IMPROVING SPACECRAFT SITE SELECTION THROUGH COMPUTER-AIDED DISCOVERY AND DATA FUSION.

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Introduction: The selection of suitable landing or exploration sites on the surface of a planetary body is necessary for any successful interplanetary mission, whether space-borne or landed, human or robotic. Conceivably, any point on a given body could be selected, but clearly some choices are much better than others; for example, attempting to land on a cliff or to explore for ice where the average temperature is 300 K will both surely lead to mission failure. The goal, then, is to assemble a list of optimal site choices based on the specific scientific goals and engineering constraints of the mission.

Choosing optimal sites is a complex task, and as currently performed the process involves dozens or hundreds of people over the course of many years [e.g. 1]. Numerous constraints and goals must be considered, such as local topographic or thermal conditions, regions of geologic interest, or planetary protection (e.g. avoiding potential biomes). As the amount of data available for planetary bodies grows, researchers will require new tools to be able to track and compare all of these variables. The current method of site selection may also lead to sites being overlooked whose value is only apparent when combining the right types of data in particular ways.

Here we describe an approach to the selection of spacecraft landing or exploration sites building on [3] and leveraging the concept of computer-aided discovery [2]. We are developing semi-automated tools which allow for quick exploration and fusion of various global and regional datasets in order to greatly expedite the process of arriving at a short-list of potential sites. In this approach, experts remain responsible for establishing selection criteria, guiding the system's exploration of the datasets, and evaluating the resulting list of sites. The final selection process, while still manual, is improved by further analyses of sites and regions.

Methods: We demonstrate our site selection system by way of a simple analysis on the Near Side of the Moon, due to the availability of numerous high-quality datasets. The entire analysis pipeline is performed on a server running the Jupyterhub multi-user web framework [4] and iPython notebook kernels.

Datasets, ranking criteria, and preprocessing. Our site selection process can potentially incorporate any observational or model data representable as a 2D geospatial array. The datasets and criteria used here (Fig. 1, col. I), therefore, are only meant to demonstrate the type of analysis which can be performed, and do not represent any particular mission or constraints. Our first example constraint is that a rover may need a flat place to land; for this, we generate a slope map from 16 px/° topographic data [5] from the Lunar Orbital Laser Altimeter instrument aboard the Lunar Reconnaissance Orbiter (LRO), and rank the shallowest slopes the most desirable. Next, we choose to include 2 px/° Thorium abundance data [6] from the gamma ray spectrometer aboard Lunar Prospector, preferring higher-Thorium sites for reasons of geologic interest and hypothetical *in-situ* resource utilization. Third, we use maps of the free-air gravity anomaly derived from a degree 900 spherical harmonic model [7] of data returned by the Lunar Gravity Reconnaissance And Interior Laboratory (GRAIL) spacecraft, giving better scores to sites with higher anomalies to represent a mission goal of studying denser volcanic or mantle rocks. Finally, we include the 32 px/° deviation of the rock-free regolith surface temperature from the global average at each local time [8] from the Diviner Lunar Radiometer Experiment aboard LRO, ranking warmer sites as better to represent limits on operating temperature. We produce greyscale rank maps for each dataset, with black always representing the best-ranked values.

Data fusion. To arrive at overall site desirability, we first assign an alpha (transparency) value to each greyscale dataset map based on the desired weighting (Fig. 1, col. I, percent values over datasets). We then generate a map of the total combined rank (Fig. 1, col. II) using simple alpha compositing. Sites which are highly ranked across several constituent datasets are thereby represented by the darkest colors in the combined image, while those which have good ranks in some datasets and poor ranks in others (blue arrows in Fig. 1) end up a moderate shade of grey.

Further analysis. The fused rank result can be used to derive further models of site desirability at higher levels of abstraction. These sorts of analyses allow for broader regional views of site desirability, as well as relationships between sites or sensitivity to changes in data processing. In our example, we first threshold the values in the combined rank map to generate a black-and-white map of points with ranks between 0–64 (not shown), and then use this set of points to derive full-covariance Gaussian mixture models of the map area

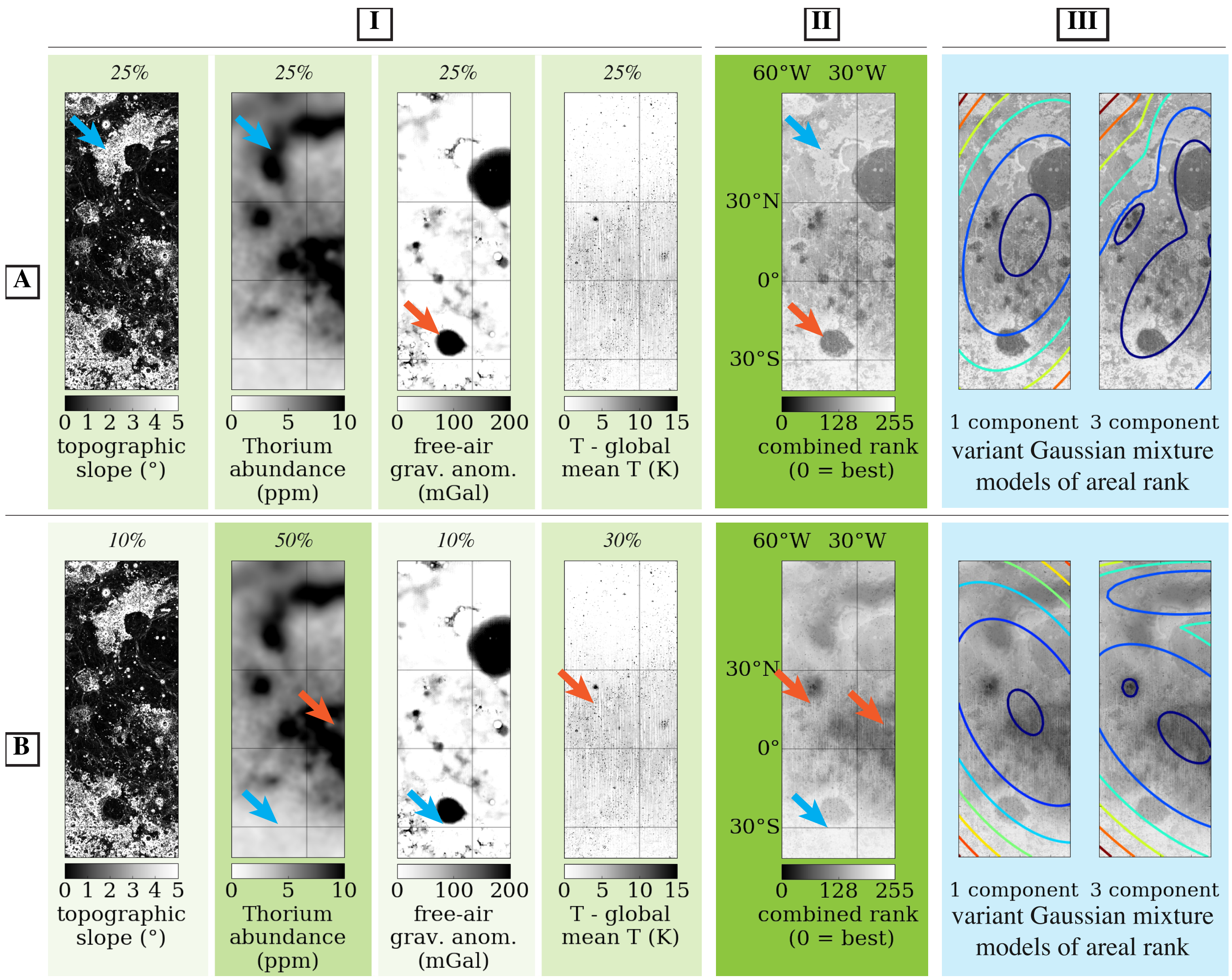

Figure 1: A variety of lunar datasets (columns I) are assigned ranking criteria (greyscale legends) and relative weights (percent values) and then fused into a map of the overall site rankings (col. II). The overall ranking result is then used as the basis for further analysis of regional desirability (col. III). Different data weightings can lead to dramatically different conclusions (rows A vs. B). Orange arrows show features which are also visible in the combined ranking; pairs of blue areas show sites which "cancel out" due to disparate rankings across the datasets.

(Fig. 1, col. III). These models provide an assessment of the overall ranking of an area, and differ based on both the combined rank data and the parameters of the mixture model itself. Other analyses could include the generation of histograms of the rank value distribution for specific regions or applying various clustering algorithms to the thresholded rank value map.

Future work: Although in this work we use the Moon as our example for demonstrating the site selection system, our process is easily applicable to other planetary bodies, including the other terrestrial planets, Jovian and Saturnian moons, or even asteroids. The incorporation of data such as geologic maps and detailed climate information would be extremely useful in expanding this work to Mars or the Earth. Another avenue for development is to create a model of an "ideal" site and then compare this to all sites on a body, potentially enabling faster and more robust exploration of parameter space.

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