Automated Detection of Craters on Pluto

And implications for surface ages and impacting populations

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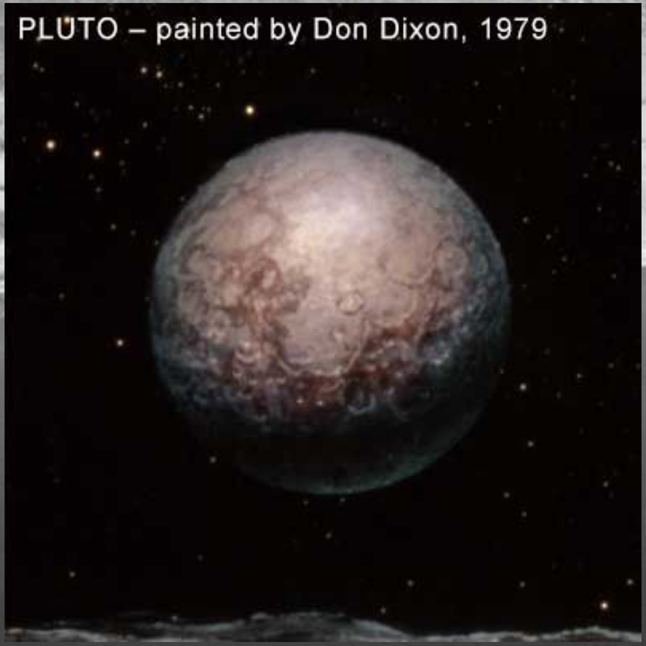
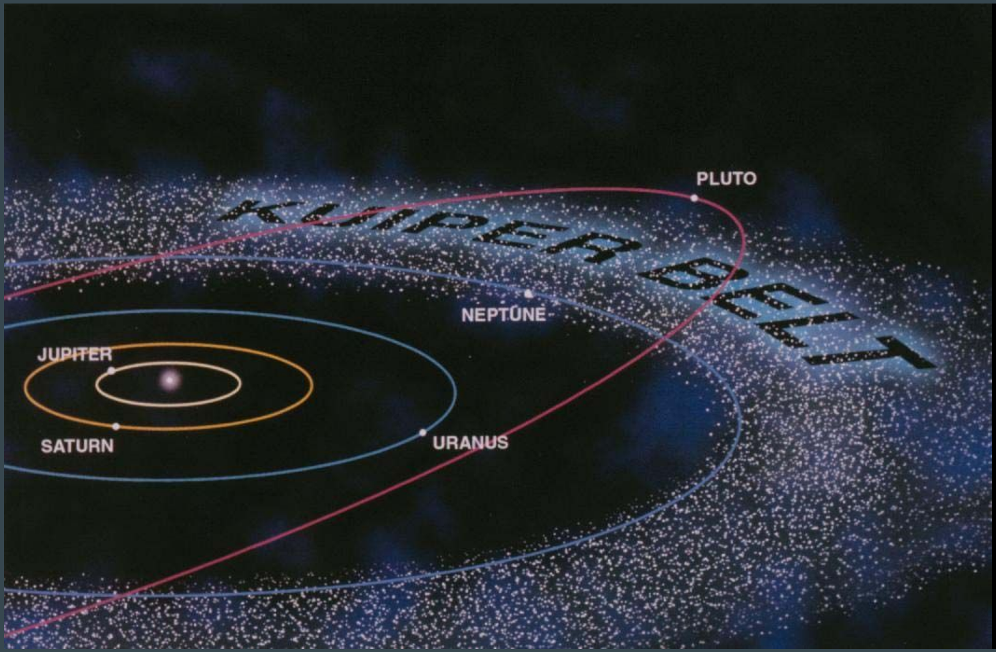
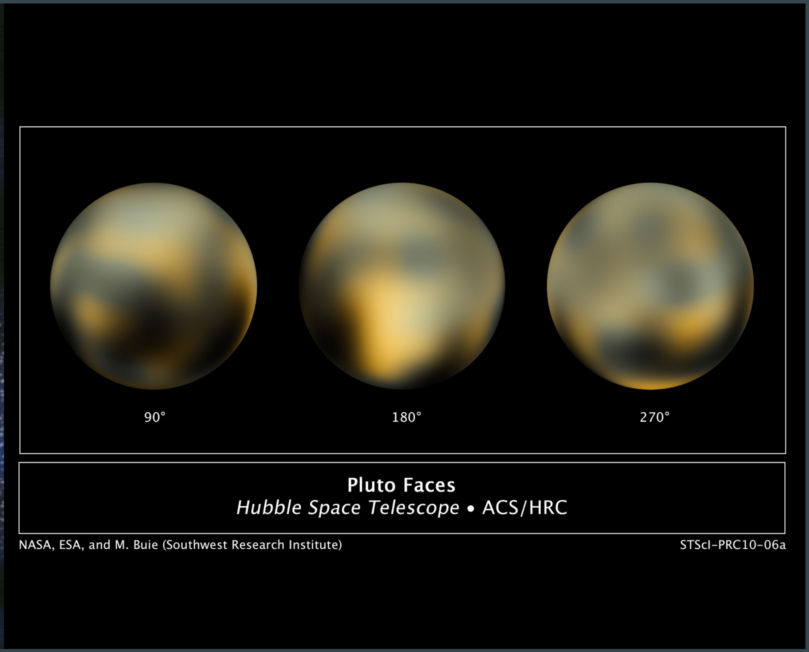
12 December 2017

Seminar Final Presentation


PLUTO – *New Horizons*, July 7, 2015


PLUTO – painted by Don Dixon, 1979





Sitting on the inner edge of the Kuiper Belt, observations of Pluto's surface were severely limited prior to New Horizons.

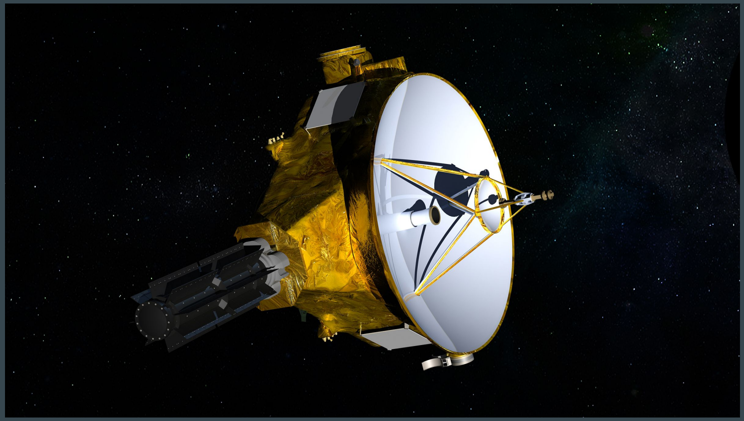
Impact craters are ubiquitous across rocky and icy planets in the solar system and inform us about ***surface ages***, ***impacting populations***, and ***geologic processes***.

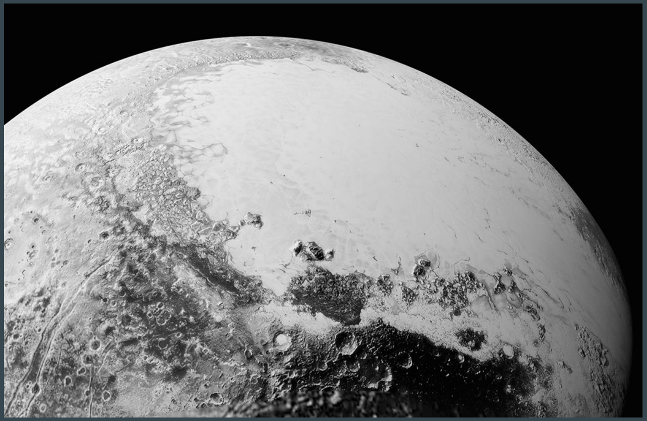
Major scientific questions motivating this work:

What are the surface ages of different regions across Pluto?

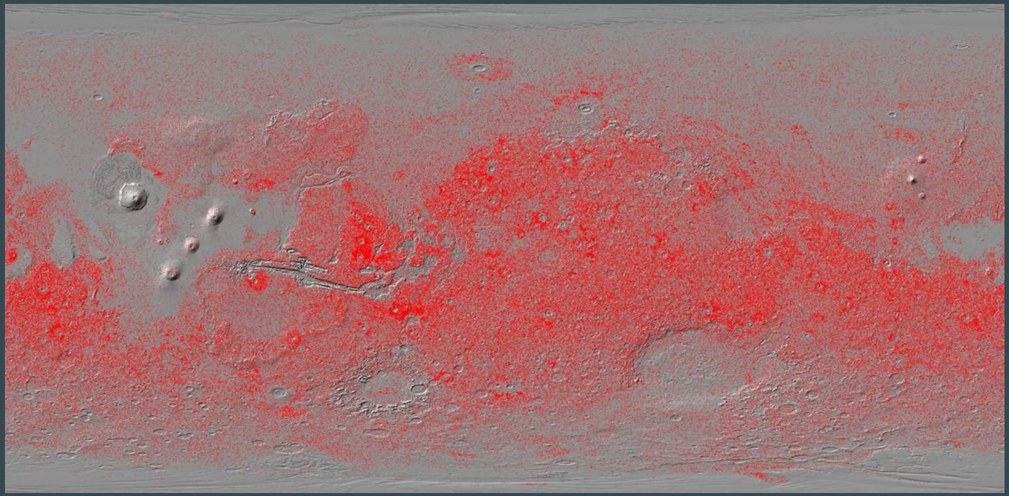
Can the size frequency distribution of craters determine the dominant impacting populations?

Are there distinct classes of crater morphologies? What do these tell us about the surface evolution of Pluto?

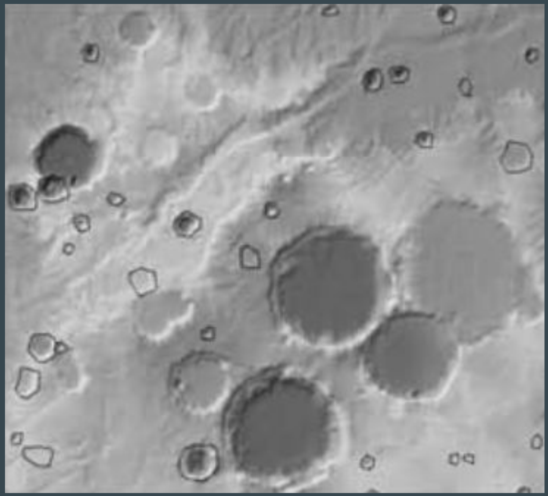




Why detect craters automatically?



Robbins et al. (2012)



Stepinski et al. (2009)

Much faster than manually identifying craters globally.

Not subject to individual biases ("Vesta controversy").

Will help to identify quickly identify areas and features of interest.

Once developed, can quickly be applied to forthcoming DEMs.

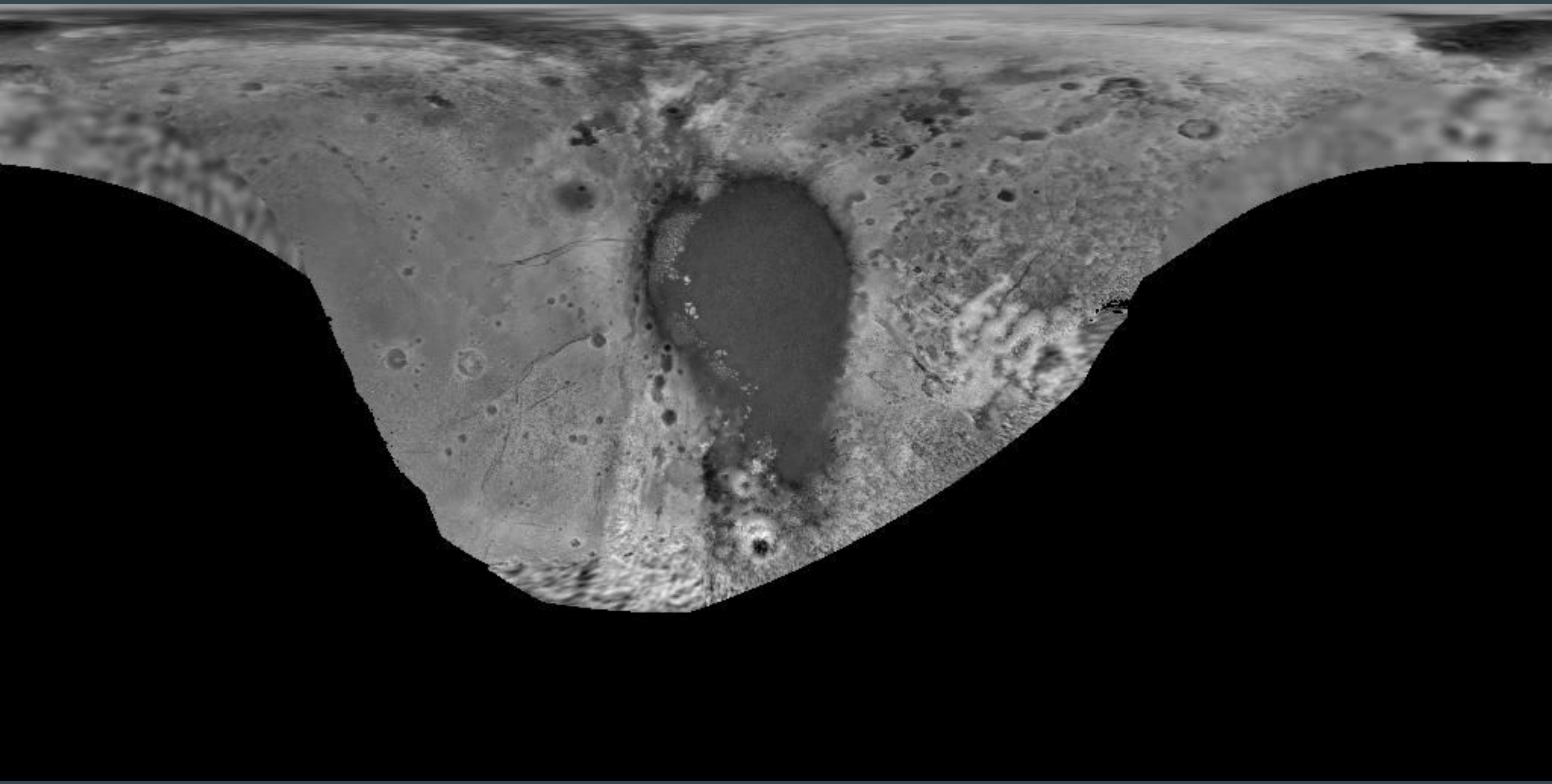
New Horizons - LORRI and MVIC (Ralph)

LOng Range Reconnaissance Imager

- Monochromatic (350-850 nm)
- Suited for low light conditions
- 0.29° field of view
- 1024 x 1024 pixels
- Best resolution of 0.5 km/pixel

Multi-spectral Visible Imaging Camera

- Panchromatic (400-975 nm) or blue (400-550 nm), red (540-700 nm), and near-IR (780-975 nm) modes
- 5.7 ° field of view
- Six 5024 x 32 pixel arrays
- Pushbroom imager
- Time-delay integration
- Best resolution of 0.5 km/pixel



Goal: Use DEM constructed from LORRI and MVIC stereo pairs to automatically detect depressions and compare results with manually identified craters.

The process to identify craters

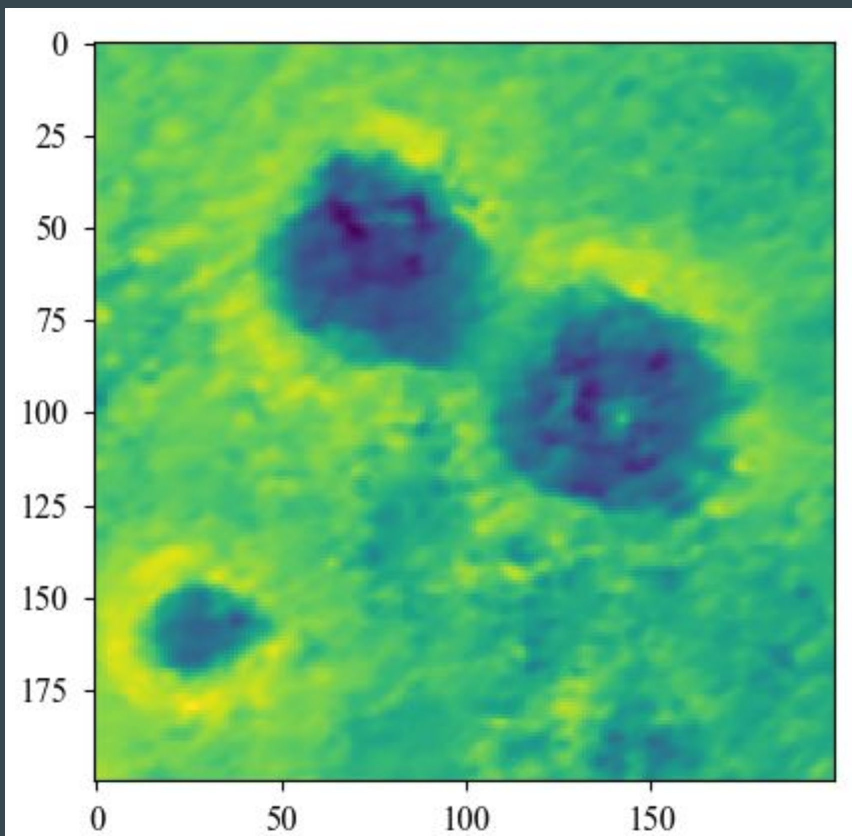
In this work:

1) Use ***derivatives in elevations*** to ***identify depressions*** at different length scales.
2) Determine a few basic shape parameters for all the identified depressions.
3) Find the craters in a region by hand and determine their parameters (comparison with published work)

Future work:

4) Create a decision tree that can filter out non-craters.
5) Apply the decision tree to the depression data set for to classify the depressions as craters or non-craters.

Use “C-transform” to convert DEM to an “artificial elevation” that represents a point’s elevation relative to that around it.



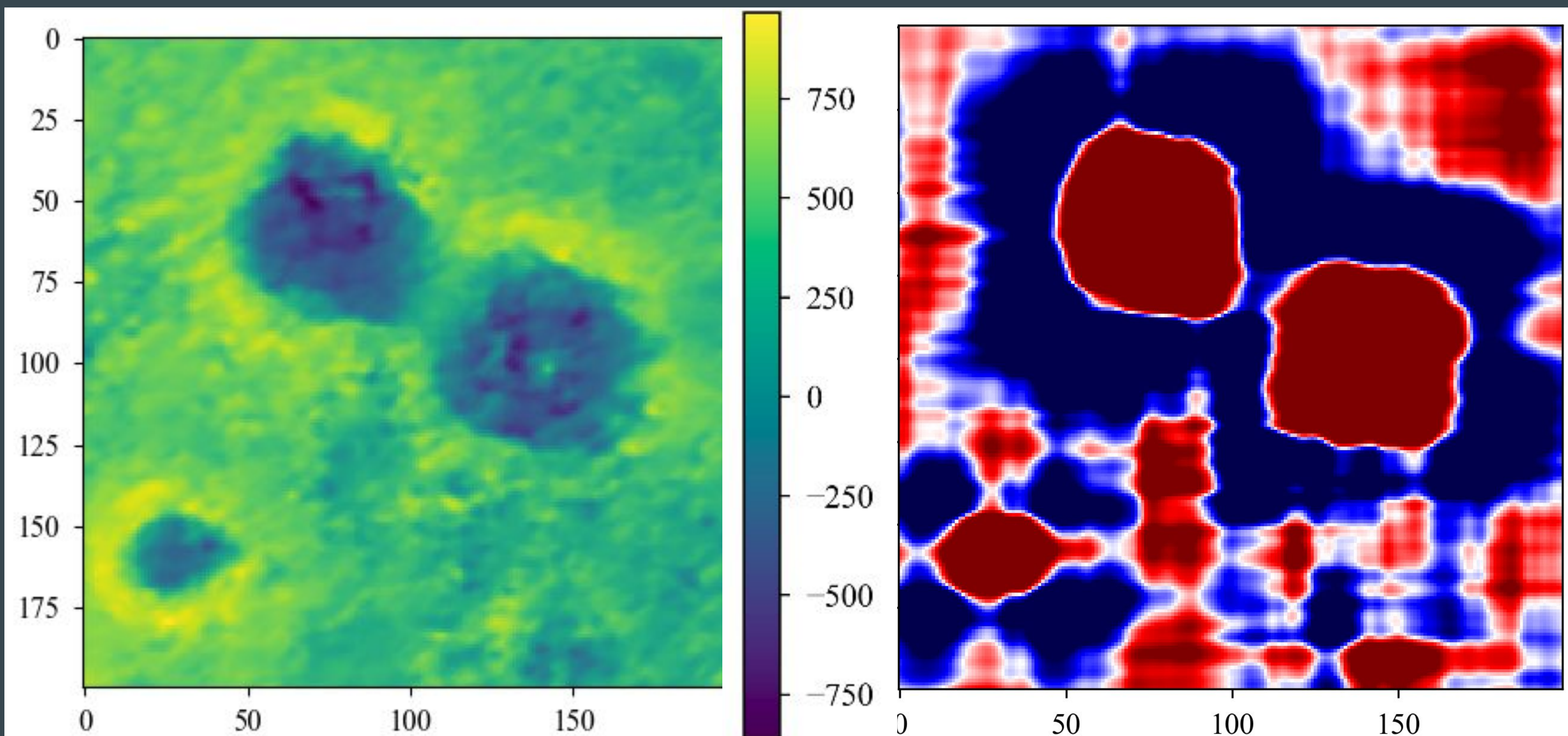
$$C_\lambda(\vec{\mathbf{x}}) = \int\int_Z e^{-\frac{|\vec{\mathbf{x}}-\vec{\mathbf{x}}'|^2}{2\lambda^2}} \nabla z(\vec{\mathbf{x}}') \cdot \frac{\vec{\mathbf{x}}'-\vec{\mathbf{x}}}{|\vec{\mathbf{x}}'-\vec{\mathbf{x}}|} \, d\vec{\mathbf{x}}'$$

Blurs over length scale, λ,...

weights pixels (x’) based on distance from given pixel (x)...

to find how strongly ***gradients*** point toward x.

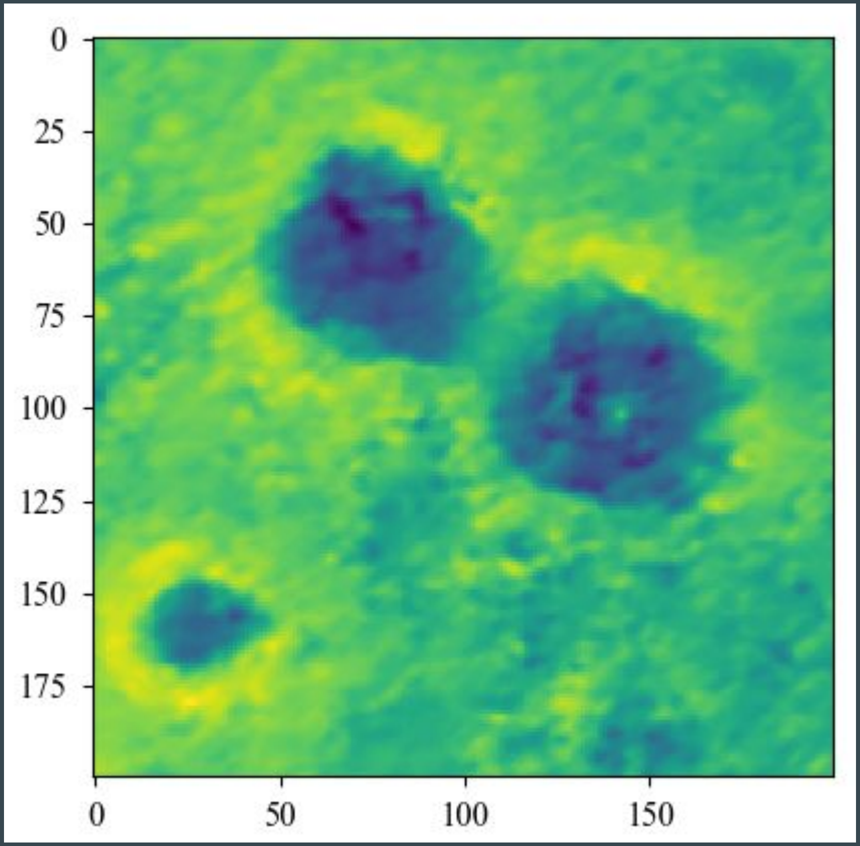
This produces a new image which I apply another gaussian blur to to remove striping...

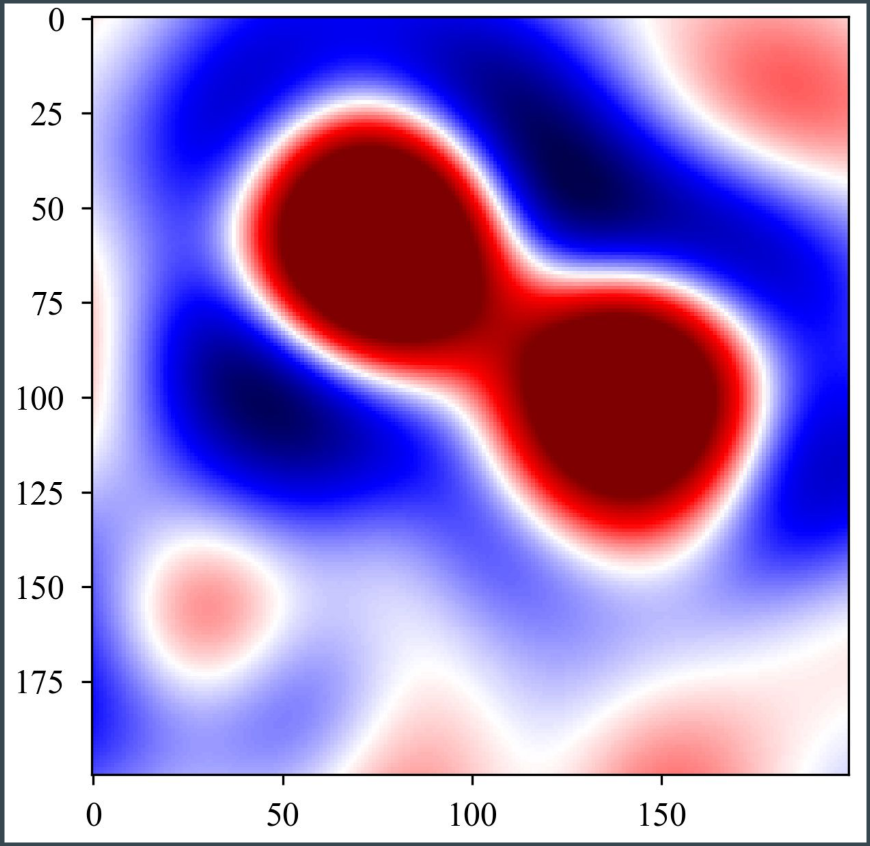


Elevation (km)

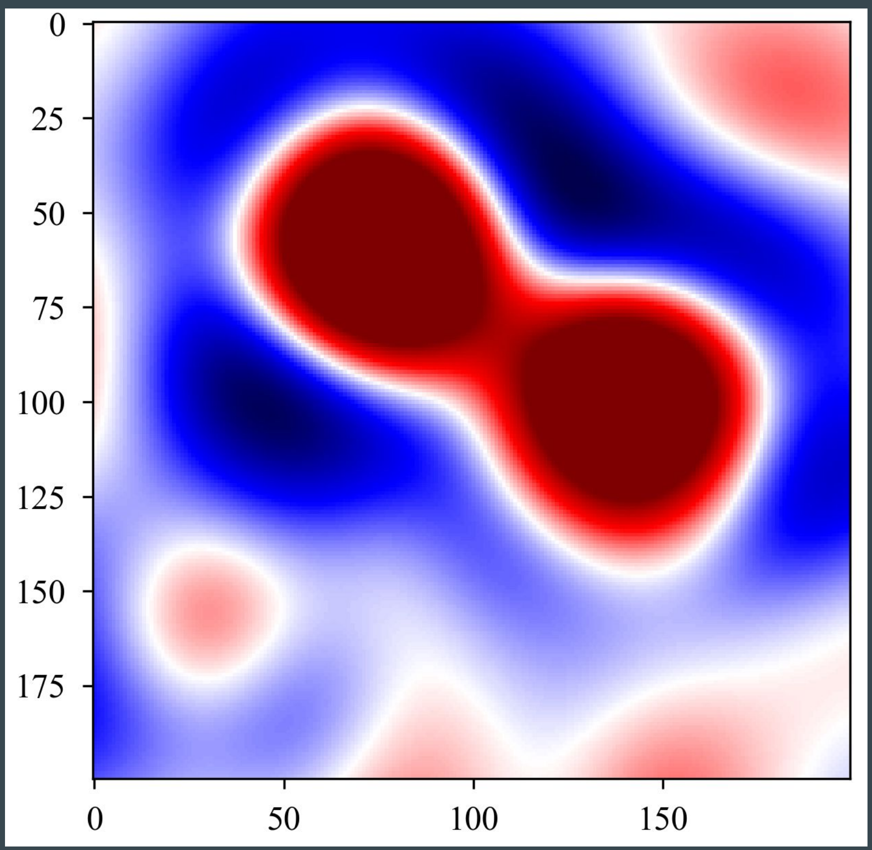
Now we can clearly see how strong the elevation changes around particular points in the image.

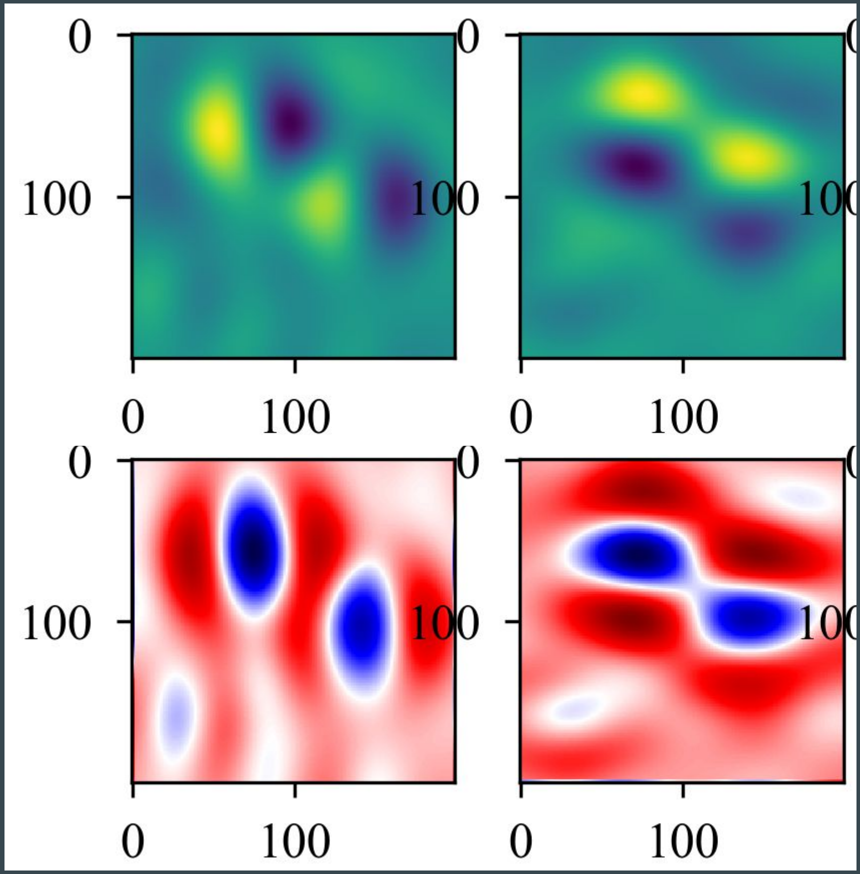
Then we take derivatives to find where it's concave-up.



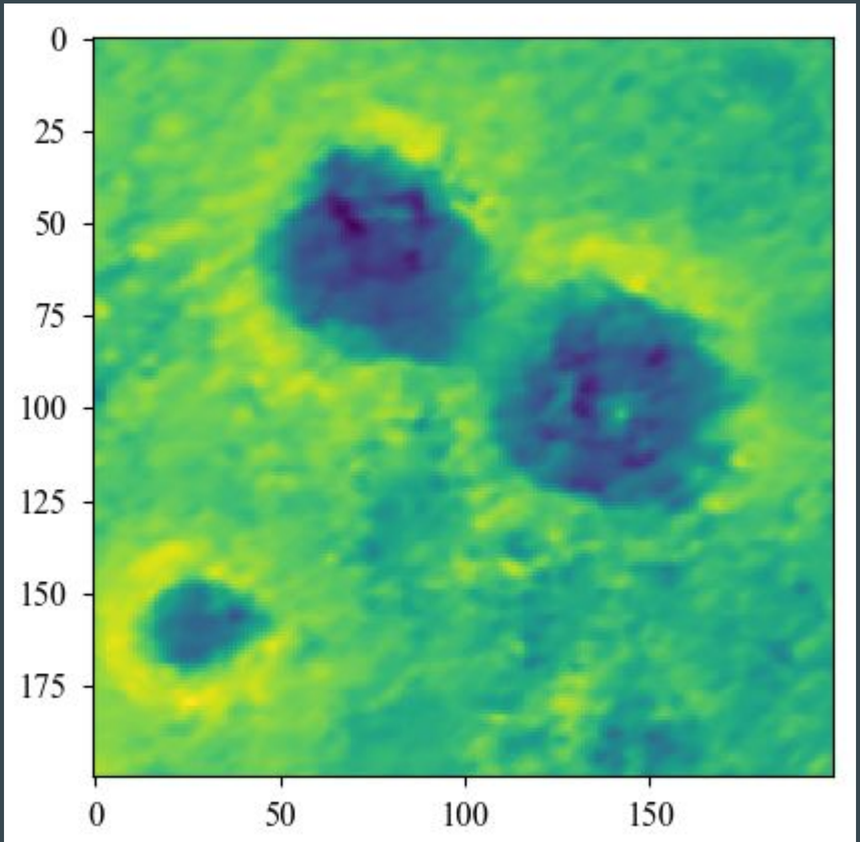


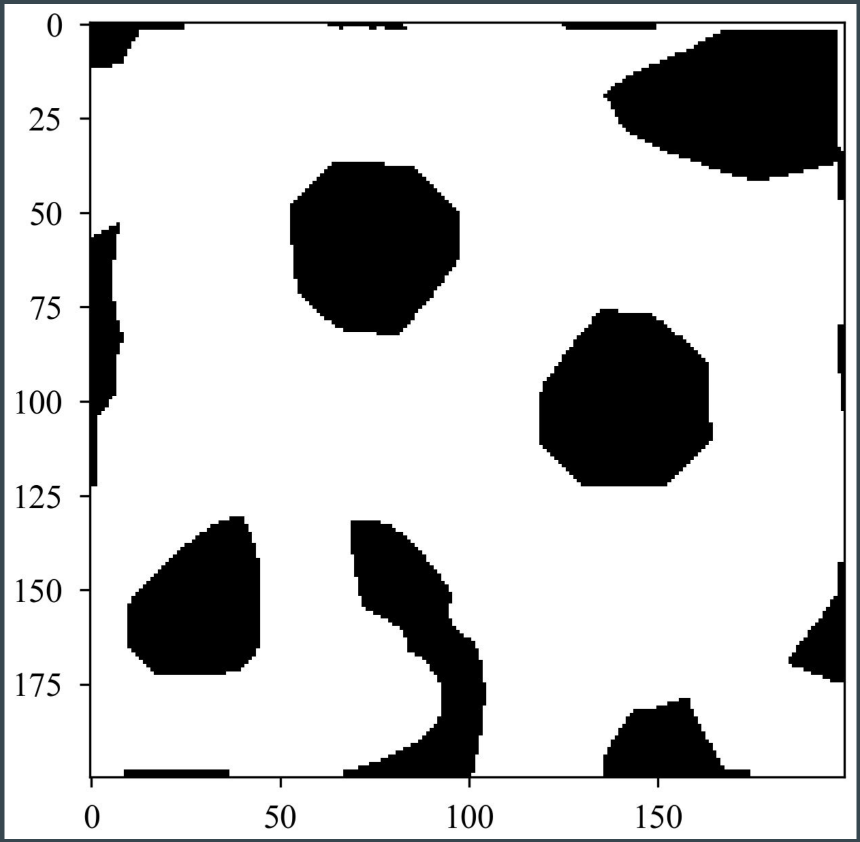
Showing first (top) and second (bottom) derivatives in x and y.
Also take derivatives along diagonals (not shown).



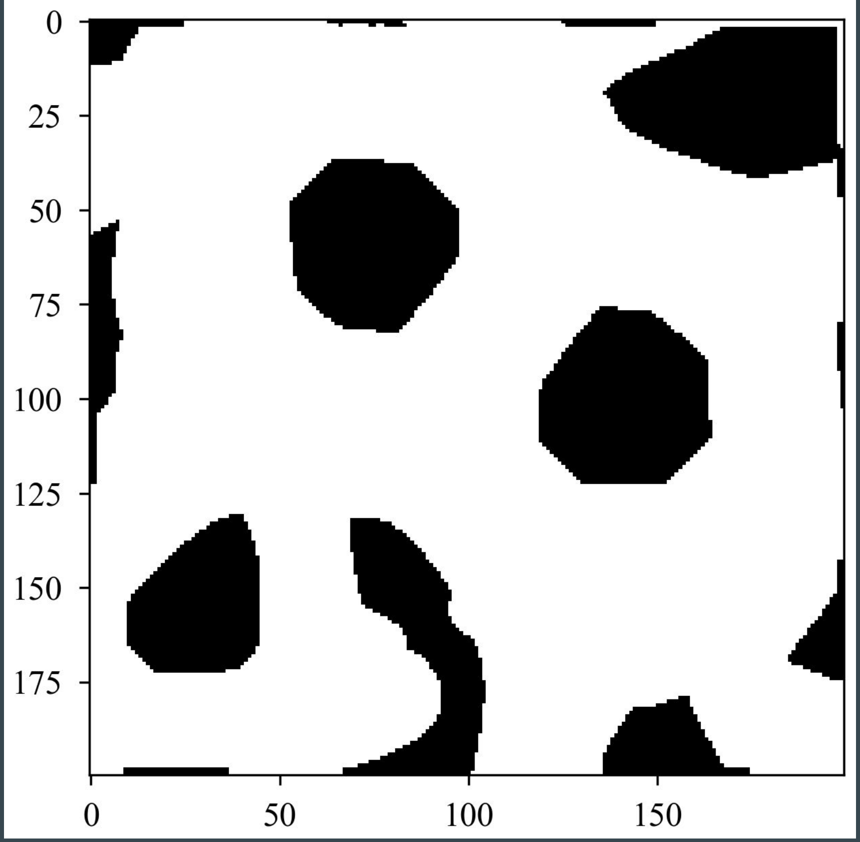


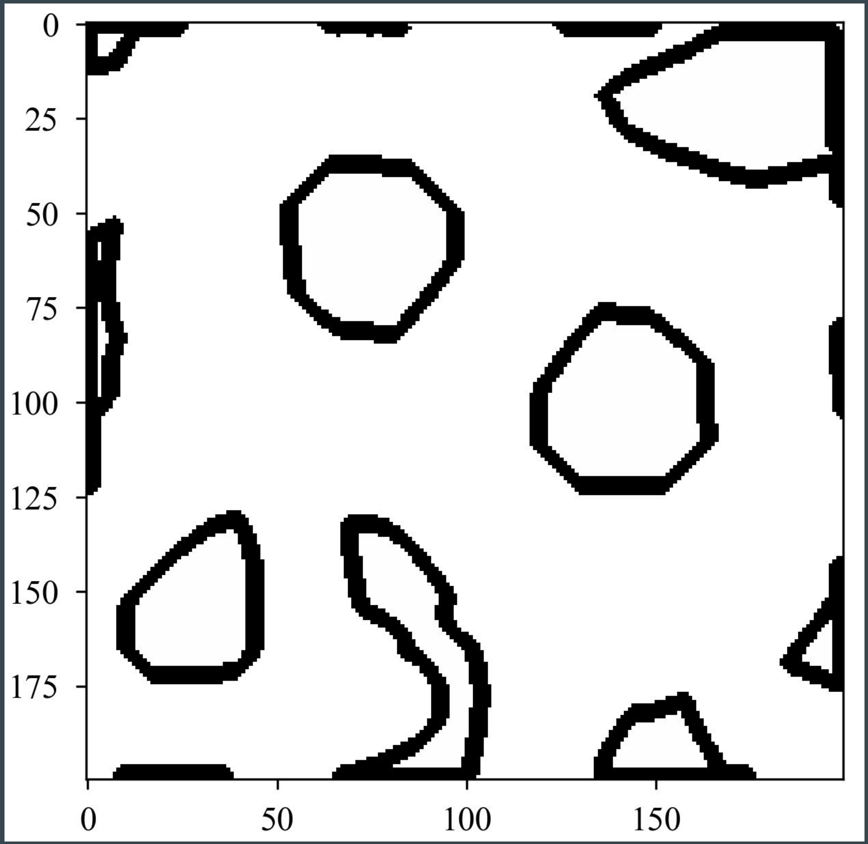
Depressions characterized by all points in image where the second derivative is concave up.



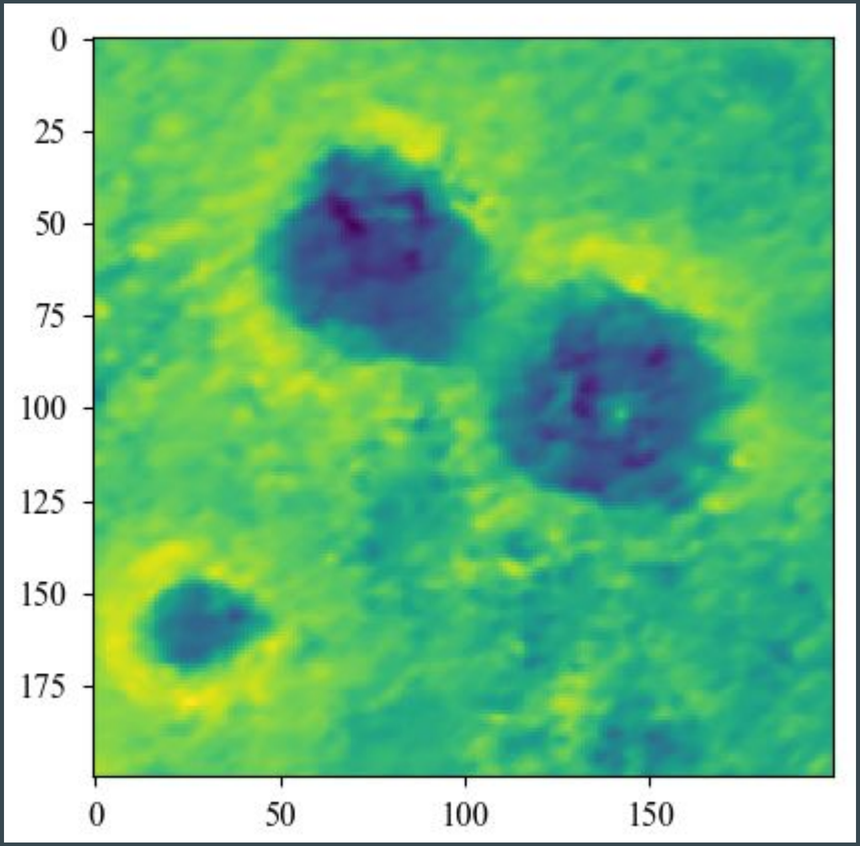


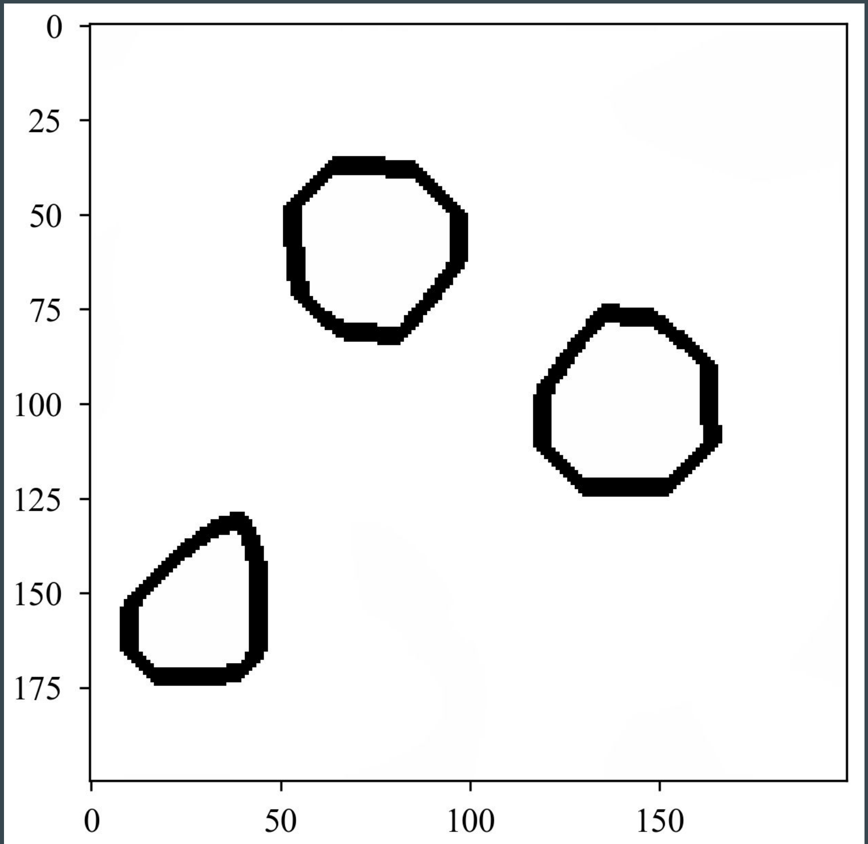
Next, take that binary image (concave up = 1, else = 0) and find the pixel coordinates of the boundaries. I use open source software that extracts contours, gives every point on boundary.





To simplify for now, ignore everything that touches the image boundaries.





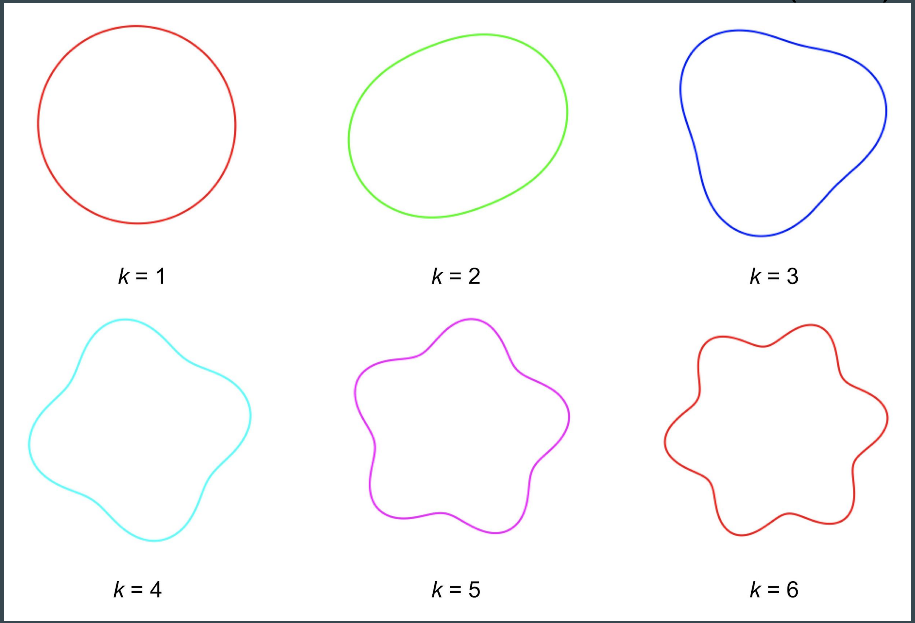
Shape parameters

$$r(\beta) = \bar{r} + \sum_{j=1}^{k} \left[a_j \cos(j \cdot \beta) + b_j \sin(j \cdot \beta) \right]$$

$$a_j = \frac{2}{n} \sum_{i=1}^{n} r_i \cos(j \cdot \beta_i)$$

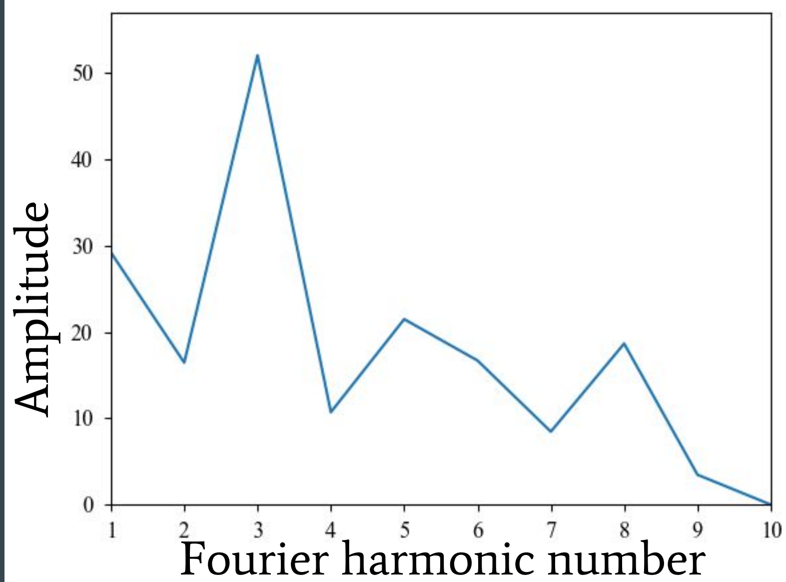
$$b_j = \frac{2}{n} \sum_{i=1}^{n} r_i \sin(j \cdot \beta_i)$$

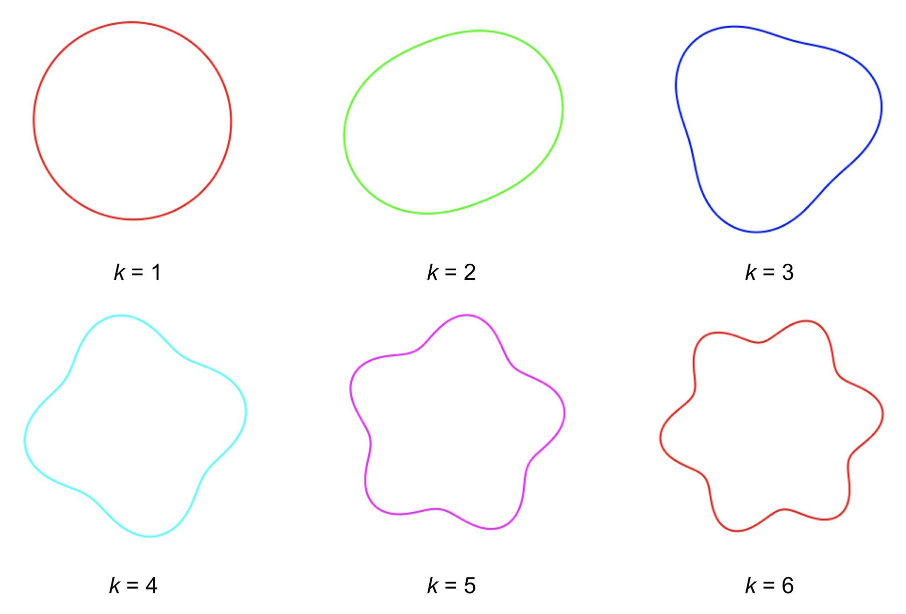
MacLeod (2011)

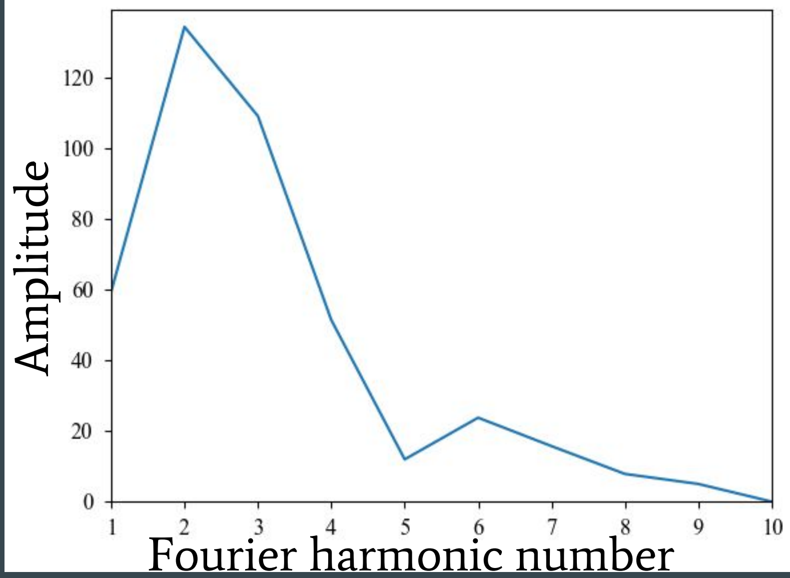


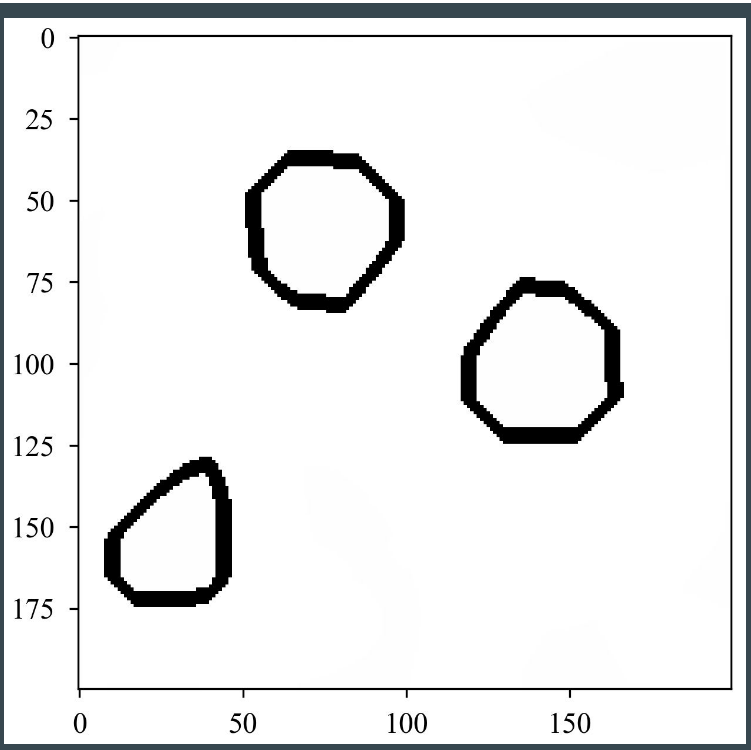
Converting the boundaries into shape parameters is important for a few reasons:

- Can use coefficients to differentiate between depressions that are craters and those that are not (requires a large sample).
- Can reduce description of the crater down to centroid location and several fourier coefficients.

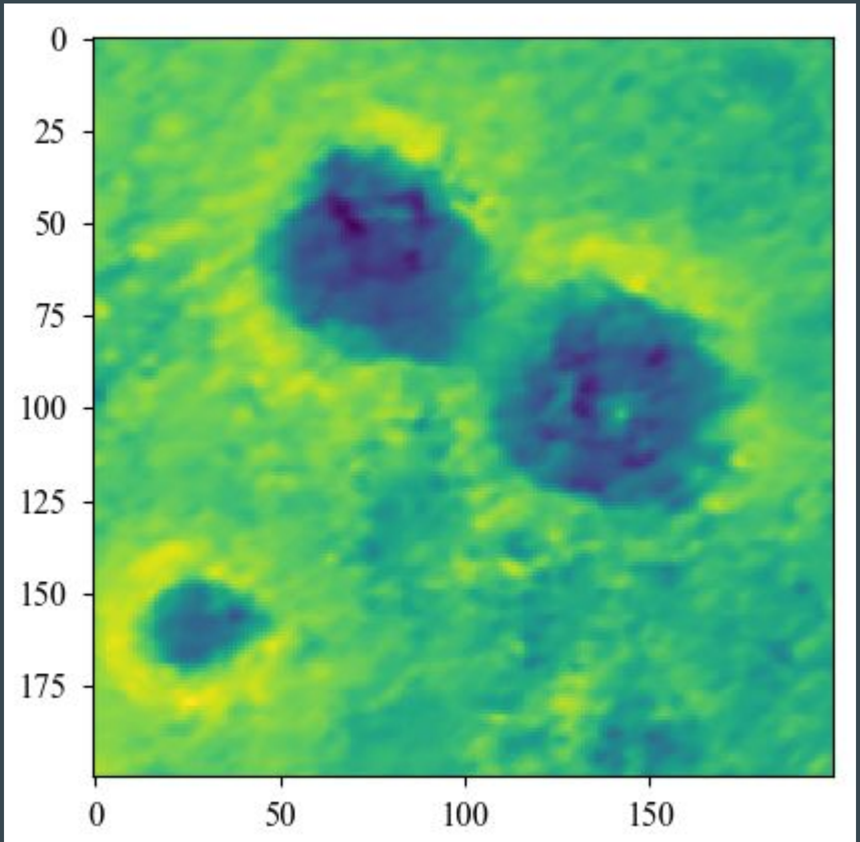

Amplitude
Fourier harmonic number

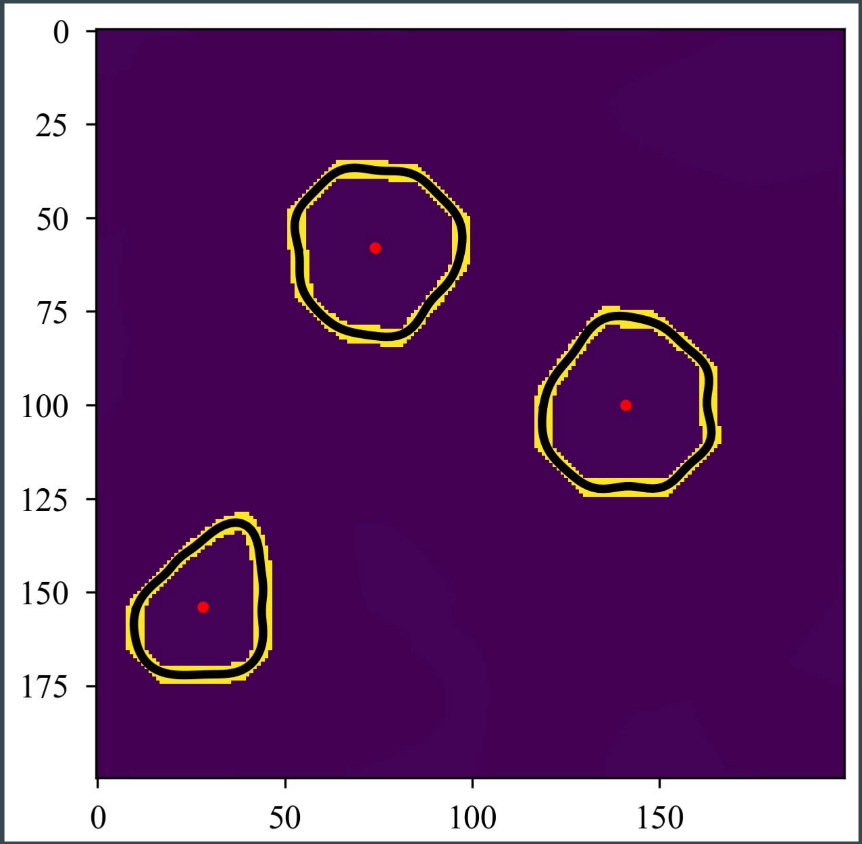

k = 1
k = 2
k = 3
k = 4
k = 5
k = 6

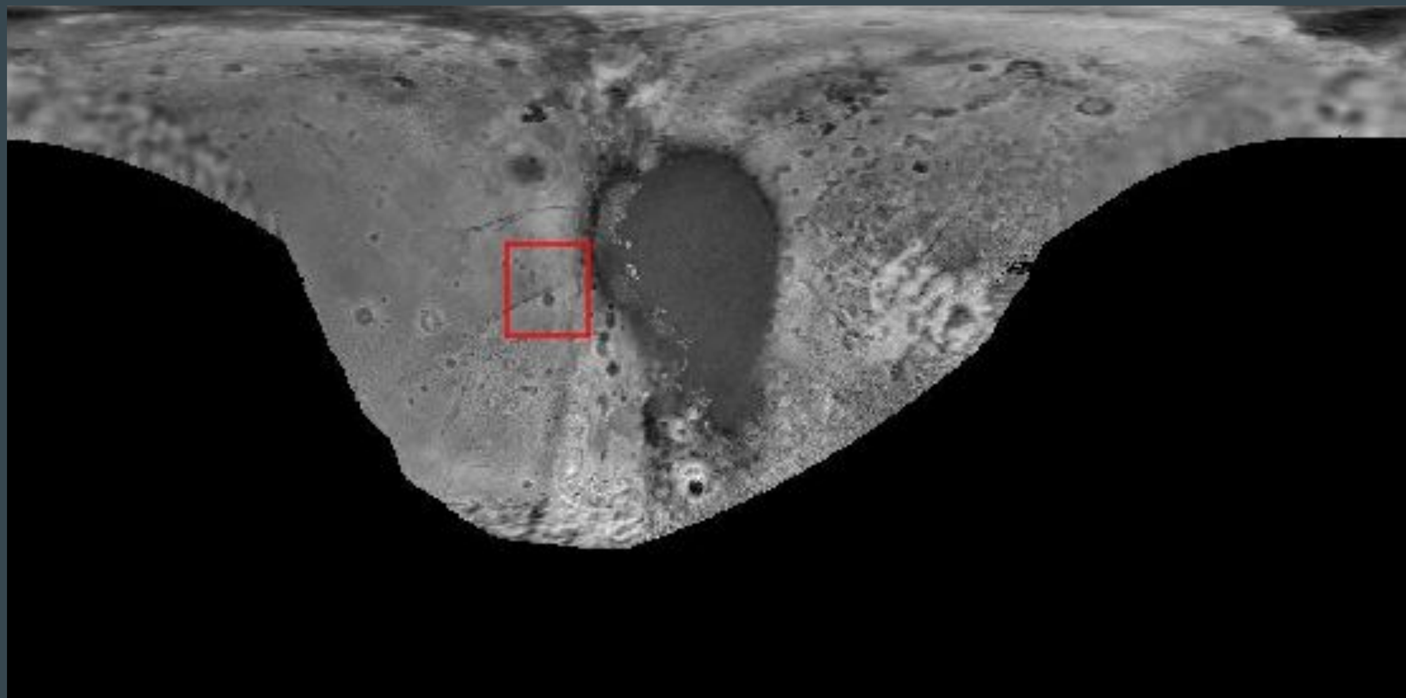

Amplitude
Fourier harmonic number



The shape parameters can be used to reconstruct the perimeters of the depressions.



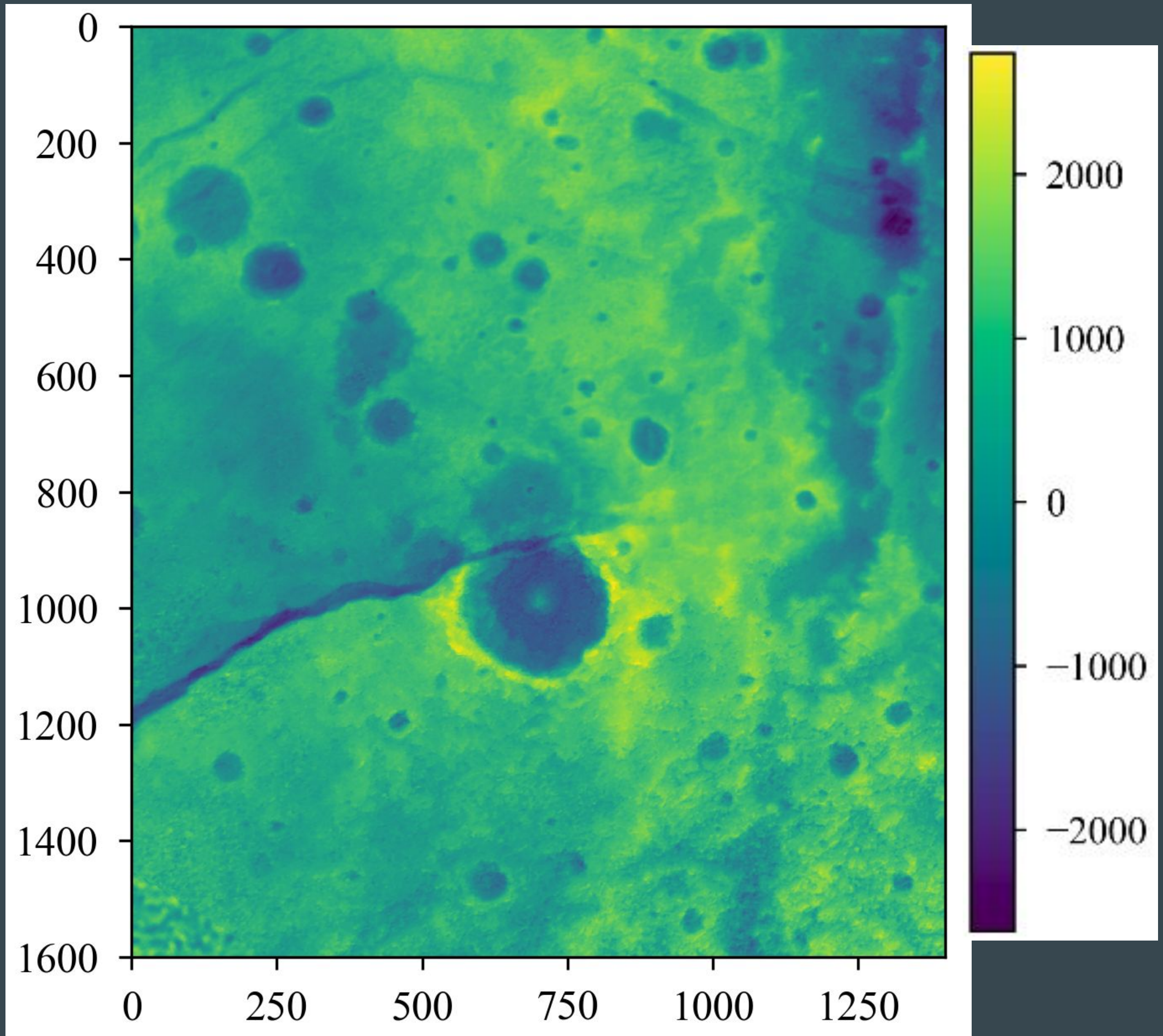




Next step: extend to a much larger region with different crater sizes.

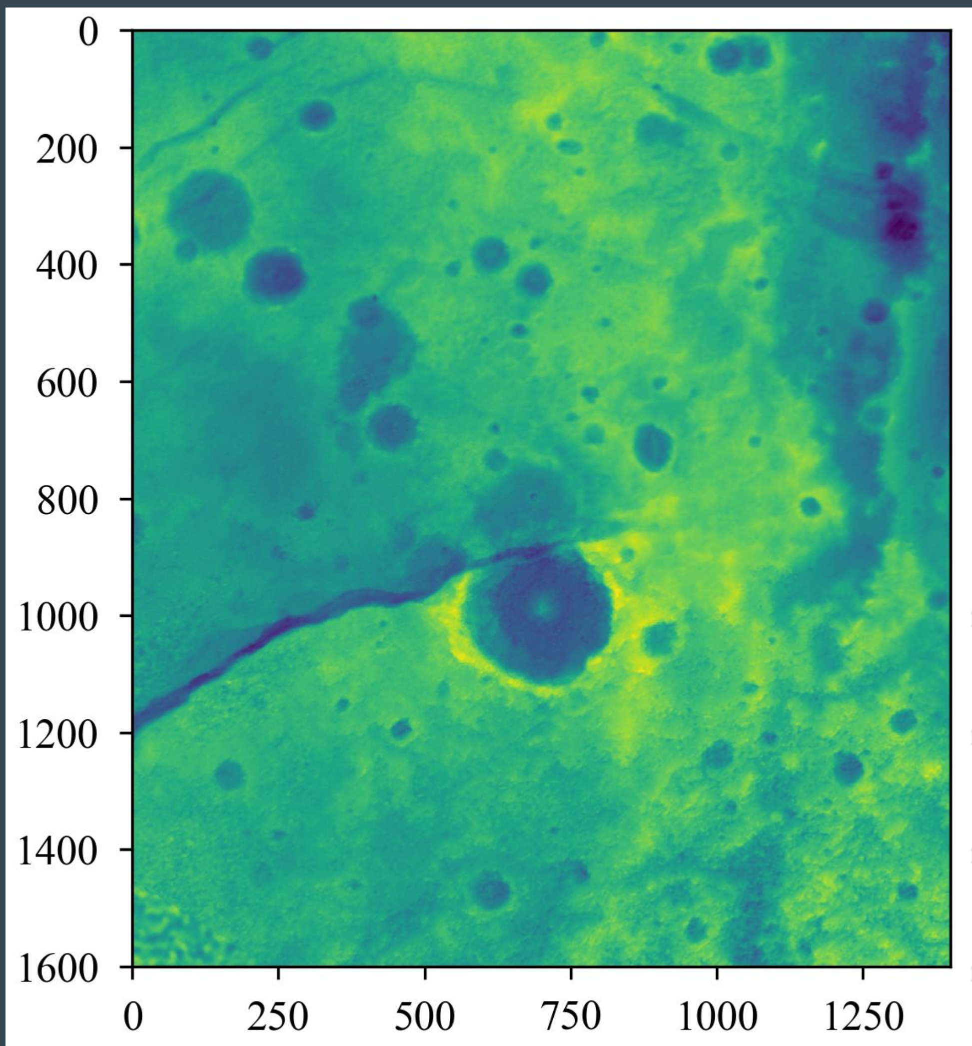
Then, bin the results by diameter to generate a size-frequency distribution.

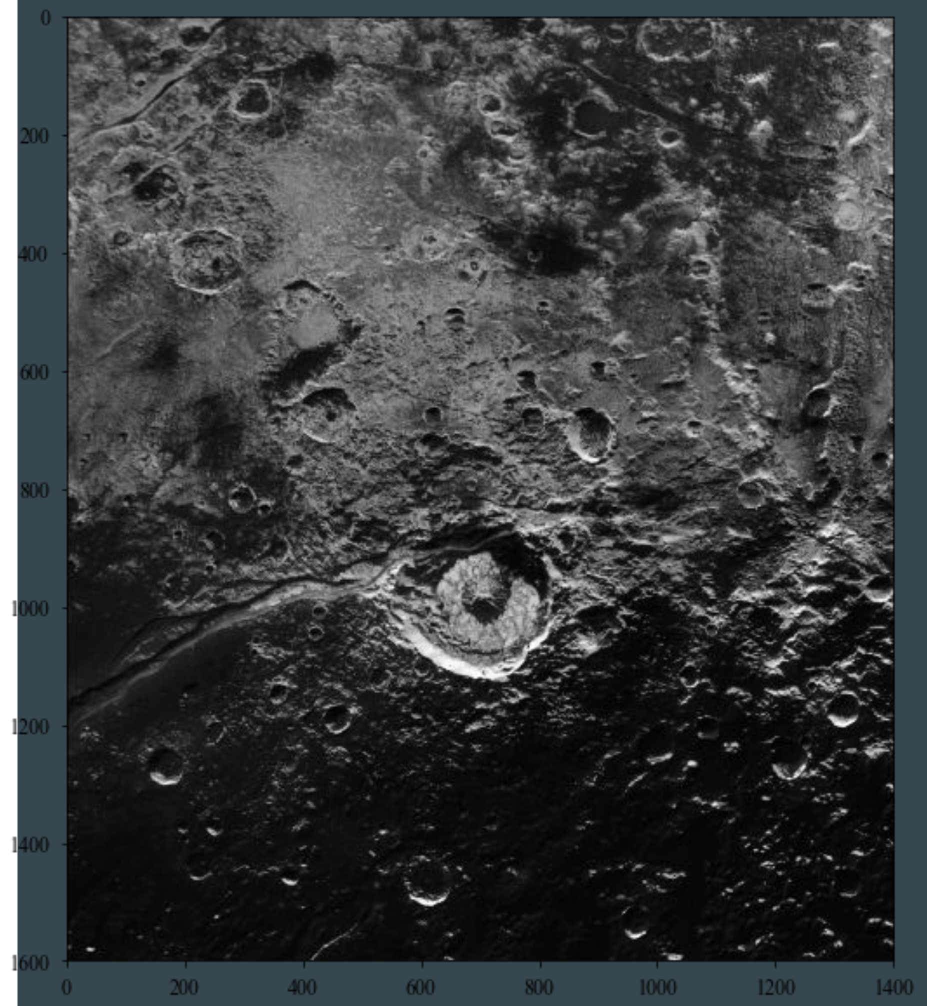
This regions has about 50x more pixels than the previous example and has degraded and complex craters in addition to simple ones.

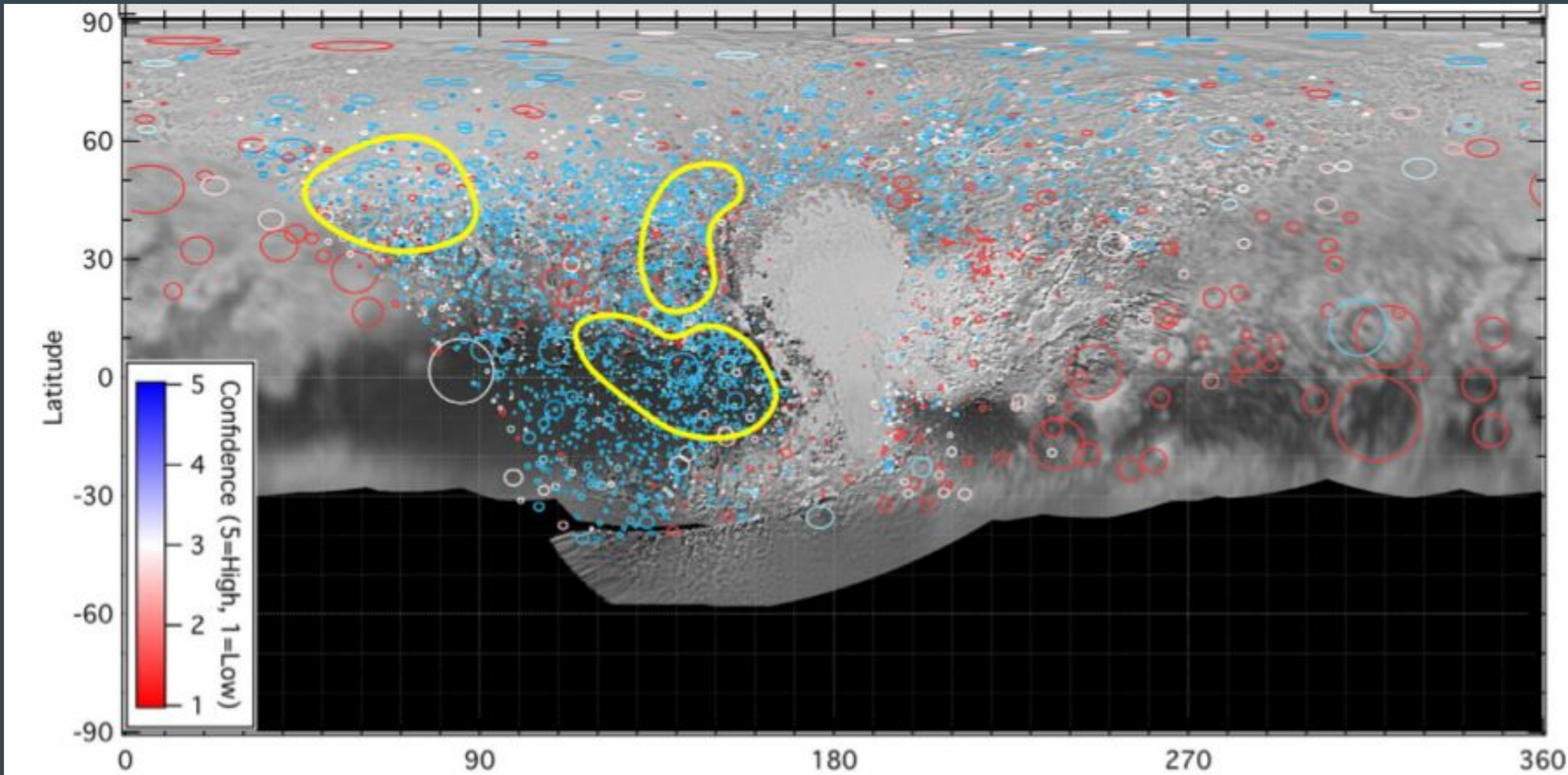


Elevation (km)

This regions has about 50x more pixels than the previous example and has degraded and complex craters in addition to simple ones.

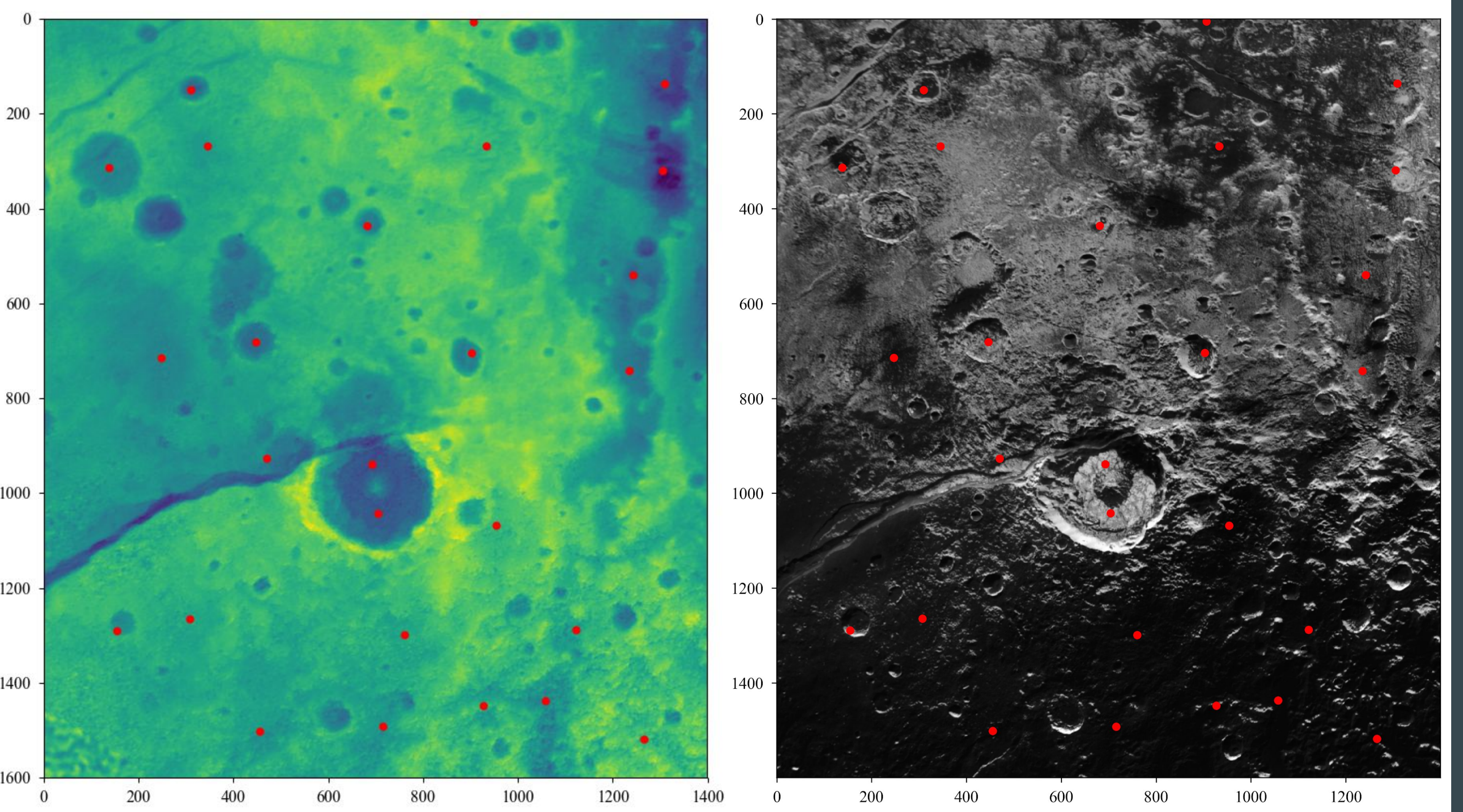






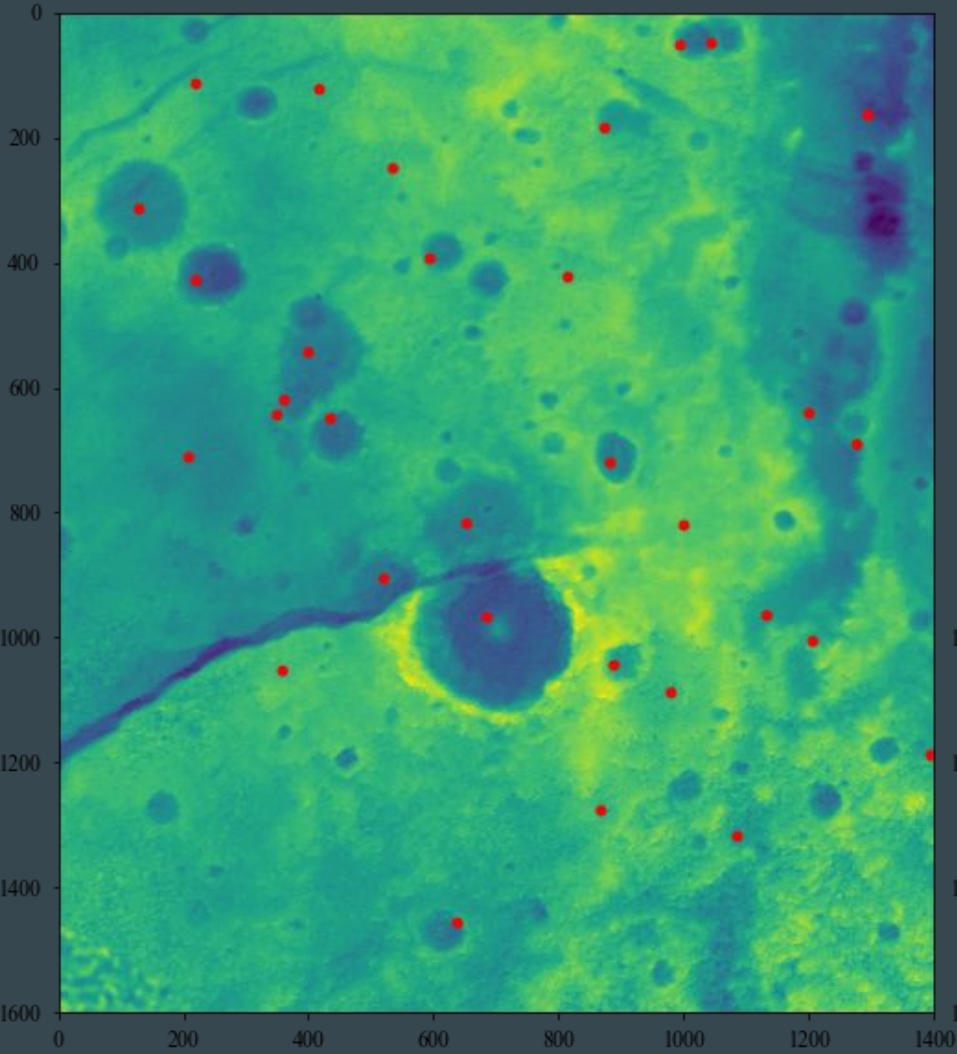
Since I’m not an experienced crater-detector, I turned to the recent manually-identified craters of Robbins et al. 2017.

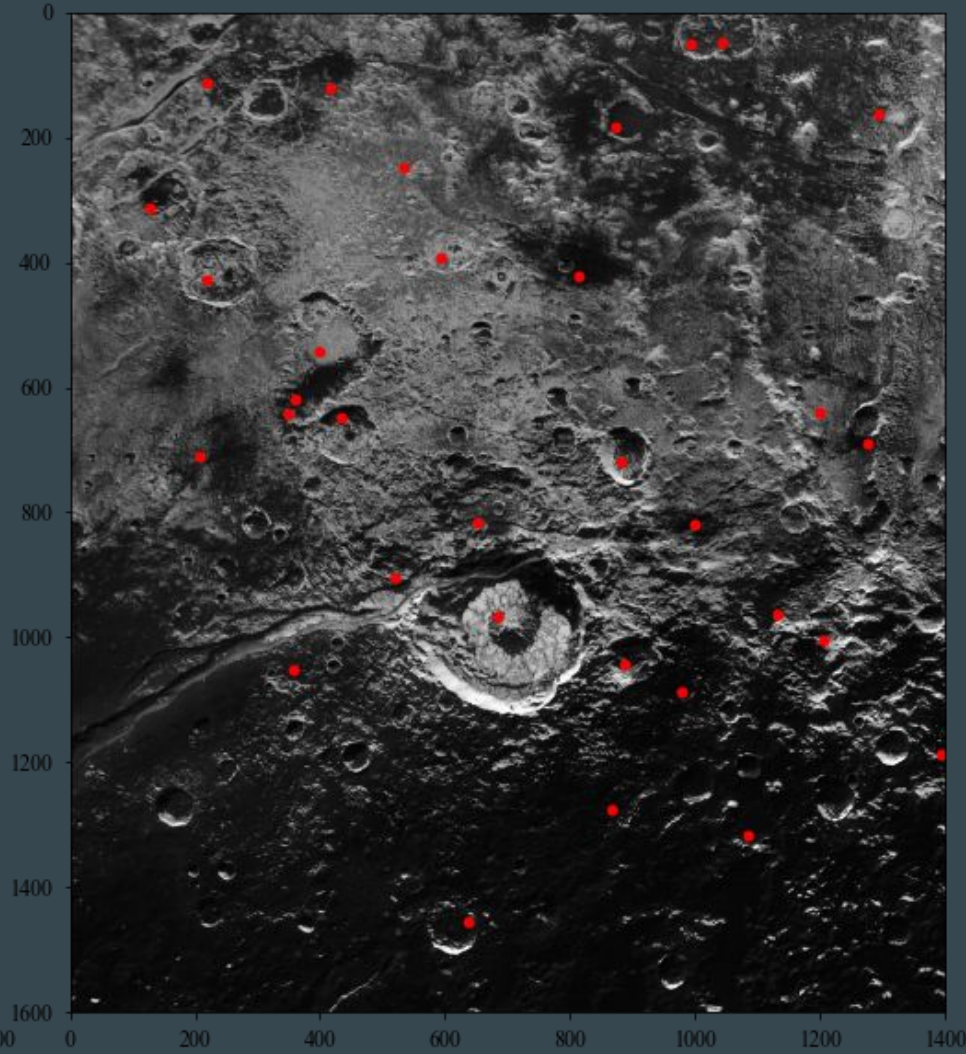
For a length scale of 50, here are the results:



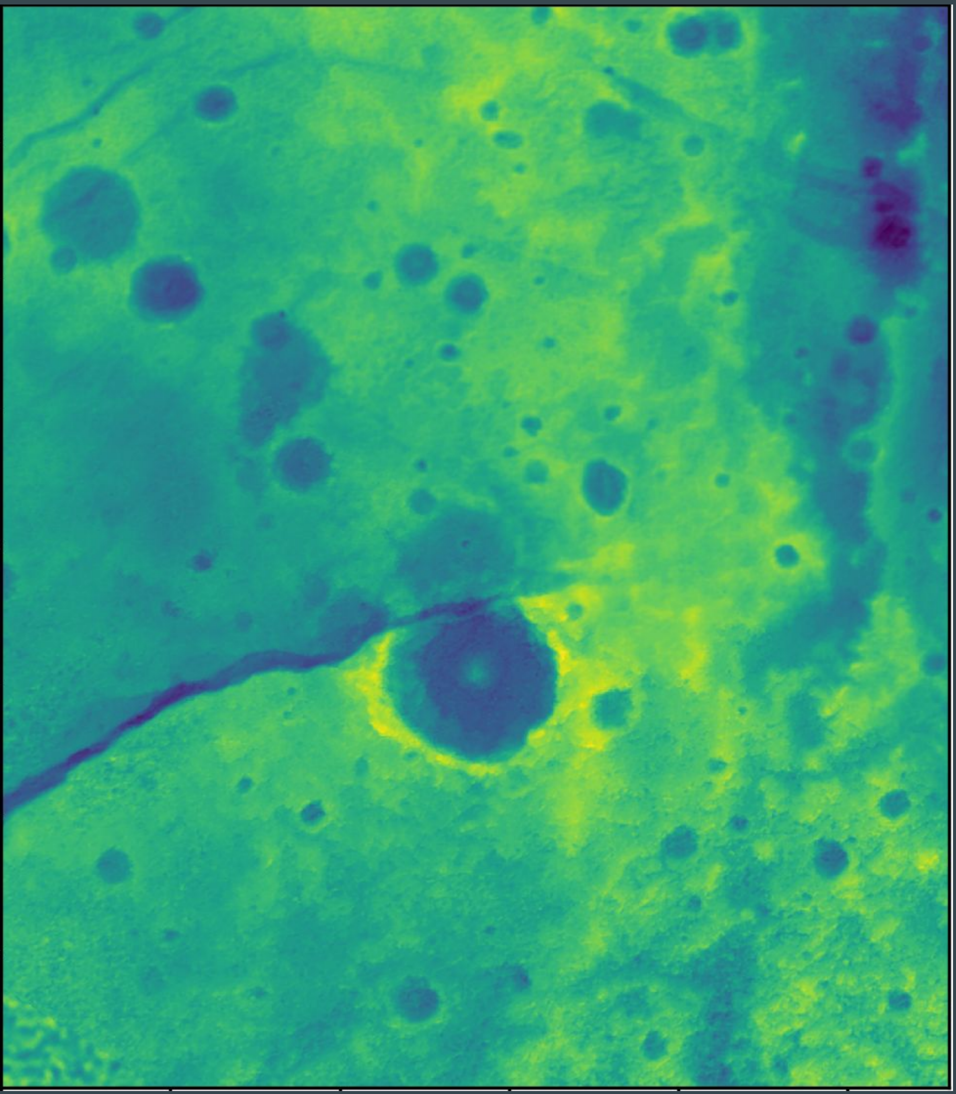
And the Robbins craters with diameters greater than 15 km:

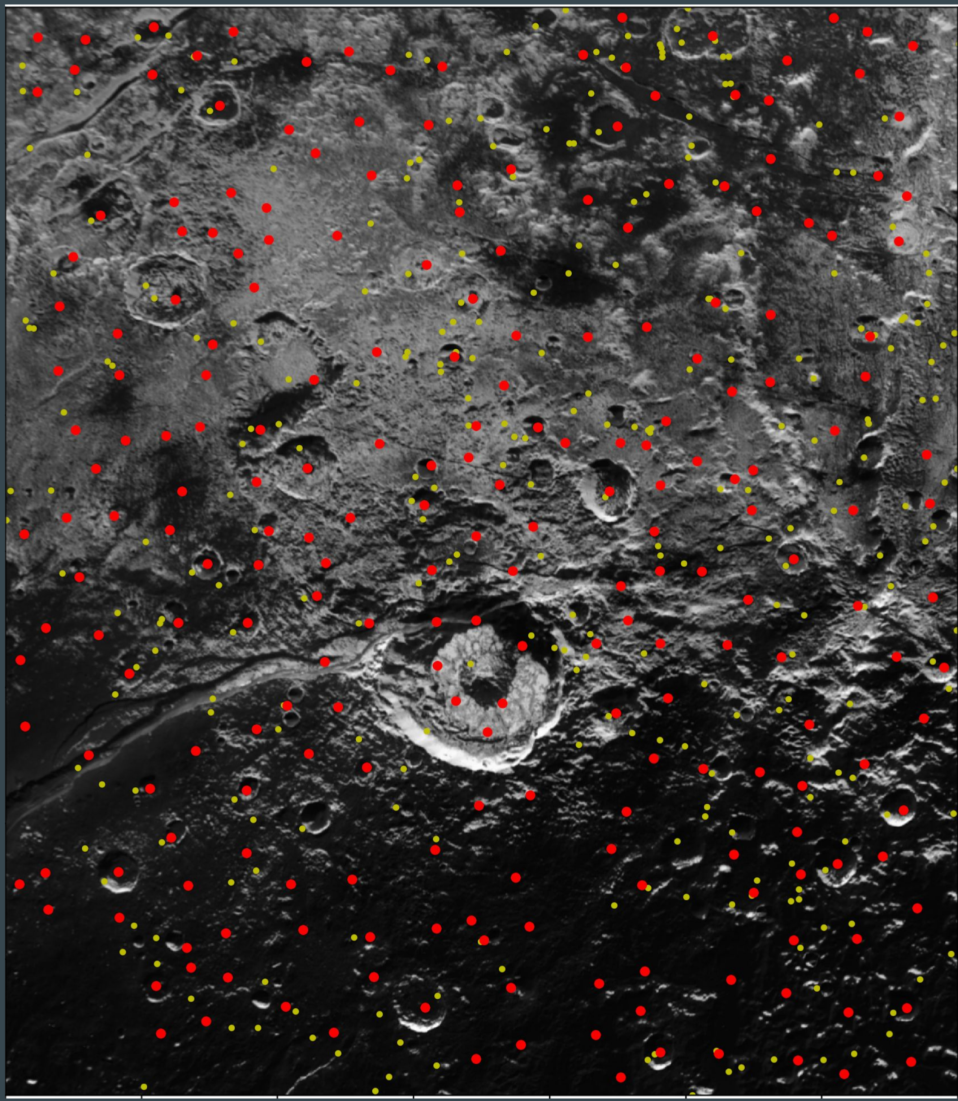
(not quite an apples-to-apples comparison)



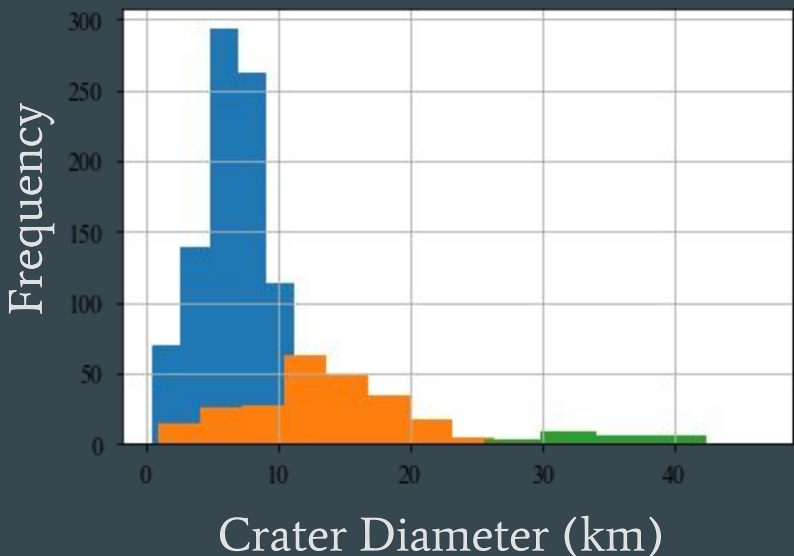


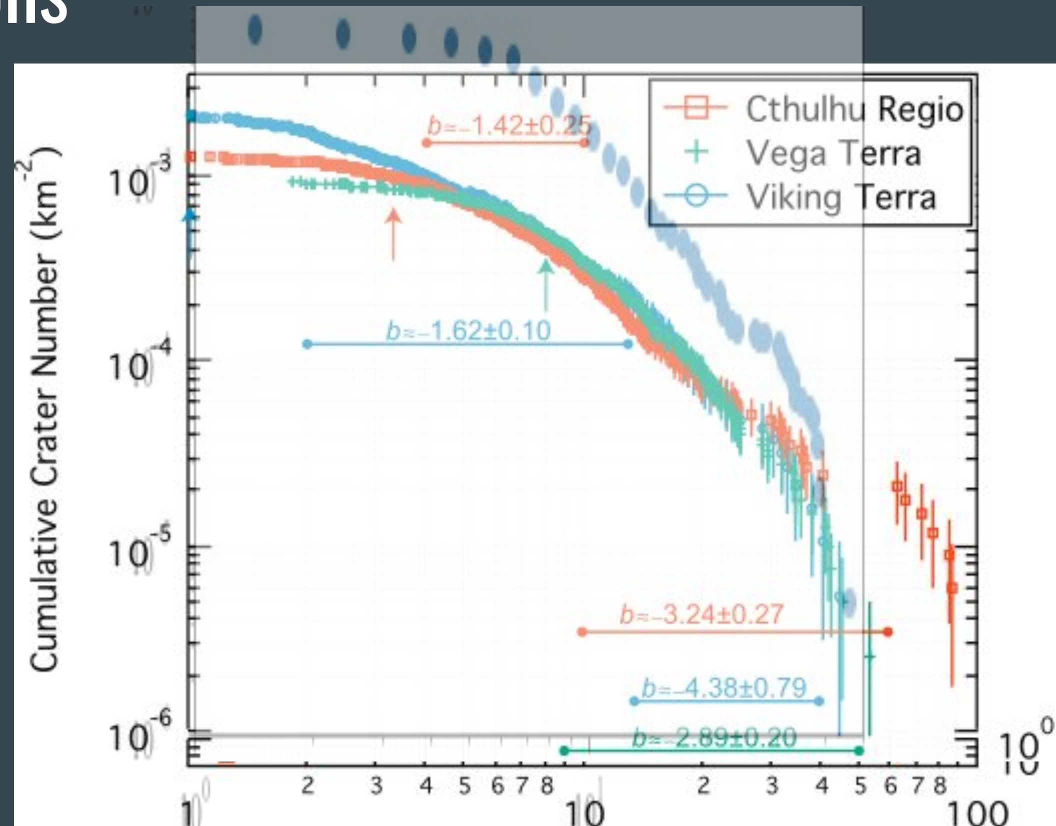
With a length scale of 20 pixels I seem to over predict the number of craters, though there is a lot of agreement.





Size frequency distributions



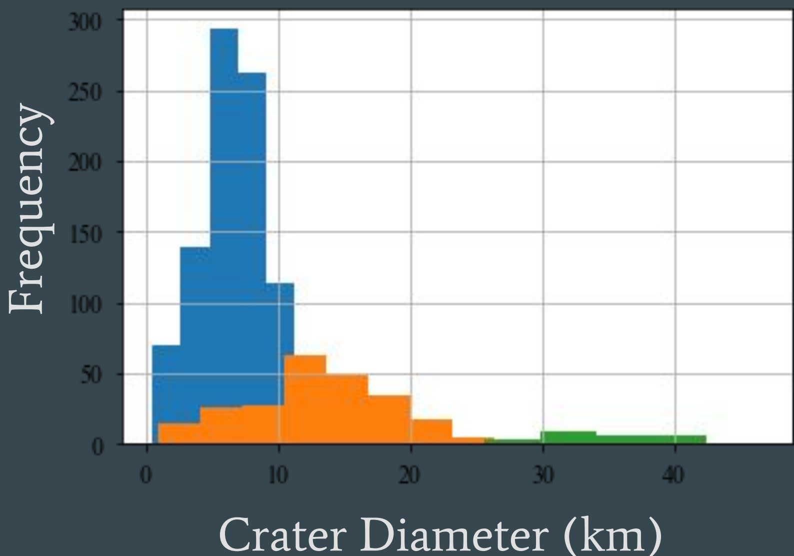


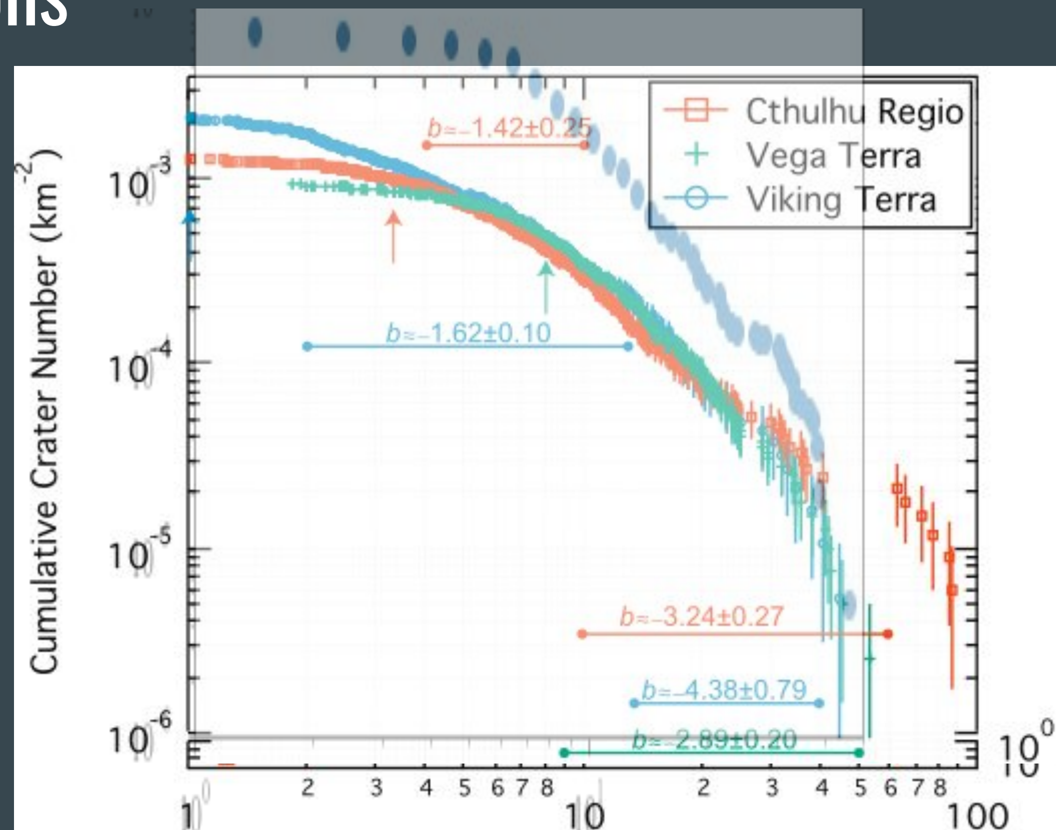
Robbins et al. (2012)

Over predicting everywhere due not rejecting any depressions and to double counting at overlap length scales.

More accurate at larger diameters - fewer spurious results. Some double counting from craters near border of moving window.

Size frequency distributions





Robbins et al. (2012)

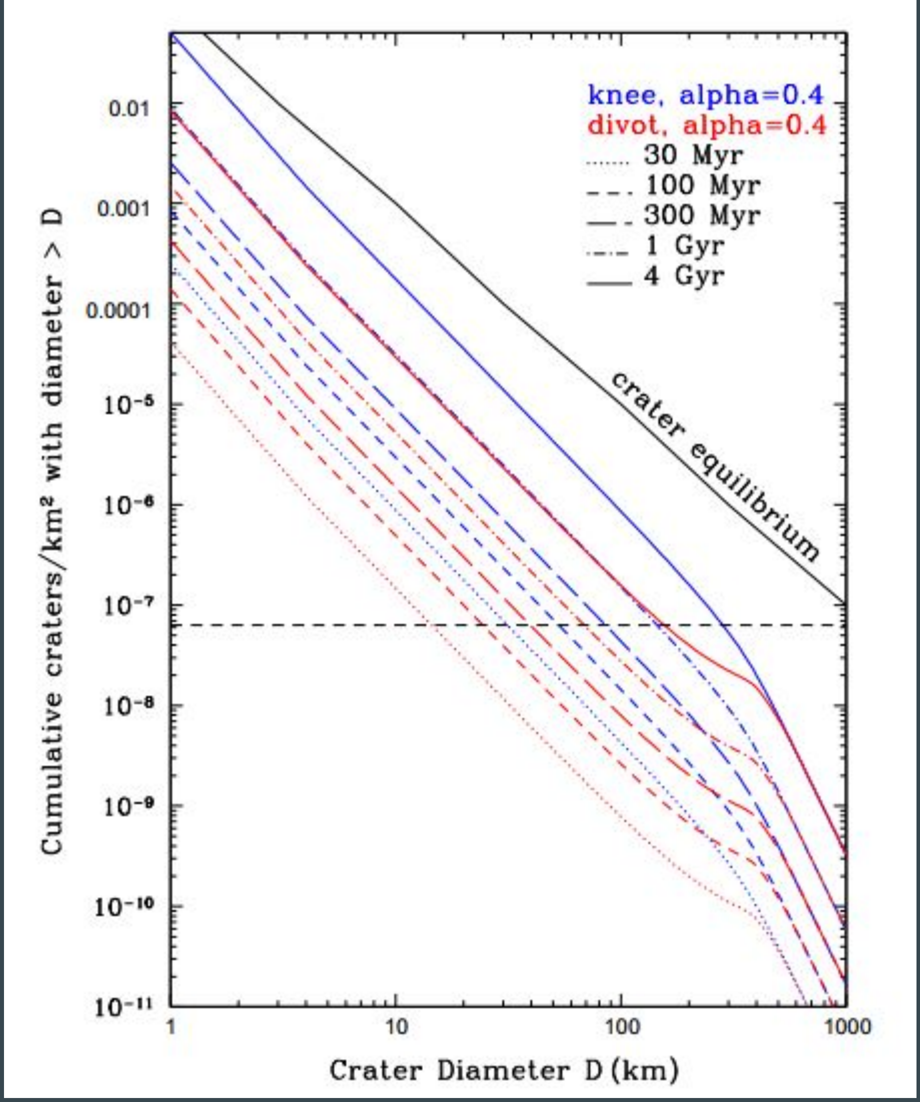
Change in slope seen around 30 km as in Cthulhu Regio (region overlap).

Fit to the differential frequency (7 km < diam < 30 km) gives a slope of -3.7, within range of Robbins et al. values.

Size frequency distributions

Models relying on observed sizes of different populations of KBO objects and dynamical simulations allow an estimate of absolute surface ages.

Unfortunately, more work is needed on cleaning up duplicates and false positives before I can incorporate this.



Greenstreet et al. (2015)

Necessary improvements, future work

Most important - Rigorous comparison of Robbins et al. 2017 database and automatically detected craters to study features that lead to false positives, especially at smallest diameters.

More efficient way to C-transform larger image.

Shape parameters need to be used to reject false positives.

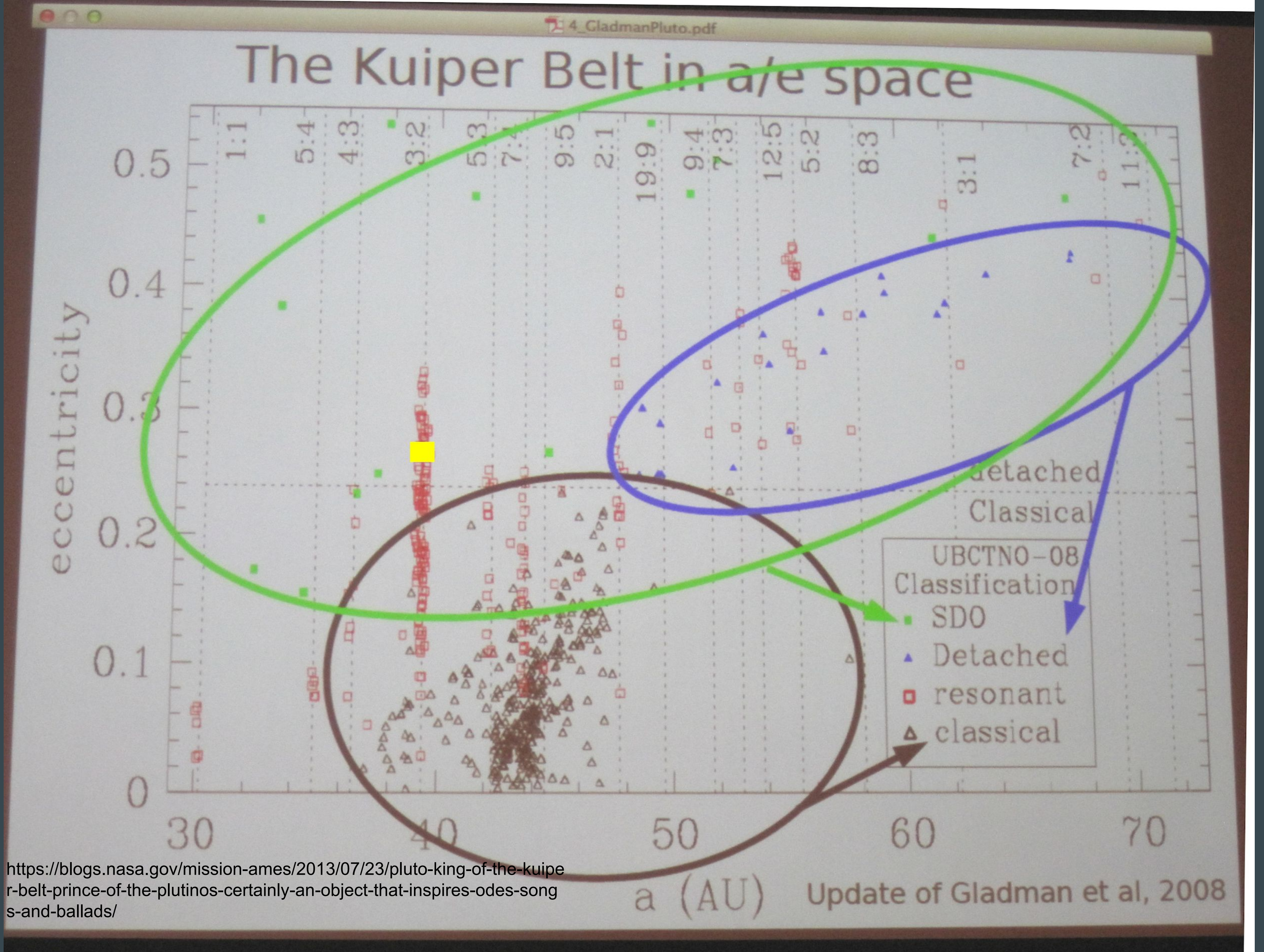
Analysis of shape parameters and depth-to-diameter ratios! Totally new and unique science!

Summary and Conclusions

Though several improvements are necessary, it is clearly feasible to automatically identify craters using DEMs constructed from New Horizons stereo pairs.

False positives need to be dealt with, but once that is done, a global database will be created with diameters, depths, and fourier coefficients to date surfaces and study morphologies.

Thanks for your attention!



https://blogs.nasa.gov/mission-ames/2013/07/23/pluto-king-of-the-kuiper-belt-prince-of-the-plutinos-certainly-an-object-that-inspires-odes-songs-and-ballads/