GENERATING A GLOBAL, MULTISCALE MAP OF MARTIAN CO_2 FROST FROM VISIBLE AND THERMAL DETECTIONS.

Serina Diniega[1], Umaa Rebbapragada[1], Gary Doran[1], Steven Lu[1], Mark Wronkiewicz[1], Jake Widmer[2], [1]Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr., Pasadena, CA 91109 (serina.diniega@jpl.nasa.gov), [2]University of California, Los Angeles.

Introduction: Mars' seasonal frost cycle is a critical area of planetary science investigation as surface frost is and has been a dominant driver for Mars' climate and surface evolution through the last ~2 billion years (i.e., the Amazonian epoch) [1]. Additionally, identification of low-latitude frosted microclimates is important for characterizing potential habitable environments and resources for future human explorers. Finally, studies of martian frost may provide an unmatched look into sublimation-driven processes that are also active in the outer solar system and that have no terrestrial analog [1].

Previous studies of Mars' seasonal frost cycle have been limited in scope because their manual surveys forced a trade-off between coverage and spatial resolution, with either a global look using coarse (>kilometers/pixel) observations [e.g., 2,3], or a local "site" focus with higher-resolution observations (sometimes including multiple datasets) [e.g., 4]. In our study, we utilized data science techniques to identify frost at global scale with both high-resolution visible and coarse resolution thermal datasets. We also combine these different datasets into one map so as to characterize frost type and reduce uncertainty.

Current Work: We used a small set of manually labeled HiRISE imagery (Figure 1) to train a machine learning (ML) classification model [5] to detect frost in meter-scale visible imagery (HiRISE, red band only). Formation of the ML training and test sets of HiRISE images included terrain and L_s/frost-appearance diversity, from a spread of latitudes and longitudes to avoid unintentional regional-bias. We initially focused on the northern hemisphere, but have since augmented the training set with terrain types and visible frost expressions unique to the southern hemisphere (Figure 2). After training, we applied our ML model to ~5000 northern hemisphere images and ~7000 southern hemisphere images (focused on the latitude-L_s space containing the contiguous seasonal frost cap as well as patchier frost at lower latitudes, accounting for ~17% of the full HiRISE archive; Figure 3).

We combined those HiRISE-based visible frost detections with ~kilometer-resolution MCS-based thermal data that are sufficiently close (in time and space; Figure 4) so as to mitigate the uncertainty of some visible detections and differentiate between CO_2 frost, water frost, and bright non-frosted terrain. To combine visible and thermal information, we use an approach based on adjusting the *a priori* likelihood of frost used by the visible model to a value derived by the MCS data [6]. The implicit *a priori* probability of the frost class learned by the model is 0.5 due to training with a balanced dataset containing roughly equal numbers of frost and non-frost tiles, but the distance between the MCS-derived temperature and locally computed frost point, along with MCS measurement uncertainty, produces a more accurate *a priori* estimate of frost likelihood for the visible model. Our combination technique is being refined so as to improve detection of patchy frost, as avoiding false positives in visible images comes with the risk of false negatives due to the large footprint of thermal data. The resultant map (Figure 5) incorporates thermal and visible observations in identifying the presence of CO_2 frost, along with a quantified estimate of confidence for each positive frost detection.

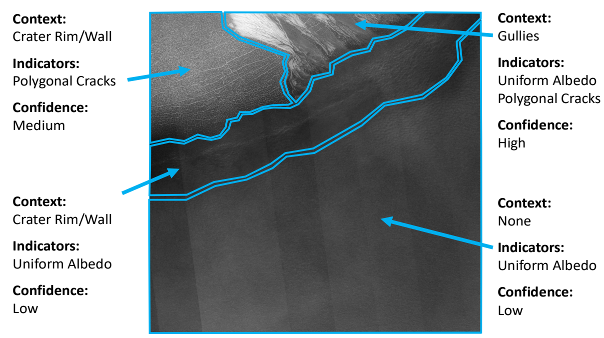

Figure 1: Frost annotation polygons on top of a HiRISE image during manual data labeling, along with contextual information (all info collected manually).

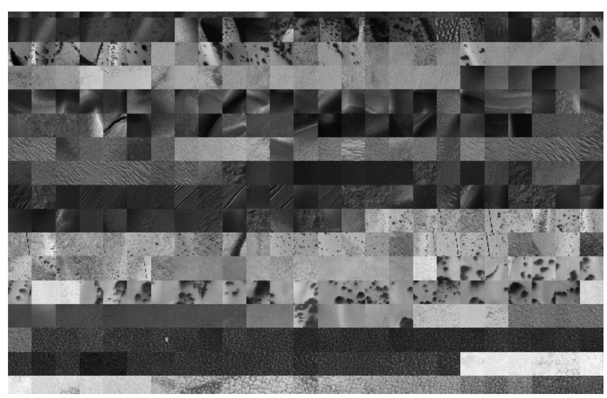

Figure 2: Example ~80 tiles from southern HiRISE images that were used to train the ML model, that contain frost. (We also used tiles without frost.)

Next steps: We next plan to integrate meters-scale, global-coverage visible (CTX) and ~100 m-resolution thermal (THEMIS) imagery into the map. Following that, we will add in spectral observations (CRISM) so as to incorporate water frost detections and increase confidence in both water and CO2 frost detections.

Harmonizing these complementary observations enables a holistic look at the martian seasonal frost cycle over a wide range of relevant spatial and temporal scales. Our final data product, capturing frost type, timing, and locations, will provide the planetary science community with a new observation-based understanding of where and when different martian frosts form. With it, the community will be empowered to better constrain and validate a wide range of models focused on Mars global/regional atmospheric circulation, volatile transport/budget, and geomorphological activity.

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References: [1] Diniega et al. (2021) *Geomorphology*, *380*, 107627. [2] Piqueux et al. (2015) *Icarus, 251*, 164-180. [3] Calvin et al. (2015) *Icarus,251*, 181-190. [4] Pommerol et al. (2013) *Icarus, 225*(2), 911-922.

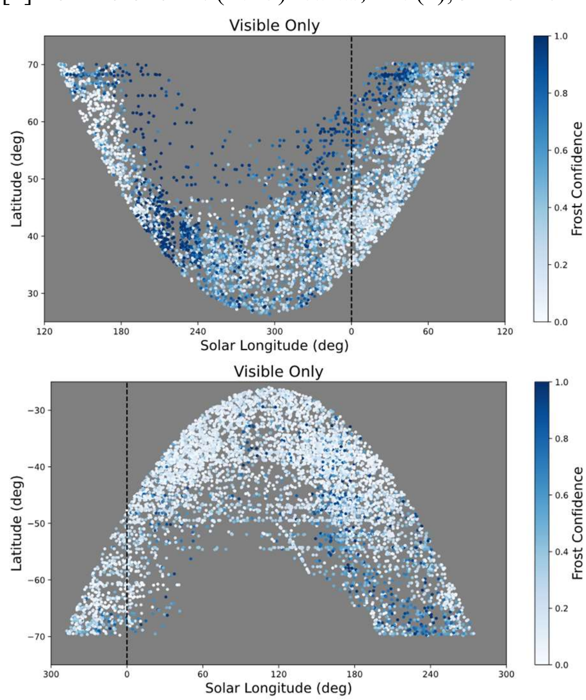

Figure 3: HiRISE frost detections within the north (top) and south (bottom), from the north-trained ML model.

Ref. continued: [5] Szegedy et al. (2015) *IEEE Conf. CVPR*. [6] Latinne et al. (2001) *IEEE Conf. ICML*.

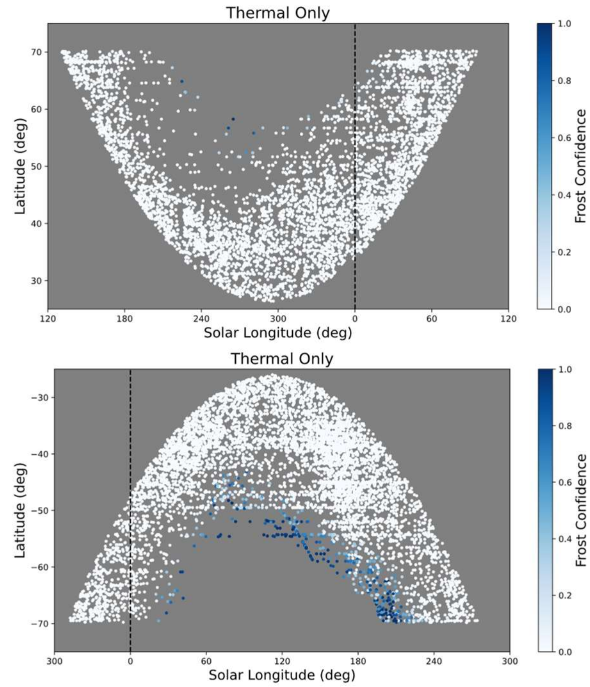

Figure 4: MCS frost detections. MCS data points were selected based on their proximity, in time and space, to the HiRISE images in Figure 3.

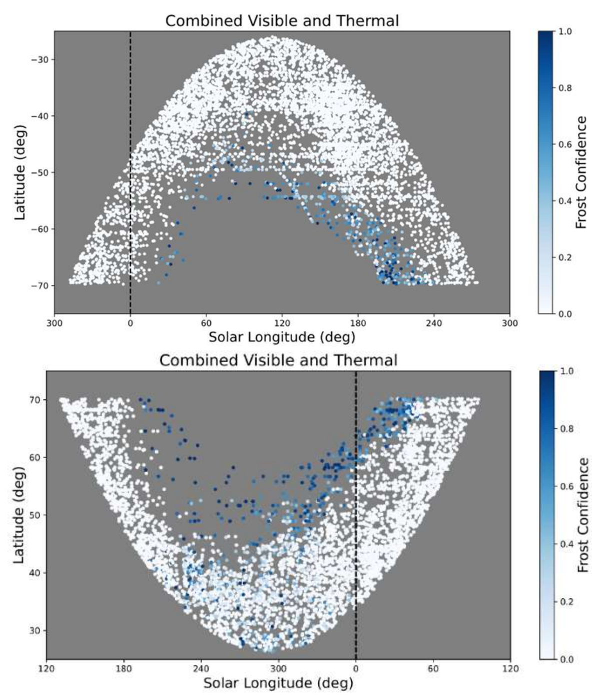

Figure 5: Preliminary global map of combined frost detections. **(The map will be improved after applying *(1)* the updated ML model across all HiRISE images and *(2)* a more nuanced methodology for combining the thermal and visible data.)**