National Aeronautics and Space Administration

Assessment of Machine-Discovered Fresh Impacts on Mars

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Objectives

Our objective was to characterize and document the properties of martian fresh impacts discovered using a machine learning classifier relative to those previously found manually by human inspection of images. We investigated two key questions:

1. How are human and machine-found impacts different?
2. Can a machine learning system find the hypothesized impacts on dust-free terrain and thereby reduce the current observational sampling bias?

Background

- The study of fresh impact craters on Mars provides insights into the planet's **atmospheric properties**, **active surface processes**, and **subsurface materials** such as ice.
- Approximately **1000 fresh impacts** have been **manually** catalogued.
- After mining the historical CTX archive, the ML classifier's top 1000 candidate detections were reviewed by experts, yielding 76 new impact discoveries [1].
- In addition, the human-curated catalog of fresh impacts is dominated by impacts found in regions with bright, dusty (low thermal inertia) surfaces, with few impacts on rocky surfaces (**Figures 1 and 2**).
- There is no natural process that would induce a correlation between impact locations and surface properties, so the imbalance must be due to observational sampling bias that we seek to understand.

Approach and Results

First, we examined all fresh impacts using follow-up images from the High Resolution Imaging Science Experiment (HiRISE) instrument. We characterized each impact in terms of several parameters, including crater diameter, dust cover index of the surface, thermal inertia of the surface, elevation, clusters versus single impacts, and appearance (light-toned, dark-toned, or dual-toned).

- We generally found a high level of similarity in the human- and machine-discovered populations (**Figure 3**), consistent with the fact that human-discovered impacts were used to train the classifier.
- Notable differences include the proportion of clusters in the impacts found by the classifier (65%) versus the full catalog (58%), and the average diameter of machine-discovered impacts (4.96 +/- 2.19m) versus the full catalog (7.22 m +/- 6.10m).
- The smaller average diameter of machine-discovered impacts likely reflects a combination of the presence of rarer large impacts in the full catalog as well as the classifier's increased sensitivity to smaller impacts relative to humans.

To directly investigate whether the classification approach can more effectively find impacts in non-dusty regions, we performed a new evaluation of impact candidates that were explicitly sampled within ten different thermal inertia (TI) ranges (**Figure 4**). Our finding is that there is a significantly higher detection rate in lower TI (dustier) terrains for both human and machine-discovered impacts, but the effect is slightly less significant for machine-discovered impacts.

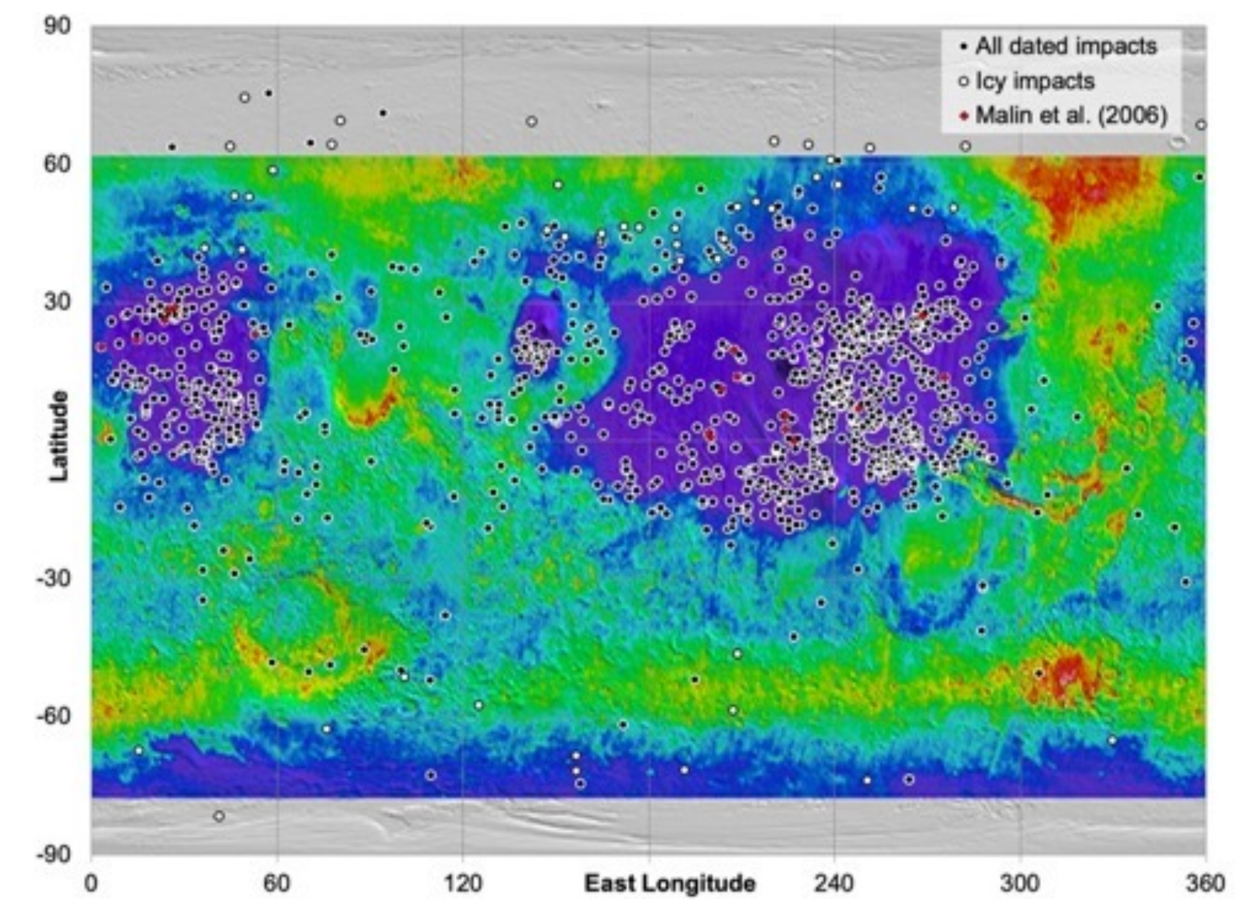

Figure 1: Locations of known fresh impacts overlaid on a thermal inertia map, a proxy for dustiness (dark/purple = low TI, bright/red = high TI).

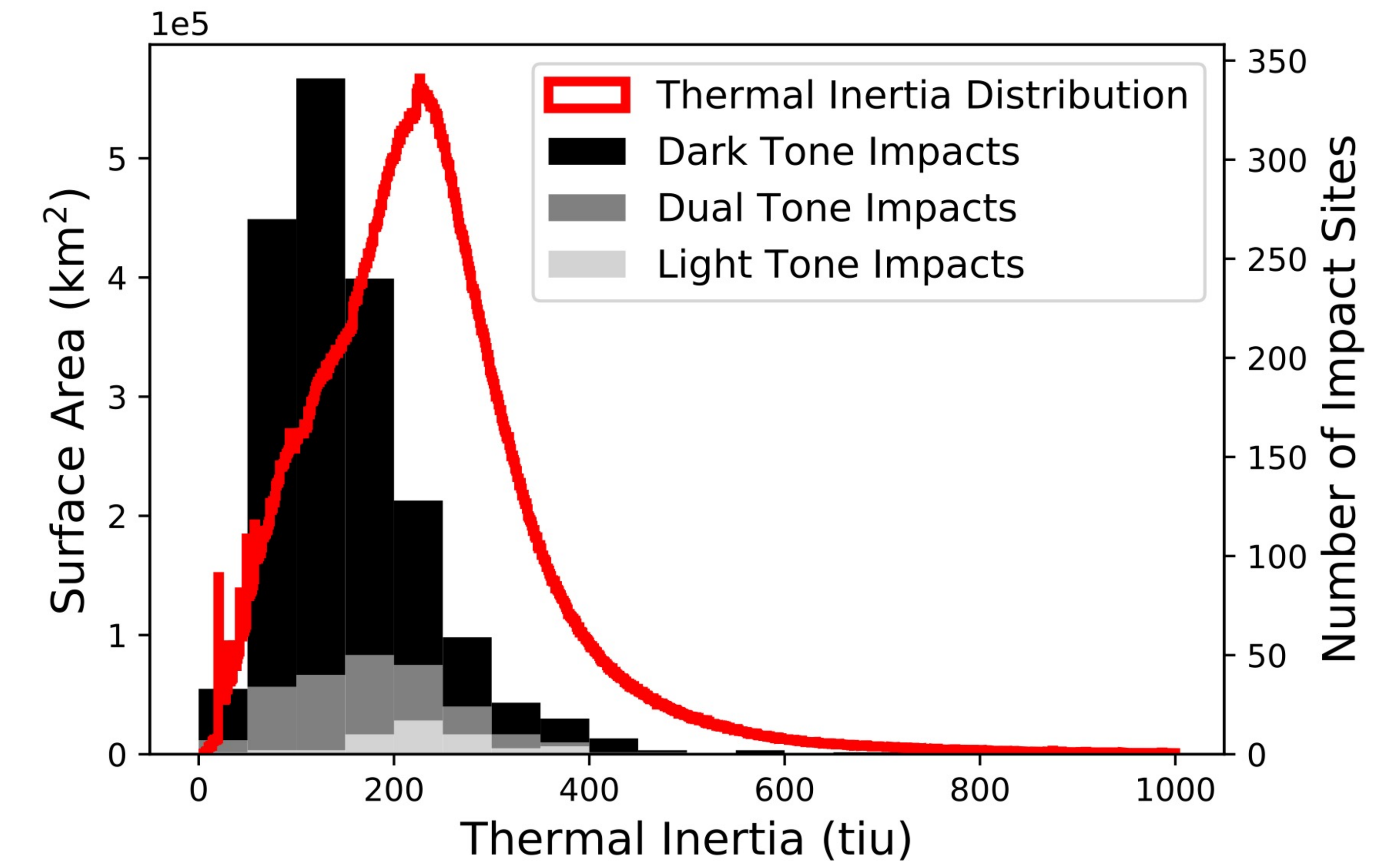

Figure 2: A comparison of human detected fresh impacts by appearance and distribution of thermal inertia by surface area.

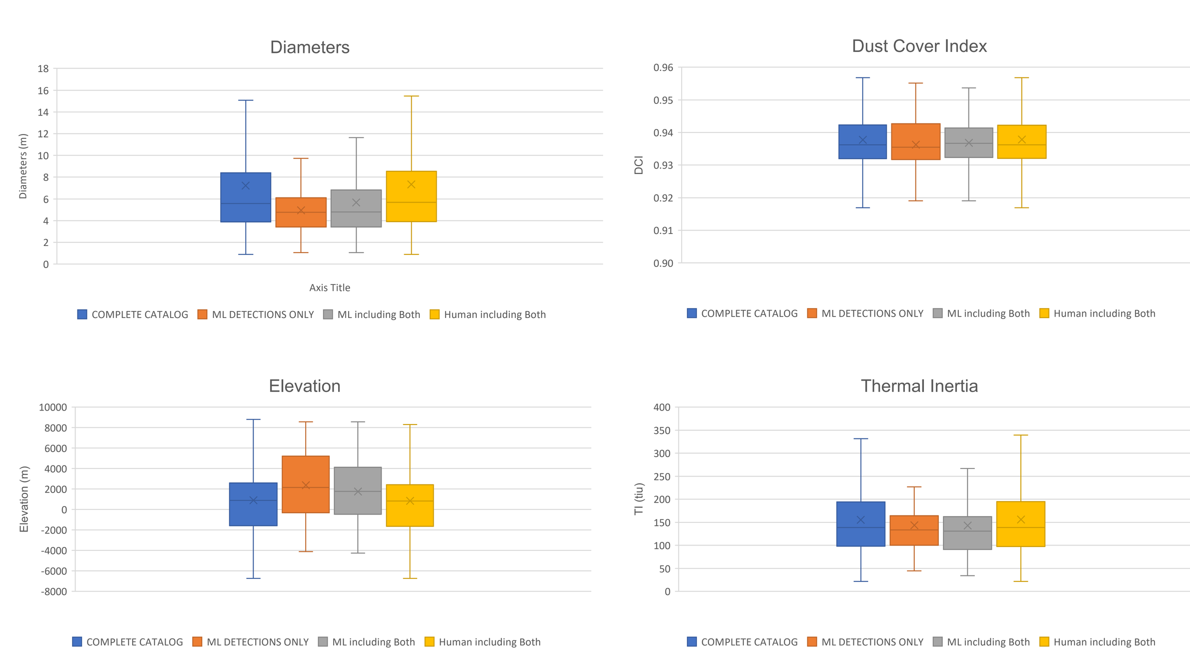

Figure 3: A comparison of several fresh impact detection properties across the complete catalog, ML detections only, ML detections including those already found by humans, and human detections, including those also detected by the classifier.

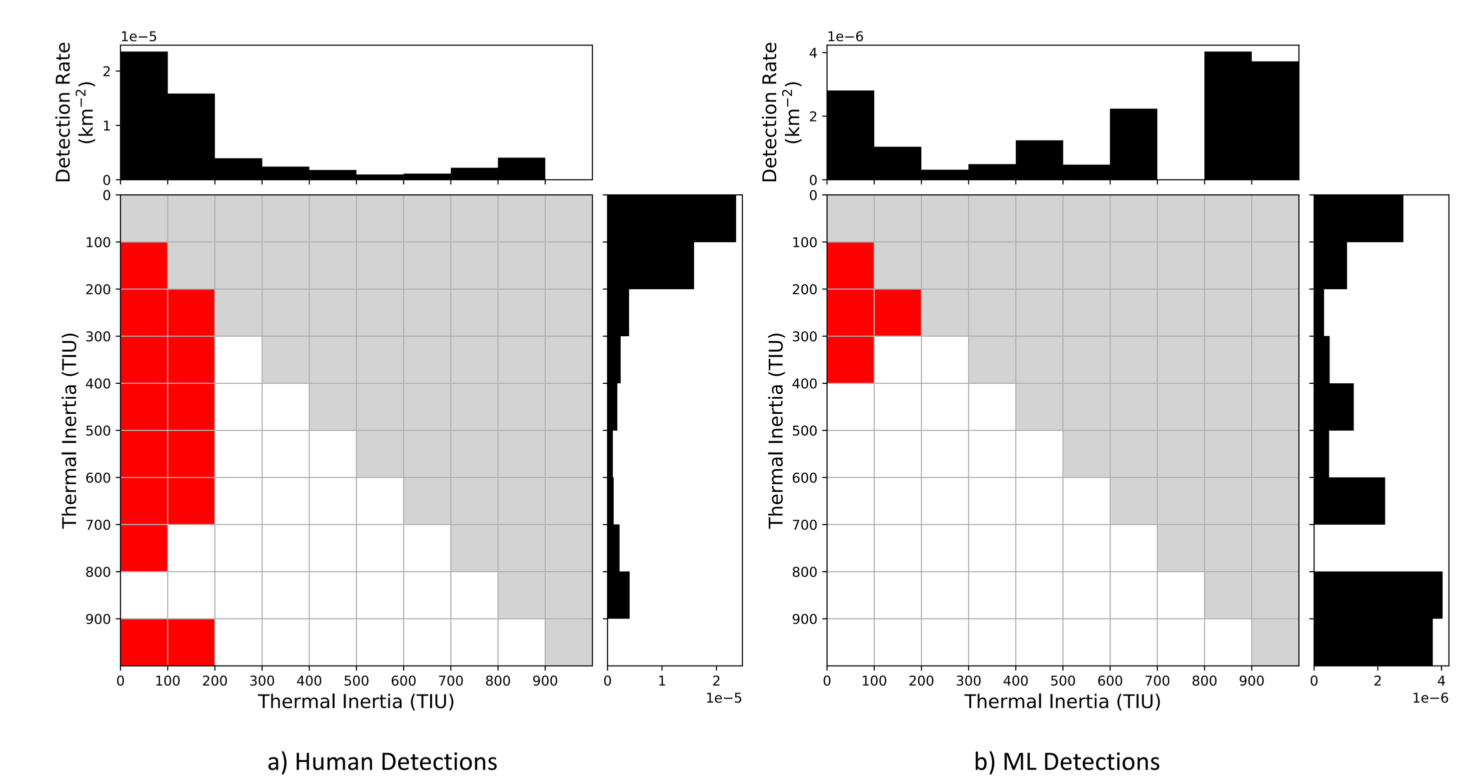

Figure 4: A pairwise comparison of fresh impact detection rates as a function of thermal inertia bin. Red squares indicate statistical significance in the differences between rates.

Significance/Benefits to JPL and NASA

The methodology used by this study can be used to quantify biases in both human- and machine-discovered impacts as more data is examined and discoveries are made. Our results also provide some evidence that stratification of detection by terrain properties like TI might help to mitigate observational sampling biases. This methodology can also be extended to other domains to investigate ML systems applied to Earth remote sensing, planet/moon flyby observations, images and spectra collected by telescopes, and more. This work enables JPL to lead the definition of careful, meaningful methodology for leveraging ML in Earth and space exploration. Finally, demonstration and documentation of our methodology [A] as well as the publication of the data [B] and models [C] used for this analysis have opened new avenues for future research and funding.

Publications

[A] Wagstaff, K. L., Daubar, I. J., Doran, G., Munje, M. J., Bickel, V., Gao, A., Pate, J., and Wexler, D., "Using Machine Learning to Reduce Observational Biases When Detecting New Impacts on Mars," in preparation for Icarus. **[B]** Munje, M. J., Wagstaff, K.L., and Doran, G. "Mars orbital images of fresh impacts from CTX [Data set]," Zenodo,2021. https://doi.org/10.5281/zenodo.5523886 **[C]** Munje, M. J. "Martian Fresh Impact Classifier," Zenodo, 2021. https://doi.org/10.5281/zenodo.5523361

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