Reconstructing Mercury's Southern Hemisphere

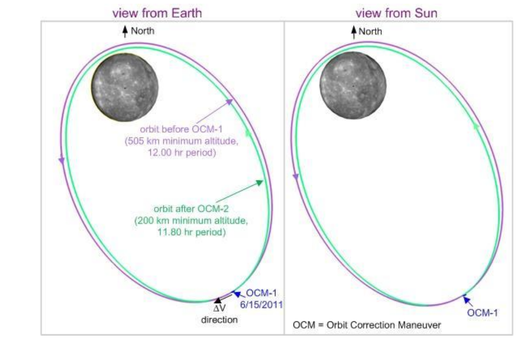
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Dense gravity reconstruction · Lunar transfer learning · Topographic refinement

Introduction

MESSENGER's eccentric orbit left Mercury's southern gravity less well resolved. We investigate reconstruction from the measured large-scale field and surface topography.

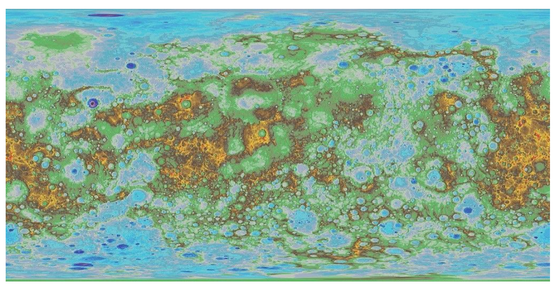
Following Zhao et al., we learn gravity structure from the Moon, adapt the model to Mercury, and refine its predictions with topography.



MESSENGER orbit schematic, retained from the original project poster.

The reconstruction task

Starting from degree 25, infer the missing bands in two steps: **25 → 50 → 100**. Both networks learn residual gravity. The supplied low-degree field is retained exactly.



Mercury surface context from the original poster. Training uses an aligned spherical-harmonic shape model.

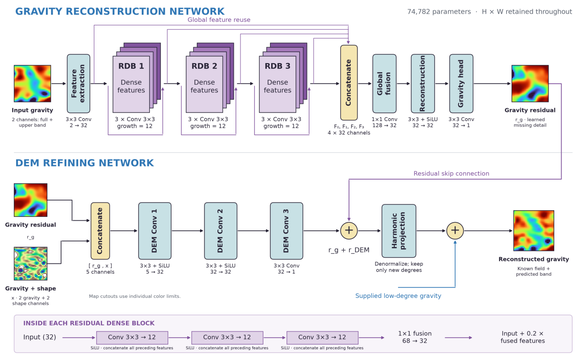
Public planetary data

Moon: GRAIL gravity + LOLA shape.
Mercury: HgM008 gravity + USGS stereo-derived shape.
Explicit coordinates and physical units throughout.

Methodology

Dense network + DEM refinement

The original two-stage design is retained. Residual dense blocks reuse features; a separate three-layer refiner learns how topography relates to missing gravity.



Dense gravity reconstruction and DEM refinement. Purple stacks show feature reuse; skip connections preserve context. Channel counts match the trained model.

Learning the missing gravity

Three residual dense blocks extract gravity structure. Their outputs are concatenated and fused, then passed to a gravity head. A separate convolutional branch uses the gravity residual and two bands of surface shape to refine the missing detail.

Training and inference

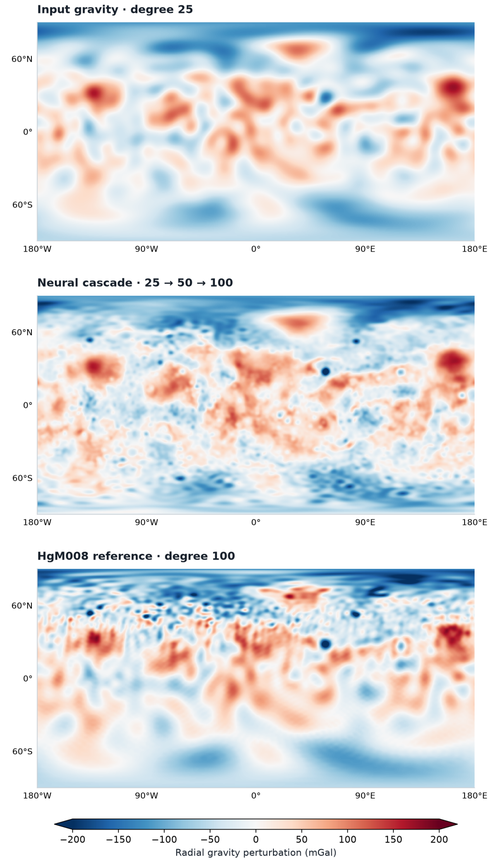
1. Lunar pretraining. Learn across degree pairs 25–50, 50–100 and 100–200.

2. Mercury adaptation. Fine-tune with geographic train, validation and test regions. Save the normalization with every model.

3. Seam-free prediction. Use a context halo around each tile and crop to valid outputs. Longitude wraps across the map boundary.

74,782 trainable parameters · AdamW · learning-rate warmup and decay · gradient clipping · validation-selected checkpoints

Results



Full gravity fields on one color scale. The neural map is a four-model deployment ensemble; northern reference pixels are not pasted into the prediction.

Reconstruction error

Task	Input	Neural
25 → 50	20.24	17.29
50 → 100	15.23	14.07
25 → 100	25.70	22.56

Mean area-weighted RMSE (mGal) over four held-out northern longitude sectors. The final row evaluates the actual two-stage cascade.

12.2% lower held-out error than the degree-25 input for the complete cascade.

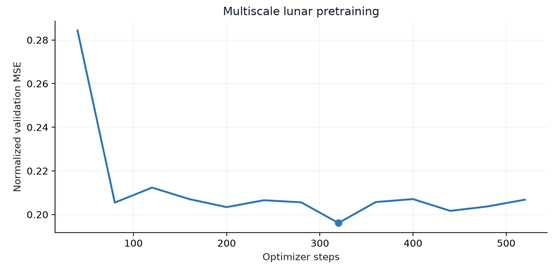
Discussion

A better reconstruction pipeline

Aligned data. Gravity and topography share the same spherical grid; polar images are not stretched into a global map.

Stable learning. The model learns missing detail around a fixed gravity input, with dense feature reuse and multiscale lunar pretraining.

Clean maps. Valid-context inference removes tile-edge artifacts without blurring or clipping the prediction.



Lunar validation curve. The selected checkpoint is marked; additional training is stopped when validation ceases to improve.

What the measurements show

The network reduces withheld northern error by 14.6% for degree 25 → 50 and 7.6% for 50 → 100. Training without lunar initialization remains competitive; transfer is not a uniform win.

Scientific interpretation

The southern map is a learned reconstruction, not a new measurement. HgM008 is a reference model, not error-free southern truth. Surface topography cannot uniquely determine subsurface density.

Sources and code

Zhao et al. (2020), Remote Sensing 12, 2293.
GRAIL / MESSENGER public gravity archives.
Maia (2024), Mercury shape; Wieczorek (2024), lunar shape.

github.com/amilcodes/mercury-reconstruction