



The chances of detecting life on Mars

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ARTICLE INFO

Available online 12 April 2015

Keywords:

Mars
Astrobiology
Exobiology
Mars surface

ABSTRACT

Missions to Mars progressively reveal the past and present habitability of the red planet. The current priority for Mars science is the recognition of definitive biosignatures related to past or present life. Success of life detection missions requires choices of the best mission design, location on Mars and particular sample to be analyzed. It is essential therefore to incorporate as much information as possible into the mission planning stages to maximize the precious opportunities provided by robotic operation on Mars. Bayesian statistics allow us to accommodate the many unknowns associated with a mission that has yet to take place. We have used Bayesian statistics to reveal that although in situ missions are less complex the overall probabilities of a successful mission to detect biosignatures on Mars are higher for sample return. If a mission has been designed with safe landing and operation as a priority, recognizing and avoiding those samples that do not contain the target biosignature is the most important characteristic, while for a mission where the best possible samples have been targeted the probability that the sample contains the target biosignature and that it can be correctly detected is the most dominant issue. Usefully, Bayesian statistics can be used to evaluate the chances of detecting past or present life for missions to different landing sites on Mars. A comparative assessment of Eberswede Crater and Gale Crater indicates a higher probability of success for the latter and the probabilities of success are consistently higher for the sample return mission variant. Bayesian statistics, therefore, can inform future Mars mission planning steps to help maximize the possibility of success.

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1. Introduction

Detecting evidence of life in samples of Mars is a major scientific preoccupation. Space missions can employ two approaches to the challenge, namely in situ analysis on Mars or the return of samples for analysis on Earth. In situ approaches have been tried but have not yet provided the searched-for evidence of life (Biemann et al., 1976; Leshin et al., 2013; Ming et al., 2014), although controversy still exists over the in situ Viking data (Levin, 2014), while sample return missions are still in the planning stages (McLennan et al., 2012). Each mission to Mars provides incremental data that improves our knowledge of the martian environment. Some of this data is sought after while other data is unexpected and fortuitous. With every increase in background knowledge subsequent planning is more informed and the probabilities of successful future missions enhanced. However, owing to the great expense of martian missions and the infrequency of their occurrence, other ways of improving mission planning are desirable.

Statistical approaches are one way in which mission design can be improved (Sims et al., 2002). Bayesian methods (Sivia and Skilling, 2006) in particular are useful because they can accommodate the significant unknowns associated with a mission that has yet to take place. Bayesian statistics produce degrees of belief or “Bayesian probabilities”. The Bayesian approach has been used previously to decide the amounts of sample needed to be collected during sample return missions to carbonaceous asteroids (Carter and Sephton, 2013) and to target samples and perform interpretations of inconclusive data on Mars organic matter detection missions (Sephton and Carter, 2014). Benefits of a Bayesian statistical approach include identification of key components to which mission success is most sensitive. While the values of estimated inputs into the statistics may be modified as new data is acquired, the relative importance of individual types of data is unlikely to change. With the parts of missions to which overall success is most sensitive constrained, future mission design can take account of these findings and allocate resources accordingly.

Increasing mission complexity requires progressively more intricate statistical analysis, so for the purposes in this paper we will consider a relatively simple mission that will capture the fundamentals of Bayesian analysis. We will assume the following: (i) only one sample will be collected, (ii) the mission has only one sampling tool and (iii) only one type of target rock is to be

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sampled. The context in which these mission objectives will be operated will be varied, but these fundamental assumptions will remain. Many choices of values to include in the calculations can be updated as more information is received from Mars and the most accurate values will be perpetually open to debate, yet we hope that the method we establish provides a useful means of comparing mission designs.

2. Defining mission components for a simple mission

To identify a space mission with the highest probability of success we need to consider four components of the mission whose probability of occurrence will influence the likelihood for mission success. These probabilities are:

1. J and $\neg J$ are the propositions that the journey required is, or is not, completed successfully.
2. S and $\neg S$ are the propositions that we can successfully, or unsuccessfully, acquire a single sample at the designated sample site.
3. L and $\neg L$ are the propositions that the sample does, or does not, contain the target biosignature.
4. T and $\neg T$ are the propositions that we have, or do not have, a positive test result for the target biosignature.

2.1. Defining mission outcomes (dependent probabilities)

There are six possible outcomes to the scientific mission and for each outcome we can calculate the probability of it occurring. The mission outcomes can be thought of as dependent probabilities and are listed in Table 1.

2.2. Defining mission steps (independent probabilities)

The six dependent probabilities above cover all possibilities and so must sum to one. From this requirement we know that we can have at most five independent pieces of information and the remaining probability is simply the sum of the five independent probabilities subtracted from a total of one. Note that changing the values of $P(\neg J|I)$ or $P(\neg S, J|I)$ will necessarily change all of the other probabilities.

So we now introduce five independent probabilities (Table 2).

The dependent and independent probabilities can appear very similar, e.g. $P(T, L, S, J | I)$ and $P(TL, S, J, I)$, but are mathematically different. To appreciate the difference one must note the position of the vertical line in the two probabilities. This vertical line divides the things we assume we do not know from those that we assume we do know. In $P(T, L, S, J | I)$ we assume that we have some background knowledge (I), but that T, L, S and J are unknown and we wish to

know the probability that T and L , and S and J occur simultaneously. Whereas in $P(T | L, S, J, I)$ we assume L, S and J are known and only the probability of T occurring remains to be calculated.

3. Probability estimation methodologies

In this section we consider how to estimate the independent probabilities for a case involving a single sample, a single sample tool and one target rock type.

3.1. Journey probabilities

The probability that a journey can be completed successfully will depend on where we start, where we want to get to and how we transition between the two. Any journey, e.g. between the points A and B , can be broken down into a series of steps. There will be an intermediate point, e.g. C , and the first step will be $A \rightarrow C$ and the second step will be $C \rightarrow B$. This process can be iterated so that any journey can be broken down into many short steps. The probability of completing a journey is the product of the probability of completing each step.

$$P(A \rightarrow B) = P(A \rightarrow C) \times P(C \rightarrow B)$$

The number of steps that a journey is broken into is a matter of convenience. What is important is the ability to assign a meaningful probability to complete the chosen steps. It is possible that a step, e.g. $C \rightarrow B$, can be completed in two, or more, ways. The particular way chosen will depend on information that is not currently available. What matters at this stage of the analysis is that we can estimate $P(C \rightarrow B)$ using some appropriate methodology.

Perhaps the most relevant example of two different journey types is provided by comparing in situ and sample return missions to Mars (Fig. 1). In situ missions rely on analyses on or near the surface of Mars to achieve their objectives. Sample return missions select samples on Mars but rely on extensive analyses in Earth laboratories to meet mission goals. To date, only in situ Mars missions have taken place. Substantial planning is taking place for Mars Sample Return and statistical approaches can form part of ongoing preparation activities.

In situ and sample return missions present different engineering challenges. While some features are common to both mission types, sample return also requires sample storage, departure from Mars, transport to Earth and recovery in a fashion that maintains sample integrity. Mission designs for Mars Sample Return involve the collection and temporary storage (caching) of material on the surface of Mars, before its recovery by a separate mission. If caching is involved, the journey can be complex because a sample must be obtained at one site and then transported to a suitable storage location.

Table 1
Mission outcomes (dependent probabilities) and their definitions.

#	Dependent probabilities	Definition
DP1	$P(\neg J I)$	This is the probability that the journey is not completed successfully. The outcome is that no sample arrives at the point of measurement. When calculating this probability we are allowed to use whatever background knowledge (I) that we have
DP2	$P(\neg S, J I)$	This is the probability that we have a successful journey but do not obtain a sample. Again we can use background knowledge when we calculate this probability
DP3	$P(T, L, S, J I)$	This is the probability for our preferred outcome. Namely, a positive test result on a sample that contains the target biosignature, which has happened after a successful journey and sample collection step
DP4	$P(\neg T, L, S, J I)$	This is the probability for an outcome we would prefer to avoid. We successfully acquire a sample containing the target biosignature, but the test returns a negative result following some sort of failure in the physical test or the analysis
DP5	$P(T, \neg L, S, J I)$	This is the probability for another outcome that we would wish to avoid. We get a positive test result from a sample that does not contain the target biosignature
DP6	$P(\neg T, \neg L, S, J I)$	This is the probability of a negative test result from a sample that does not contain the target biosignature. This outcome is one we would prefer not to experience, but as a true result is better than the outcomes that involve testing errors

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