information (Bratvold et al., 2009), or in other words, is the difference between the posterior expected value (PoV) and the prior expected value (PV) of the

Table 1
Effect of the information cost on the rewards.

Geological Outcome	Categorical value	Reward from appraisal wells	Reward from remaining wells
Outcome 0	#0	r_0-IC	r_0
Outcome 1	#1	r_1-IC	r_1
…	…	…	…
Outcome n	#n	r_n-IC	r_n



	s				$p(s)$	$Opt(AS,s)$	Remaining sequence	$EV(RS/s)$
Optimal appraisal policy paths	E=#0	-	-	-	0.13	-10	B,C,D	2.3
	E=#1	A=#0	H=#3	F=#3	0.03	2	-	0
	E=#2	H=#5	-	-	0.01	5	C	1.1
	E=#3	F=#1	A=#0	-	0.23	3	B,C,D,G	5.9
	...	...	...	...	...	...	...	...

Fig. 3. Example of CS, AS, RS, and corresponding optimal policy.

decision process (Eidsvik et al., 2015). In this work the value of sequential information (VoSI[4]) is defined as in Equation (3.4):

$$VoSI(CS,AS) = PoV(CS,AS) - PV(CS) \tag{3.4}$$

In the DC context, the PV is the sum of positive individual EV from the wells in CS with no additional information. PV is a function of the CS, meaning that different candidate sets can implicate in different PVs but the drilling order is irrelevant. The PoV is the CEV obtained from optimally acquiring sequential information with wells in AS and exploiting the information with RS as in Equation (3.1). Not only PoV is a function of the total CS but also a function of how CS is separated into AS and its complement RS. The VoSI then becomes as presented in Equation (3.5).

$$VoSI(CS,AS) = CEV(CS,AS) - \sum_{w\in CS} max(EV(w),0) \tag{3.5}$$

Note that in this formulation, IC is already discounted from the rewards obtained from the wells in AS implicating that the VoSI is the average net value added from the acquisition campaign. Another implication of this formulation is $VoSI \geq 0$ as a consequence of the SDP procedure used to optimally drill the appraisal campaign, which enforces $PoV(CS,\ AS) \geq PV(CS)$. This means that the flexibility from sequentially revealing information from the appraisal can only add value to the campaign.

3.2. Selecting AS based on the maximum VoSI

The optimization process searches within the space of all possible combinations of candidates from CS for the AS that results in the maximum VoSI. The selection criterium of the optimal AS is described by combining equations (3.1) and (3.5) resulting in equation (3.6). During the search, for every new evaluation of the CEV, a new optimal policy must be found through SDP (or any suitable heuristic method).

$$AS_{opt} = \underset{AS\subseteqq CS}{\operatorname{argmax}} \left(\sum_{s\in S} [Opt(AS,s) + EV(RS|s)]p(s) \right) \tag{3.6}$$

The maximum VoSI in Equation (3.4) and maximum CEV in Equation (3.1) occur for the same argument AS and differ only from a constant value $PV(CS)$. For this reason, the term $PV(CS)$ is omitted in (3.6). An exhaustive search for the optimal AS requires N_e evaluations calculated according to equation (3.7), where $n(CS)$ is the number of elements in CS. For a small CS the exhaustive search is feasible and guarantees optimality but as the size of CS increases, heuristic methods might be required.

$$N_e = \sum_{c=0}^{n(CS)} \binom{n(CS)}{c} \tag{3.7}$$

3.3. The effects of AS and RS in the CEV

The terms inside the summation of Equation (3.1) can be separated into the contribution of appraisal campaign $PoV(AS)$ and the contribution of the remaining campaign $PoV(RS)$, as in Equations (3.8) and (3.9). They respectively mean the posterior value of the appraisal campaign and the remaining campaign given the information optimally acquired by the AS. This separation of effects is insightful when analyzing the application results.

$$PoV(AS) = \sum_{s\in S} Opt(AS,s)p(s) \tag{3.8}$$

$$PoV(RS) = \sum_{s\in S} EV(RS|s)p(s) \tag{3.9}$$

4. Application case

The application of the method requires a CS, a PM, and a value function. First, CS describes how many candidates should be assessed, their corresponding spatial positioning, and their names. Next, the PM describes the probabilistic relationships among the candidates' possible geological outcomes. Finally, the value function relates every possible outcome in the PM with a corresponding expected reward (profit or loss), both when geological information is acquired or not.

In this work, the application case follows the one presented in Morosov and Bratvold, 2021 which has CS = $\{A,B,C,D,E,F,G,H\}$ positioned according to Fig. 4. The PM considers four possible discrete

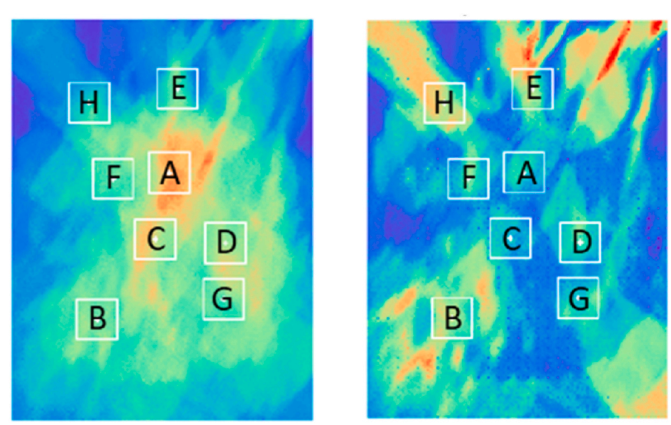


Fig. 4. *Summary of the probabilistic field developed in* Morosov and Bratvold, 2021.

[4] Our definition of VoSI is different from the one defined in the in Miller (1975). That definition account for the extra value obtained by the flexibility of having different data acquisitions in the future and attributes it to the first data acquisition operation and it works as a ranking process to choose which should be the first. Our VoSI is already the net value added by the data acquisition scheme because the costs of the acquisitions are required in the sequential assessment. Such costs are already discounted in the rewards of the uncertain outomces.

geological outcomes: non-reservoir (#0), poor-quality (#1), medium-quality (#2), and high-quality (#3) which can occur in any one of the eight candidates. The spatial probabilistic relationship among these outcomes was built from 250 spatial realizations of the reservoir-quality variable in an area represented by a 150-by-200 grid. Fig. 4 shows on the left the reservoir-quality average taken along the 250 realizations, and on the right the variance, with warmer colors indicating higher values. The samples of joint geological outcomes used to build the JPD are collected inside the white squares, whose size incorporates spatial uncertainty of the underlying geological structures and is a modeling choice defined by the geosciences experts. Joint probabilities are calculated by dividing the counts of joint unique events by the total number of samples.

The value function is shown in Table 2 where each outcome entails a constant economical reward and a constant IC, regardless of the candidate. A general summary of the model is presented in Table 3, where candidate *A* has the highest prior EV and candidates *E*, *F*, and *H* have negative prior EVs. Without any further information, the DC is limited to five wells {A,B,C,D,G} corresponding to $PV(CS) = 10.1$.

The model presented here is a simple description of the drilling campaign context and is intended to prove the concept of the appraisal campaign selection method. A more complex model could have different geological outcomes for different candidates with rewards evaluated through subsurface flow simulations.

5. Results

This section will present the results of the appraisal campaign selection method when applied to the DC model described in the previous section. The results change with the discount factor (DF) used in the SDP (see equation (1)), and with the information cost (IC) used in the value-function, and are organized in different sections according to how these parameters change. The DF varies from 1 to 0.85 in intervals of 0.01, which is equivalent to discount rates between 0 and 17,6%, and the IC varies from 0 to 2 in intervals of 0.1, meaning that the information cost is between 0 and 20% of the drilling cost.

There are 5 dimensions of data in the implemented method: DF, IC, AS configuration, campaign metrics (PV, PoV, and VoSI), and policy branches. For every pair of DF and IC values, an exhaustive search of the possible AS configurations is performed, meaning that the SDP procedure is repeated 256 (see Equation (3.7)) and the optimal AS is guaranteed to be found. The policy branches are used to calculate the campaign metrics and are suppressed in the following results.

5.1. Reference case (DF = 1 and IC = 0)

We start by introducing the case where there is no cost of information and no discounting is applied because it helps to understand how the VoSI changes with any possible instances of AS. The optimal solution is obtained when $AS = CS$ with $CEV(CS) = 16.7$ and consequently $VoSI(CS) = 6.6$ representing an increase of 65.7% in the $PV(CS)$ due to optimally acquiring sequential information. As anticipated in section 3, when $IC = 0$ there is no reason to avoid data acquisition and all wells in CS will be in AS.

Fig. 5 presents a summary of the case using box plots for the main distributions, where each element of the distributions corresponds to

Table 2
Value function used in the application example.

Reservoir Description	Categorical value	Reward from remaining wells	Reward from appraisal wells
Non-Reservoir	#0	−10	−10-IC
Low Quality	#1	−5	-5-IC
Medium Quality	#2	5	5-IC
High Quality	#3	10	10-IC

Table 3
Marginal probabilities in the JPD and corresponding EV of candidates.

Candidate	Probability of each outcome				EV	max (EV,0)
	P (#0)	P (#1)	P (#2)	P (#3)		
A	0.02	0.20	0.36	0.42	4.8	4.8
B	0.19	0.24	0.38	0.19	0.7	0.7
C	0.05	0.22	0.50	0.23	3.2	3.2
D	0.04	0.44	0.30	0.23	1.3	1.3
E	0.26	0.38	0.23	0.13	−2.1	0.0
F	0.12	0.44	0.34	0.11	−0.7	0.0
G	0.09	0.42	0.34	0.15	0.3	0.3
H	0.38	0.31	0.16	0.16	−3.0	0.0
Campaign	0.14	0.33	0.33	0.20	4.4	**10.1**

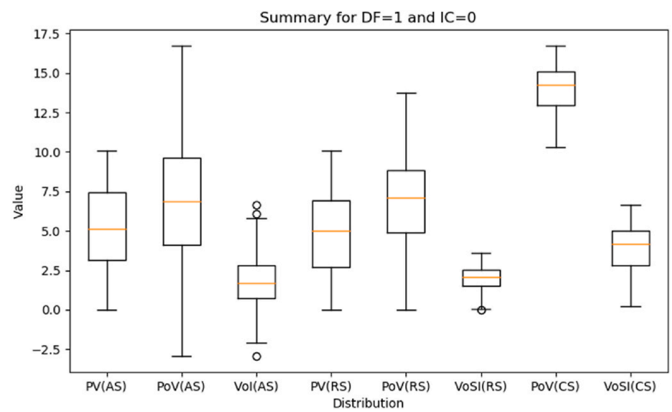


Fig. 5. Box plots of the main distributions for the case with DF = 1 and IC = 0.

one of the 256 different AS and RS combinations. Distributions $PV(AS)$ and $PV(RS)$ are always positive as they do not admit drilling any well with prior negative EV. When DF = 1, $PV(AS) + PV(RS) = PV(CS) = 10.1$ holds for every combination of AS and RS. Their comparison of the prior values with the corresponding $PoV(AS)$ and $PoV(RS)$ shows the effect of information in each section of the drilling campaign and valued by the distributions $VoSI(AS)$ and $VoSI(RS)$.

There are 7 instances of AS resulting in negative $PoV(AS)$ and consequently negative $VoSI(AS)$. One of them is AS = {E,F,H} which according to Table 3, would not be drilled because their individual EVs are negative, adding to −5.8. This AS results in $PoV(AS) = -0.54$ meaning that the SDP could not turn the appraisal campaign attractive, but the information obtained from this endeavor increased the remaining campaign expected value from $PV(RS) = 10.1$ to $PoV(RS) = 11.2$, resulting in $VoSI(CS, AS) = 0.56$. The same phenomenon happens with all other instances of AS with negative $PoV(AS)$, ultimately resulting in a distribution of $VoSI(CS, AS)$ in which the minimum value is 0.22 when AS = {F}, AS = {F,H}, or AS = {E,F}.

5.2. Varying DF with no information cost

Again, $IC = 0$ entailing that the optimal information acquisition happens when all candidates are in the appraisal campaign as presented in Fig. 6. For this reason, the results presented in Fig. 7 explores how the discounting affects the SDP results when AS = CS. Decreasing the DF, from 1 to 0.85, there is a decrease in the PV and PoV but since the reduction in PoV is steeper, the VoSI for the campaign decreases.

Generally, the more candidates in AS the higher the $PoV(CS, AS)$ as observed by the different colors in Fig. 6. The trends are not the same and depend on which candidates are present in AS, and whose contributions will be less penalized by discounting. Flatter lines occur when candidates with high prior values (e.g. *A* and *C*) are excluded from AS and are drilled later being subject to higher discounting.

All combinations of AS have positive VoSI when DF = 1, however, as

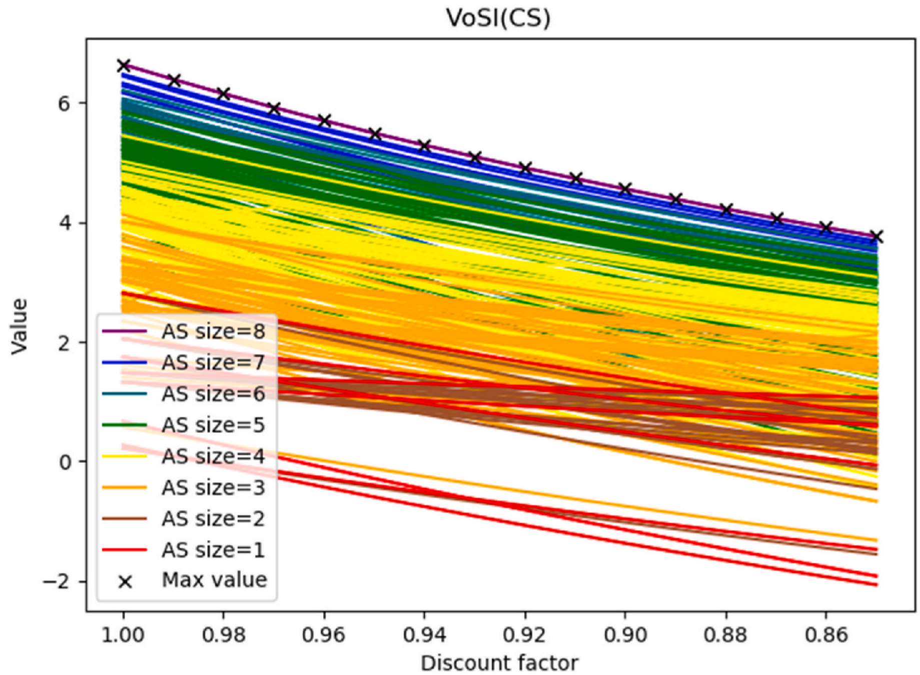


Fig. 6. Variation of the posterior value of the DC with the discount factor.

Discount Rate	Discount factor	PV(CS)	PoV(CS)	VoSI(CS)
0	1.00	10.11	16.74	6.64
0.010	0.99	10.02	16.41	6.39
0.020	0.98	9.93	16.08	6.15
0.031	0.97	9.85	15.77	5.92
0.042	0.96	9.76	15.46	5.70
0.053	0.95	9.68	15.17	5.49
0.064	0.94	9.60	14.89	5.29
0.075	0.93	9.52	14.61	5.09
0.087	0.92	9.44	14.35	4.91
0.099	0.91	9.36	14.08	4.73
0.111	0.90	9.28	13.83	4.55
0.124	0.89	9.20	13.58	4.38
0.136	0.88	9.12	13.34	4.22
0.149	0.87	9.05	13.11	4.06
0.163	0.86	8.97	12.88	3.91
0.176	0.85	8.90	12.66	3.76

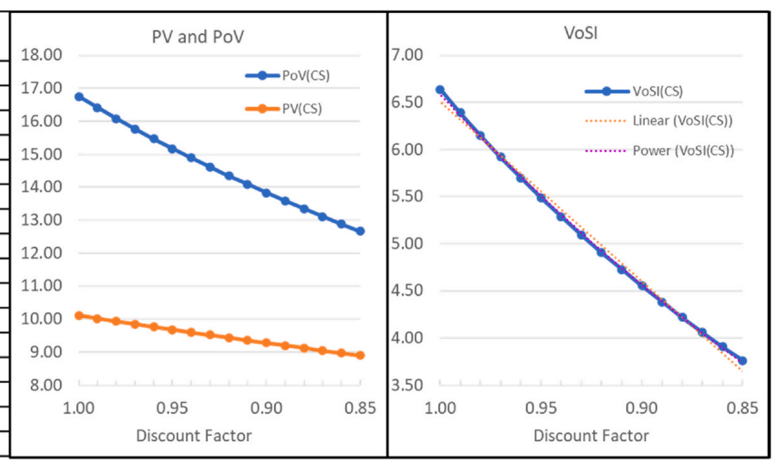


Fig. 7. Effect of DF in the drilling campaign economics when optimized with SDP.

DF decreases some combinations of AS present negative VoSI. They occur when candidates that would not be originally drilled are tested in AS to check if the information used in RS can compensate their losses in AS, and are naturally disregarded in the optimization process.

5.3. *Varying IC with no discounting*

When IC varies, the AS that optimizes the DC changes according to the balance between the value added by the spatial information and the corresponding acquisition cost. These changes can be observed in Fig. 8 where the optimal AS depends on the IC value. The plot on the right side shows how the different configurations of AS overtake the previous as the most valuable solution to the appraisal campaign. As the cost increases, the number of appraisal candidates is reduced from 8 wells to 1.

5.4. *Varying both DF and IC*

An optimization summary varying DF and IC together is presented in Fig. 9 and Table 4. The maximum values of PoV and VoSI decrease monotonically with the increase of IC and with the decrease of DF. For the considered ranges, the effect of IC alone on the VoSI is higher (5.83) than the effect of DF alone (2.88). The VoSI surface in Fig. 9 (right) has a flat null region, around DF = 0.85 and IC = 2, corresponding to the situation where it is better to avoid any information collection, i.e. AS = {}.

5.5. *Optimal appraisal campaign*

Each pair of DF and IC values requires finding the AS which corresponds to the optimal appraisal problem. The workflow adopted obtains the SDP policy for the whole search space of every pair, meaning that for the 336 pairs and 256 possible configurations of AS, were found 86.016 optimal policies. For each policy, the PV, PoV, and VoSI values were calculated and stored in a dataset. Searching this dataset provides the optimal appraisal solution results presented in Fig. 10 and Fig. 11.

It is clear that IC has a major impact on the solution, especially related to the size of AS. The discount factor has no impact on the solution for IC values up to 0.4 but starts having a significant impact for

Cost of information	VoSI(CS)	Optimal AS
0.00	6.64	A,B,C,D,E,F,G,H
0.10	6.14	
0.20	5.66	
0.30	5.18	
0.40	4.74	A,B,C,D,E,G,H
0.50	4.31	A,B,D,E,G,H
0.60	3.96	
0.70	3.63	
0.80	3.30	A,B,D,E,H
0.90	3.02	A,D,E,G,H
1.00	2.73	
1.10	2.45	
1.20	2.18	
1.30	1.94	
1.40	1.67	
1.50	1.38	
1.60	1.22	B,E,H
1.70	1.11	B
1.80	1.01	
1.90	0.91	
2.00	0.81	

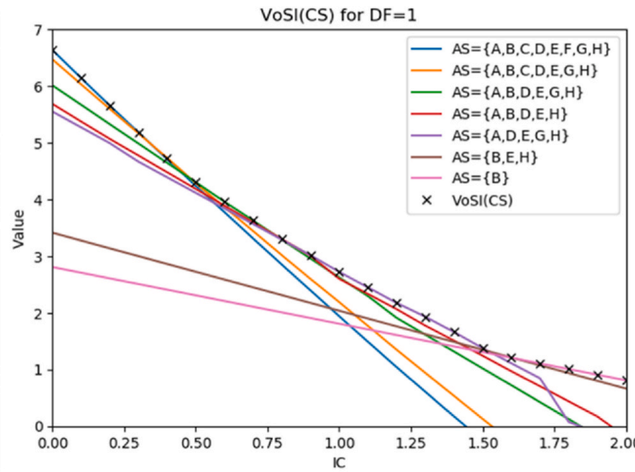


Fig. 8. AS selection based on the maximum VoSI.

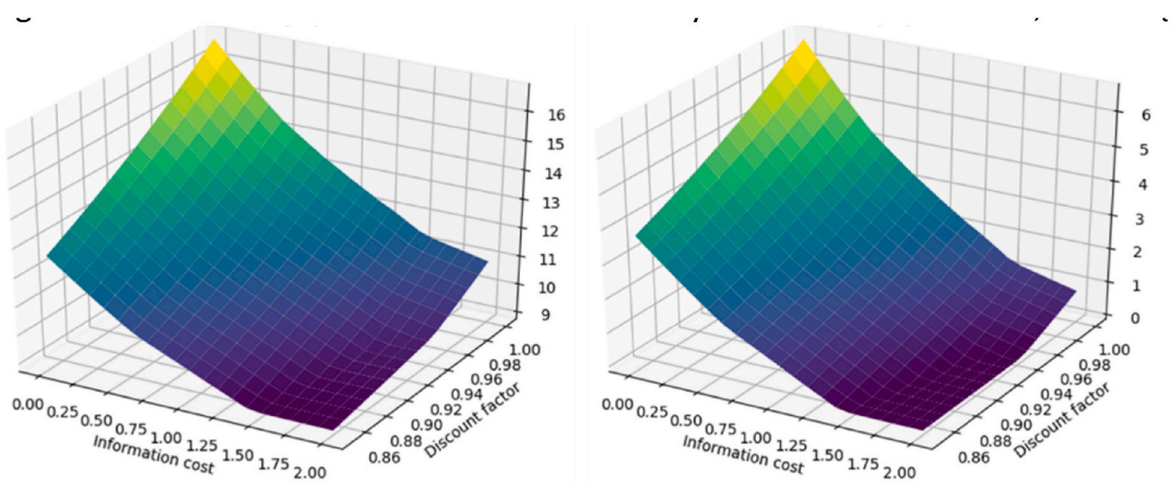


Fig. 9. Maximum value of PoV(CS,AS) (left) and VoSI(CS,AS) (right) for every pair of DF and IC.

Table 4
Optimal campaign metrics for extreme values of DF and IC.

DF	IC	PV(CS)	max PoV(CS,AS)	max VoSI(CS,AS)
1	0	10.1	16.74	6.64
1	2	10.1	10.92	0.81
0.85	0	8.9	12.66	3.76
0.85	2	8.9	8.90	0.00

values higher than 0.4. When $IC = 1.6$, the decrease of DF from 1 to 0.85 has the highest solution change passing through regions 8, 9, 7, and 10, implicating that the AS size can vary from 1 to 4. When both DF and ID are close to their end-of-scale values no information should be acquired (Region 10).

6. Discussion

The different regions in Fig. 10 are a consequence of different AS configurations overtaking the highest VoSI place, similar to the observed in Fig. 8 but on both parameter axes. Each solution in the table of Fig. 10 means the best set of candidates to participate in the appraisal campaign depending on the parametric region. These solutions were found using the maximum VoSI as the objective function, which is obtained by the difference of the maximum PoV of the campaign and the PV of the campaign. PV is the EV of the DC without any data acquisition, hence its value is affected only by DF, as shown in Table 4.

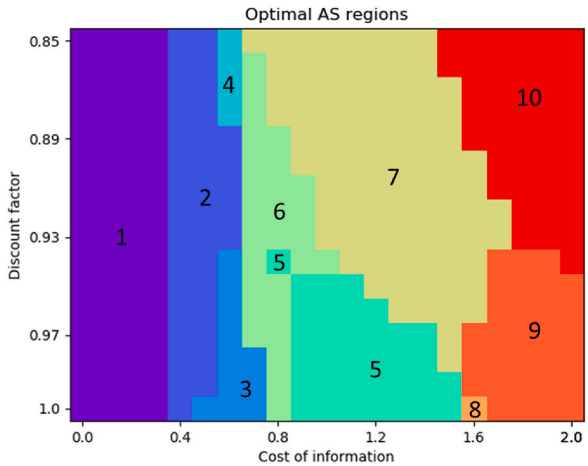
Given a chosen AS in Fig. 10, the actual appraisal campaign is a dynamic process where the number of drilled wells and the drilling sequence depends on the geological information obtained after drilling each wellbore. This process is controlled by the optimal appraisal policy of AS and guarantees the best course of action for any considered outcome.

6.1. Method input considerations

All results presented are built on top of the model presented in section 4, which is composed of the CS, the PM, and the value function. Changing any of these building blocks requires a novel application of the method as the solutions might greatly vary because of the non-linear character of the decision process. For this reason, it is encouraged to perform a sensitivity analysis in the CS, the PM, and the value function, to understand how they affect the AS solution.

Having a larger CS helps value creation as it provides more positions for information gathering and more flexibility to the decision process. For example, the addition of a candidate whose position can bring pivotal information to the decision process will result in better solutions as a consequence of different drilling policies. This effect was demonstrated in the application with IC = 0, where the most value was created when AS = CS.

The PM is perhaps the most critical input as it contains the geological



Region	AS	Size
1	A,B,C,D,E,F,G,H	8
2	A,B,C,D,E,G,H	7
3	A,B,D,E,G,H	6
4	A,B,C,D,E,H	6
5	A,D,E,G,H	5
6	A,B,D,E,H	5
7	A,B,D,H	4
8	B,E,H	3
9	B	1
10	{}	0

Fig. 10. Optimal AS solution.

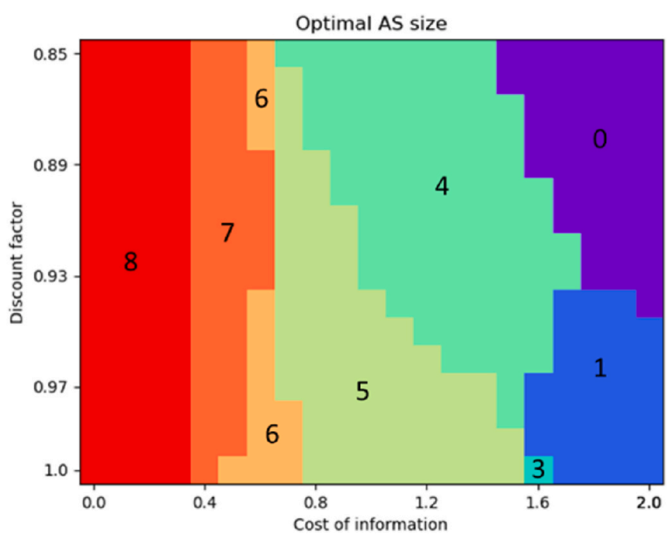


Fig. 11. Optimal AS size regions.

dependency among the candidates, i.e. how the data can change the EV and consequently the decisions in the drilling campaign. Although not new (Claeys and Walkup, 1999; Bickel and Smith, 2006: Bickel et al., 2008; Cunningham and Begg, 2008; Brown and Smith, 2013; Martinelli et al., 2013a, 2013b; Martinelli and Eidsvik, 2014; Jafarizadeh and Bratvold, 2020; Morosov and Bratvold, 2021, Morosov & Bratvold, In press b), probabilistic modeling of the subsurface through the use of JPDs is not widely used in practice because it is not part of subsurface frameworks, which are more concerned about precise production forecasting. Our work shows some potential benefits of modeling the subsurface using a JPD to support decision-making in appraisal campaigns.

The value function greatly influences the benefits of acquiring data in the SDM because depending on the reward values, data might lose its decision-changing characteristic. If the model described in section 4 had much higher rewards of the positive outcomes #2 and #3, the EV of drilling every candidate would be positive even for low probability os success P (#2 or #3). In this situation, geological information could only change the drilling decision, i.e. avoid drilling any candidates, in situations where it confirms a high probability of having negative outcomes (#0 or #1). This is a consequence on deciding using the EV criterium. Suppose that the rewards of outomces #2 and #3 are 100 with P (#3 or #2) = P (positive) and the rewards of outcomes #0 and #1 are −10 with P (#0 or #1) = P (negative). The decision maker would avoid drilling any well only when the information reveals P (negative) $>$ 0.9, as a consequence new information would hardly add any value to the drilling campaign. The same effect occurs when the rewards of the negative outcomes are much lower relative to the positive outcomes. Now suppose that outcomes #2 and #3 are 10 and outcomes #0 and #1 are −100. The decision maker would only drill any candidate if the information could confirm that P (negative) $<$ 0.1, otherwise it adds no value because it does not change the course of action. This is known in a real-options valuation area when alternatives are all “in the money” or all “out of the money”. A sensitivity analysis in the value function is presented in Fig. 12 with the maximum VoSI map for the original case positioned in the center, for more pessimistic values is positioned in the left and for more optimistic values is positioned on the right.

A big assumption in our value function is that the rewards do not change with the choices made during the appraisal campaign. In Eidsvik et al. (2015) this characteristic is called value decoupling. In other words, the estimated rewards of a certain well X will be the same regardless of how many wells were previously drilled and will be producing or injecting in the field. If the rewards are measured in hydrocarbon-in-place the assumption holds but if the hydrocarbon production is used to estimate the rewards, this might not always be the case. It might be necessary to develop a value function that counts both with the geological findings and the wells previously drilled because production and injection in different places of the porous media can impact differently the production of the drilling candidates. This coupling of the value function adds much more complexity to the SDP and might require a significant reduction of the CS to keep the problem tractable.

6.2. Approximation of the solution

To find the optimal AS solution, the single most demanding task is to run the SDP to find optimal policies, especially when AS = CS. In the exhaustive search, the SDP is repeated N_e for every pair of DF and IC, which in our application means 86.016 times. One way of reducing the repetitions of the SDP is to assume that the rewards of the candidates in AS are the same regardless of the IC value whilst the rewards of the candidates in RS increase with IC as presented in Table 5.

In this assumption, IC value does not mean the information cost but the difference between the rewards obtained from wells in the appraisal campaign and wells in the remaining campaign. Now $PoV(RS)$ changes with IC but $PoV(AS)$ doesn’t, which means that the number of required SDP runs is significantly reduced. This also means that $PoV(CS)$ and $PV(CS)$ increase with IC but as the objective function $VoSI(CS)$ is the difference between them, its value is the same except for a less accurate value of $PoV(AS)$. The method was applied in the same problem described in section 4 using the economic model in Table 5 resulting in

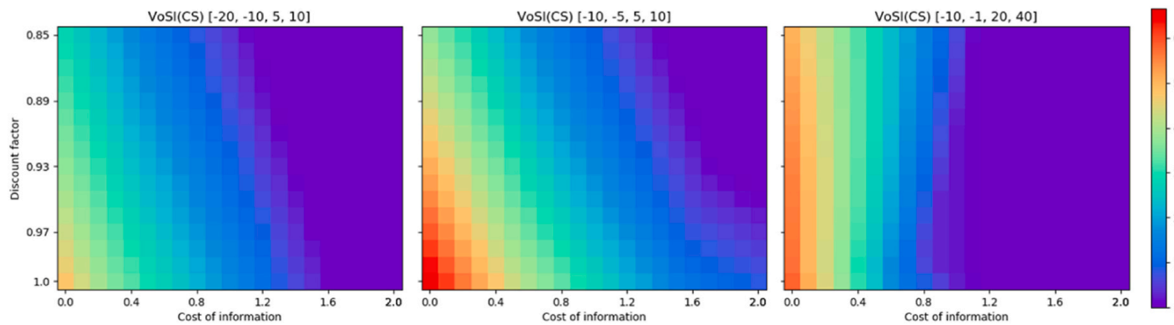


Fig. 12. Maximum VoSI for a pessimistic (left), original (center), and an optimistic (right) set of rewards.

Table 5
Heuristic approach to reduce the required number of SDP.

Reservoir Description	Categorical value	Reward from remaining wells	Reward from appraisal wells
Non-Reservoir	#0	−10 + IC	−10
Low Quality	#1	−5+IC	−5
Medium Quality	#2	5 + IC	5
High Quality	#3	10 + IC	10

the solution presented in Fig. 13.

By comparing the regions on the left of Fig. 13 with the optimal regions in Fig. 11, it possible to conclude that the solutions are similar. The relative difference of $VoSI(CS)$ between the optimal and heuristic approaches is presented on the right of Fig. 13, showing that the less accurate approach differs more where $VoSI(CS)$ is close to zero. The increase in region without data acquisition in highlighted in red as 100% difference in $VoSI(CS)$.

6.3. *Advantages of modeling AS and RS separately*

In section 3, the remaining campaign was introduced as the complement of the appraisal campaign that will not have data acquisition with the purpose of exploiting the information acquired. In practice this means that even if geological information is acquired without cost, it is not used to decide which well will be drilled in RS. In reality, in the absence of extra acquisition cost and with decision-changing opportunity, additional information is beneficial as demonstrated in sections 5.1 and 5.2.

Considering the presented decision model where every data acquisition has an associated IC, the benefits of RS to the campaign can be demonstrated by calculating how much AS and RS contribute to the total $VoSI(CS, AS)$. $VoSI(RS)$ is calculated by subtracting $VoSI(AS)$ from $VoSI(CS)$ when both have the same prior $PV(CS)$. Fig. 14 shows the relative contribution of AS (on the left) and RS (on the right) to the VoSI and Fig. 15 the corresponding absolute contribution.

It is clear that AS dominates the VoSI when the cost of information is low and progressively loses influence until $VoSI(AS)$ is zero because the optimal solution is AS = {}, consequently resulting in a 100% contribution from RS until $VoSI(RS)$ is zero. In absolute value, AS contribution reaches a maximum of 6.64 whilst RS contribution a maximum of 1.49.

7. Conclusions

Our method directly addresses the big question: "How much data is enough?" and proposes a systematic way to find the answer using the value of information rationale. The decision context required to value the spatial geological data is embedded in the sequential character of the appraisal campaign where each well in the sequence is a decision-making point.

The method is demonstrated in a synthetic example with 8 candidates from which a subset must be selected to participate in the appraisal campaign after an exhaustive search in the candidate-combinations space. The search is repeated for every desired information cost (IC) and discount factor (DF) resulting in solution regions for these parameters.

The main conclusions from the method application are:

1) The proposed method is general and effective in finding the optimal appraisal campaign, provided that the subsurface modeling is available in the form of a joint probability distribution.

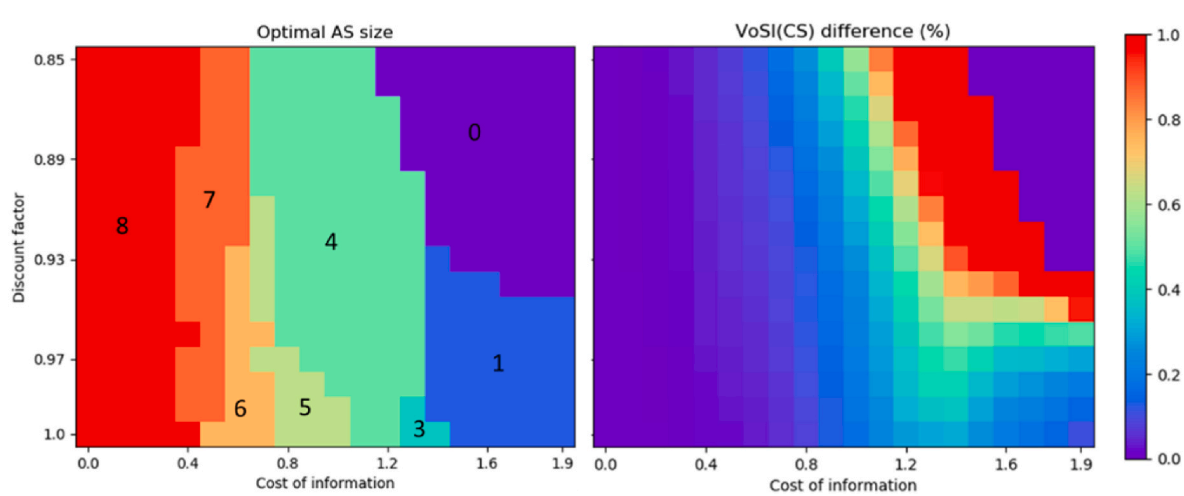


Fig. 13. Heuristic solution of the application.

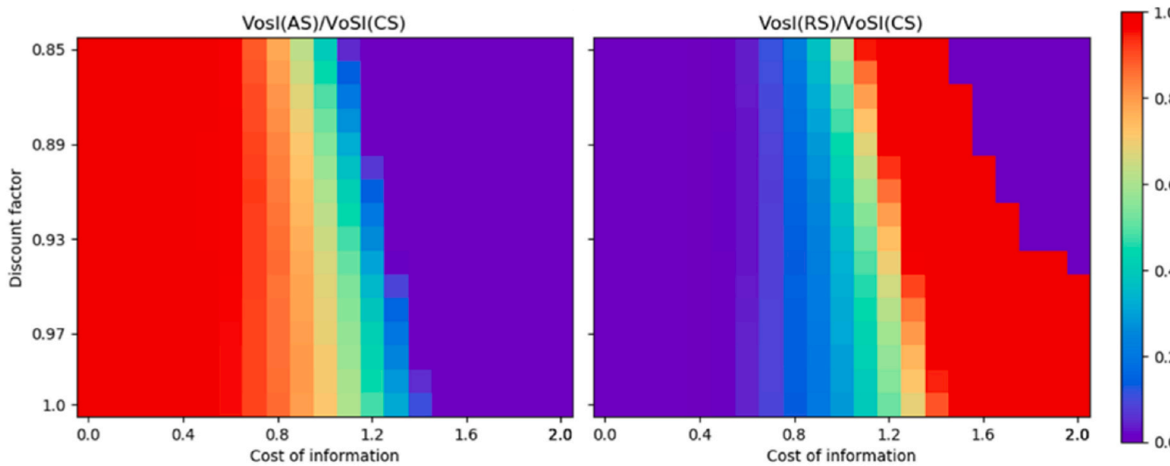


Fig. 14. Relative contribution of AS and RS to VoSI.

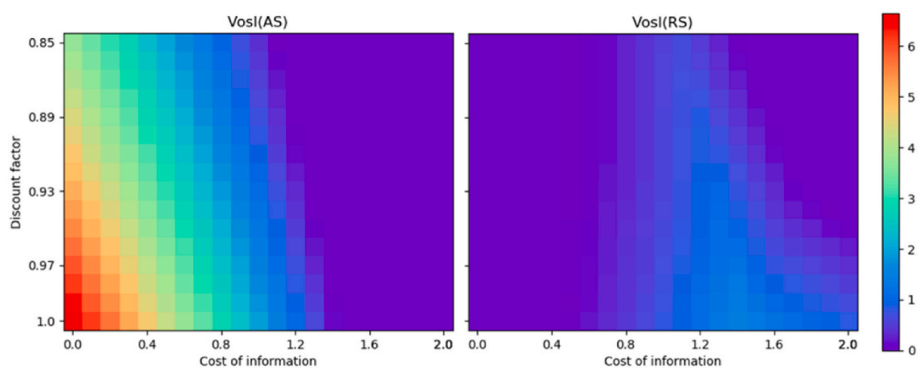


Fig. 15. Absolute contribution of AS and RS to VoSI.

2) It consistently adds value to the development plan and provides appraisal solutions tailored for different DF and IC, which are grouped in a solution map.
3) The IC and the DF highly affect the VoSI and consequently play a major role in the selection of the appraisal candidates. IC has a bigger influence on the solution, especially related to the number of appraisal candidates. The discounting influence increases with the cost of information.
4) Dividing the development campaign into the appraisal section and remaining section increases the domain of information exploitation. The remaining campaign progressively adds extra value to the campaign as the cost of information increases.
5) Using the information cost as a relative reward difference between appraisal wells and remaining wells, reduces the computing time required by lowering the accuracy of VoSI estimation. In our application, it reduced the computing time by 87% and provided a solution that mainly differs around the region where it is optimal to avoid data acquisition (AS = {}).

Real applications would require cost assessments to each candidate individually, as the data acquisition operation could be significantly different. In this case, the IC is an array of values instead of a single scalar.

Given the potential benefits of the appraisal selection method presented here, we would like to encourage the modeling of spatial geological dependencies through probabilities as it can be done using already established geological-uncertainty-assessment frameworks. Future work could explore the use of subsurface flow-simulations the enhance the accuracy of the value function and consider AI techniques to account for value coupling estimations.

Author statement

André Luís Morosov: Conceptualization, Methodology, Software, Formal analysis. **Reidar Brumer Bratvold:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

a	– Possible alternative in decision i.
$A(i)$	Set of possible alternatives in decision i.
AS	Appraisal set of wells where data is acquired and used in decision-making
AS_{opt}	AS that optmzizes the development campaign EV
CS	Candidate set of all potential well locations
$CEV(CS,AS)$	Development campaign EV for a given AS (economic unit)
$CEV(CS)$	Development campaign EV when $AS = CS$ (economic unit)
$EV(RS\|s)$	Expected value from the RS when joint-event s occurs (economic unit)
i	Decision node index
IC	Information cost (economic unit)
N_e	Number of evaluations for an exhaustive search of AS_{opt}
$Opt(AS,s)$	Revenue obtained from the AS when joint-event s occurs (economic unit)
s	Possible joint-event of spatial geological outcomes within the optimal policy obtrained from AS
S	Set of all possible joint-events of spatial geological outcomes within the optimal policy
$p(s)$	Probability of joint-event s occurring
$P(x\|\omega_i)$	Probability of outcome x occurring given ω_i
$PoV(CS,AS)$	Posterior EV of the CS, using optimal sequential data acquisition and decision-making on AS (economic unit)
$PoV(CS)$	$PoV(CS,AS)$ when $AS = CS$ (economic unit)
$PoV(AS)$	Fraction of $PoV(CS,AS)$ attributed to the AS section (economic unit)
$PoV(RS)$	Fraction of $PoV(CS,AS)$ attributed to the RS section (economic unit)
$PV(CS)$	Prior EV of the CS wells, disregarding sequential data acquisition or decision-making in between drilling (economic unit)
$PV(AS)$	Prior EV of the AS wells (economic unit)
$PV(RS)$	Prior EV of the RS wells (economic unit)
r_a^x	Immediate reward of outcome x from alternative a (economic unit)
RS	Remaining set of wells where data will not be acquired or used in decision-making
$V_i(\omega_i)$	Optimal expected value in decision i given the state of knowledge ω_i (economic unit)
$V(\omega_i^{a,x})$	Future optimal expected value when outcome x from alternative a occurs (economic unit)
$VoSI(CS,AS)$	Value of sequential information using DP to optimize a certain AS (economic unit)
$VoSI(CS)$	$VoSI(CS,AS)$ when $AS = CS$ (economic unit)
$VoSI(AS)$	Contribution o AS wells in $VoSI(CS,AS)$ (economic unit)
$VoSI(RS)$	Contribution of RS wells in $VoSI(CS,AS)$ (economic unit)
x	Possible outcome from choosing a
$X(a)$	Set of possible outcomes from choosing a
δ	Discount factor, also referred here as DF
ω_i	State of knowledge in i. Collection of geological outcomes prior to decision i
$\omega_i^{a,x}$	State of knowledge in decision i updated with outcome x from alternative a

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