**Introduction:** The analysis of crater size—frequency distributions and absolute densities forms the basis of current approaches for estimating the absolute and relative ages of planetary surfaces. The techniques depend upon the idea that impact crater formation is a random process, and that its cumulative effect on a given finite area should be characteristic of the age of the surface [1,2,3].

Two assumptions are important for the method to be valid. The first is that the studied surface has a uniform age, i.e. was formed over a period which was short compared to its age. Such surfaces can sometimes be identified rather easily—a lava flow, for example—but in most cases it is less clear. The second is that the crater population should not contain members which cannot be considered to be of independent origin: i.e. anything other than single primary impacts. Fragmented impactor primaries and secondary clusters pollute the population and need to be excluded. Fully (homogeneously) dispersed secondaries may be considered, for the purpose of crater dating, to have a behaviour similar to that of primaries.

The purpose of this work is to suggest the routine use of a spatial randomness analysis, in addition to the more common crater density counts, to ensure that the populations being used for assessing ages—or more fundamentally—assessing the impactor flux, are consistent with the uniformity and independence assumptions.

**Method:** Measuring the randomness of a configuration of craters requires knowing their positions as well as the form of the boundary enclosing them. We do this using the latest iteration of T. Kneissl’s Crater-tools [4]. We then divide up the population into diameter bins (clustering may be present at some scales but not others) and apply some kind of measure which characterizes the spatial distribution of the crater centres. Various measures are possible, such as mean closest neighbor distance (MCND): the ones we find most useful are mean 2nd closest neighbor distance (M2CND) and standard deviation of adjacent area (SDAA) (see [5] for more detail).

It is not easy to interpret the measures directly, since their absolute values depend very much on the influence of the enclosing boundary, which is different in every case. However, by comparing the measured value with those obtained from a series of randomly generated configurations within the same boundary, it is possible to discover how the measured value lies relative to those of the random configurations.

Figure 1 shows the results for two different bins from a single crater count, using two different measures. In Fig. 1a the craters are represented by points; the 2nd nearest neighbors are indicated with lines. The apparent cluster at the NE edge is reflected in the analysis in Fig. 1b: the measured value of M2CND sure occurs towards the clustered edge of the histogram (the left). The same cluster is still apparent in the next bin in Fig. 1c, although less prominently. It is revealed by an analysis using the SDAA measure (Fig. 1d) (for this measure, the right edge indicates ‘more clustered’).

![Figure 1](https://example.com/fig1.png)

**Fig 1:** a) 24 craters from 500m bin, line segments indicate closest neighbours. b) Mean 2nd closest neighbor distance (M2CND) marked with vertical line, superimposed on histogram of 3000 random realisations of 24 craters in the same area. More clustered configurations have a lower value of M2CND c) 7 craters from 710m bin, lines demarcating adjacent areas (the area closer to each crater than to any other). d) Standard deviation of adjacent area (SDAA) marked with vertical line, superimposed on histogram of 1000 random realisations of 7 craters in the same area. More clustered configurations have a higher value of SDAA.

Figure 2 presents a complete randomness analysis, covering the whole range of crater size bins, using two different analysis measures. We see that the measures
are roughly consistent in their indication of clustering, although the SDAA measure is significantly more sensitive. This particular count distinctly shows the presence of clustering over the range 125—500m. When interpreting this plot, it is useful to keep in mind that of truly random configurations, 14% would fall beneath -1 sigma, 2.1% beneath -2 sigma, and 0.1% beneath -3 sigma. A point, therefore, beyond the -3 sigma level indicates clustering with ~99.9% confidence.

Fig 2: Spatial randomness analysis for each bin, measured in standard deviations from the mean, using two different randomness measures (M2CND and SDAA).

**Conclusion:** It is both possible and reasonably straightforward to perform a test of spatial randomness as a routine step in making an analysis of a crater count. To do so permits the exclusion of data which does not satisfy the assumptions of uniformity of the area’s history, or independence of the formation of craters present, by a means which is objective and repeatable. The importance of the method for the analysis of the impactor population is especially emphasized, since such measurements calibrate any system of crater dating.

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