FDL 2020 MOON FOR GOOD

LOW-LIGHT IMAGE ENHANCEMENT OF PERMANENTLY SHADOWED LUNAR REGIONS WITH PHYSICS-BASED MACHINE LEARNING

THE MOON FOR GOOD
FDL 2020

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INTRODUCTION

In recent years the international space community has gained **significant momentum** for continuing the exploration of the **Moon**.

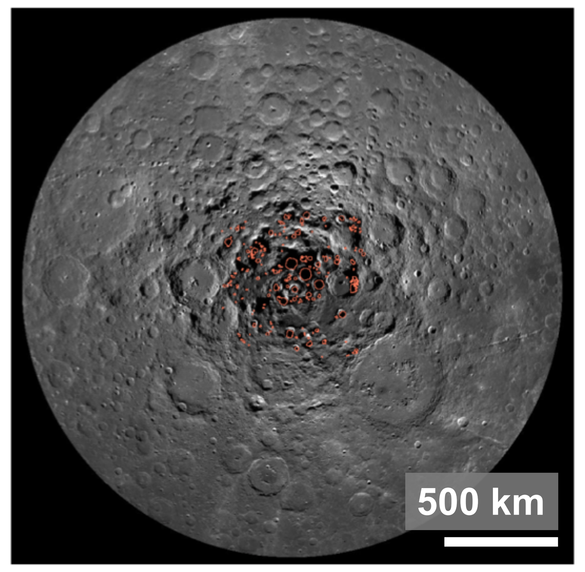
Water is a key resource for establishing and sustaining a human presence.

Water is likely to exist at the lunar poles, specifically inside the **permanently shadowed regions (PSRs)** – topographic depressions which see no direct sunlight.

However, **direct detection** of surface water-ice has **not yet been possible**.

Bright surface ice could potentially be detected using **high-resolution optical imagery** from the Lunar Reconnaissance Orbiter Narrow Angle Camera (LRO NAC).

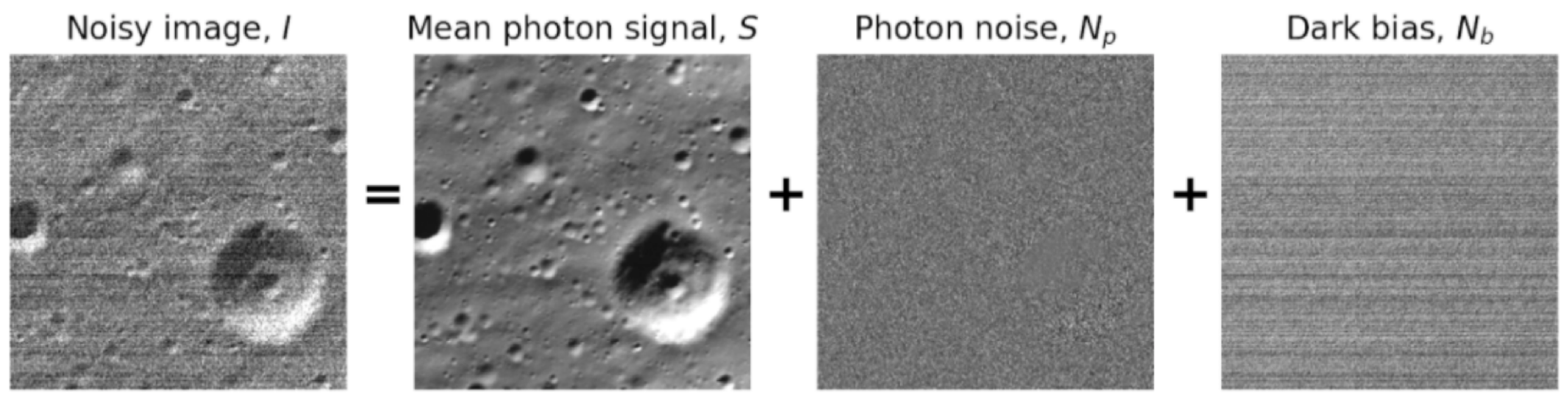

Image credit: NASA



Map of PSRs (orange polygons) at the lunar south pole. Image credits: LROC/ASU/QuickMap

PROBLEM

However, due to the **extreme low-light** conditions, **Charge-Coupled Device (CCD) sensor–related noise** and **photon (Poisson) noise** dominate these images, strongly limiting our ability to make meaningful observations.



Physical noise model of the NAC CCD
Raw image credits: LROC/ASU/GSFC

PHYSICAL CCD NOISE MODEL

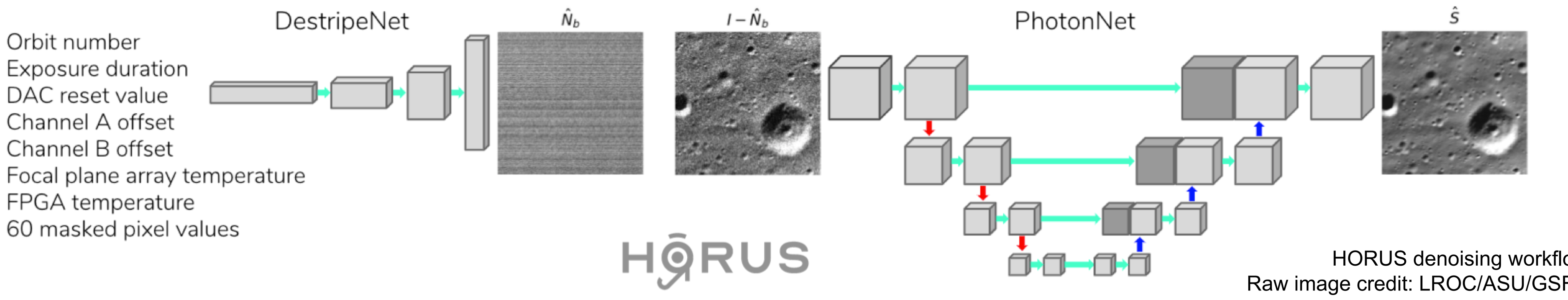
We assume that an image captured by the LRO NAC can be formulated as

$$I = S + N_p + N_d + N_b + N_r$$

where I is the raw image in detector counts, S is the **mean photon signal**, N_p is stochastic **photon noise** (Poisson-distributed), N_d is stochastic **dark current noise** (Poisson-distributed, from to thermally activated charge carriers in the CCD), N_r is **readout noise** and N_b is **dark bias noise** (deterministic, due to a pixel-to-pixel varying voltage offset applied).

SOLUTION

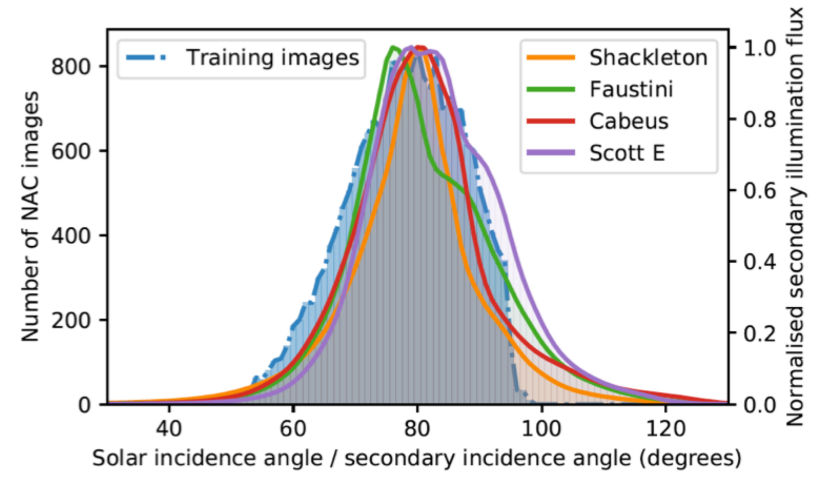
We use two **physics-driven deep neural networks** to model and **remove** CCD-related and photon noise in LRO NAC images. We name the workflow Hyper-Effective Noise Removal U-Net Software (**HORUS**).



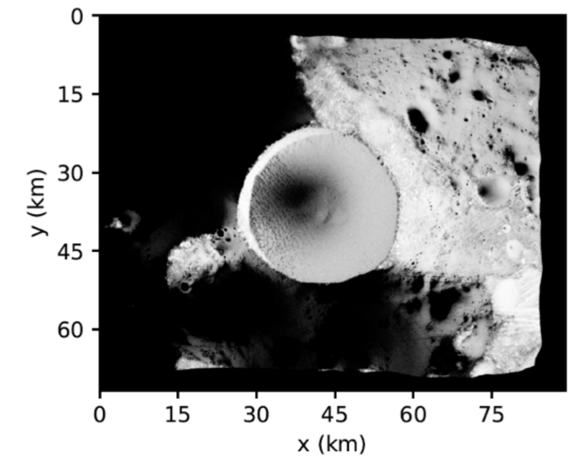
HORUS denoising workflow
Raw image credit: LROC/ASU/GSFC

We apply the two networks sequentially to denoise the images:

- **DestripeNet predicts the dark bias noise** N_b from the **camera environment meta data** available at the time of image capture, and is trained using 100,000+ dark calibration frames as labels. It uses a convolutional decoder design.



Distribution of solar incidence angle in training images vs secondary illumination angle from 3D ray tracing



Secondary illumination render over Shackleton PSR from 3D ray tracing

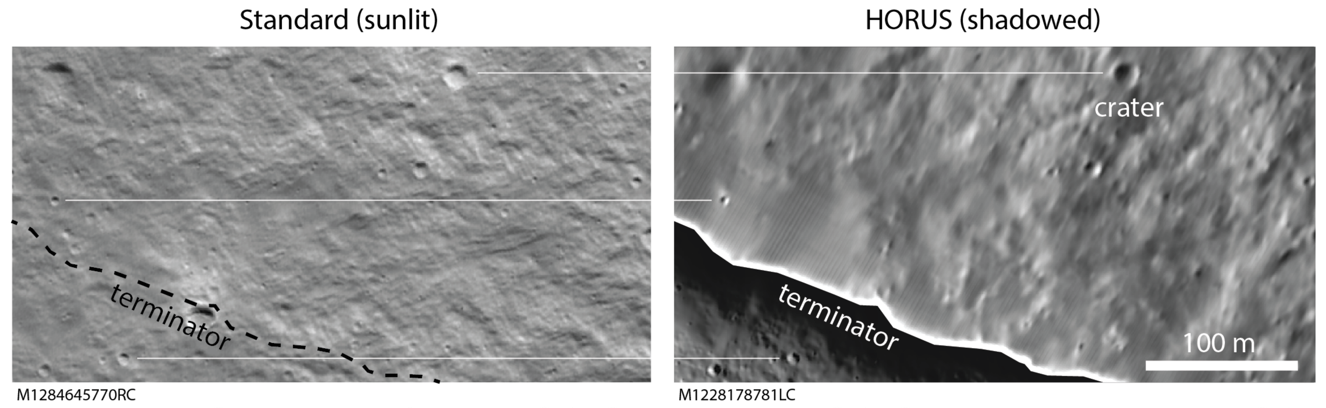
- **PhotonNet predicts the photon noise** N_p in the image, and is trained by adding synthetic Poisson noise to 1M randomly selected rescaled image patches of the lunar surface in normal sunlit conditions. It uses a U-Net architecture.

Importantly, PSRs can only be illuminated by **secondary light scattered** from their surroundings. In order to best **match the illumination conditions** of the training data to these conditions, we match the distribution of solar incidence angles in the sunlit training images for PhotonNet to the expected distribution of secondary illumination angles in PSRs estimated from 3D ray tracing.

RESULTS

HORUS is able to **significantly improve the quality** of both synthetically-generated and real low-light images.

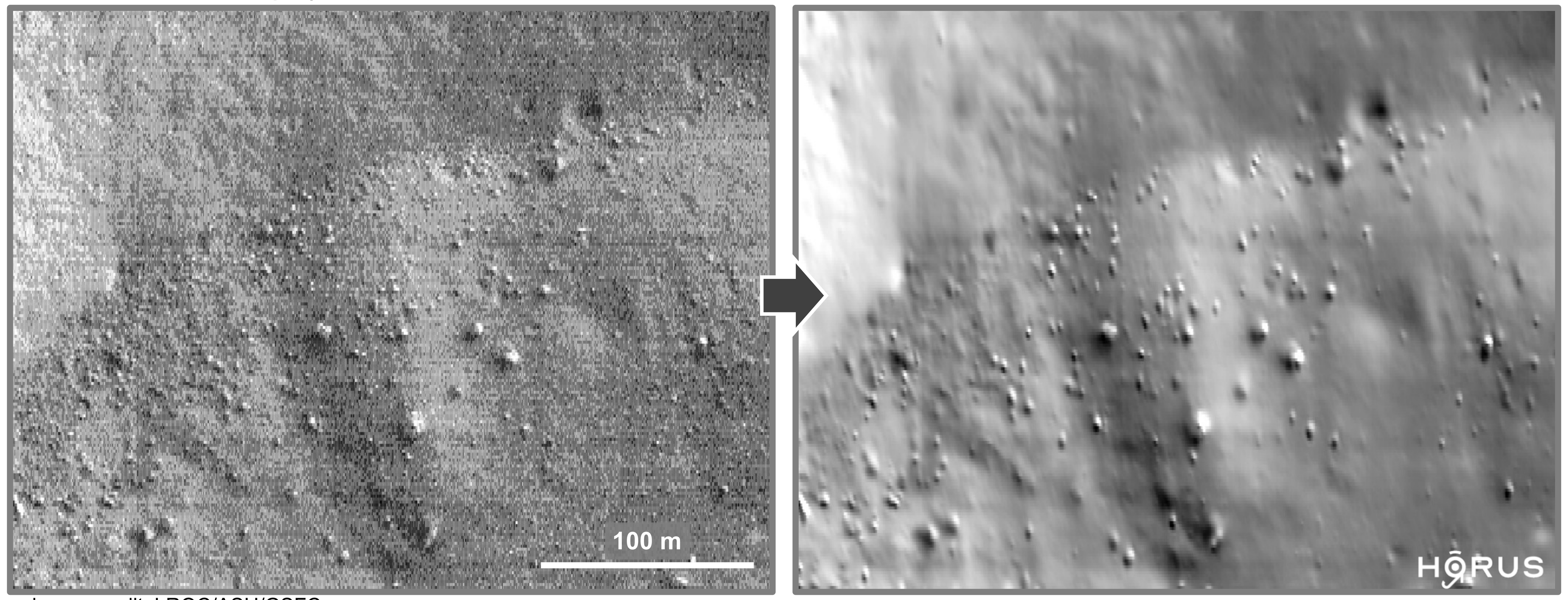
We **validate** our approach by comparing HORUS denoised shadowed images in Temporarily Shadowed Regions (TSRs) to their corresponding overlapping sunlit images.



Comparison of a non-HORUS sunlit and a HORUS shadowed Image in a TSR.
Non-HORUS image credit: LROC/ASU/GSFC

Real raw NAC image | Wapowski crater (82.9°S 53.5°E)

Our result (HORUS)



Raw image credit: LROC/ASU/GSFC

CONCLUSION

We have shown it is possible **to significantly enhance extremely low-light images of PSRs** on the Moon. Future work will **analyse these images for surface-ice related signals**, quantitatively assess performance using TSRs, and investigate joint training of the networks to improve performance.

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CONTRIBUTIONS VTB and BM were involved in the conceptualization of this project. VTB, BM, ILF and LR were involved in the methodology, software, validation, formal analysis, investigation, resources, data curation, writing, preparation, visualization. VTB, BM, ILF, LR, AZ, DW and MOM were involved in the review, administration, supervision. NS and EDE implemented the 3D ray-tracing.