

**POINT PATTERN ANALYSIS OF INTRACRATER DEPOSITS IN WESTERN ARABIA TERRA, MARS.**

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**Introduction:** Common throughout western Arabia Terra on Mars are layered deposits, which have been studied using early Mariner and Viking Orbiter data [1-9] and more recently using Mars Global Surveyor, Mars Odyssey, and Mars Reconnaissance Orbiter data [10-25]. These deposits are both intercrater and intracrater in nature, but analyses of this region suggests that the two may be unrelated, possibly formed by different geological processes [13,19]. Many of the most well-exposed deposits are within impact craters which act as traps, retaining materials that may potentially yield information on past geologic processes and environments that were once active in Arabia Terra.

A variety of formation mechanisms for the layered deposits have been proposed. One study suggests episodic deposition in a terrestrial shoreline-like environment, repeat volcanic ash and dust deposits, erosional unconformities, wave-cut terraces, and thin lava flows as potential processes [16]. Deposits in Vernal crater may have had a lacustrine origin [17-18]. The layered deposits in Becquerel crater may have formed cyclically, caused by Martian obliquity changes [20-21]. Deposits in Crommelin crater may be lobes of extruded salt [22] or pulses of spring-fed travertine-like deposits [23-24]. Other studies have suggested the deposits are ice-cemented dust [19,21] or mixtures of evaporites and cemented sediments from ancient groundwater upwelling [25]. However, there is no consensus on a single common formation mechanism.

Intracrater deposits in western Arabia Terra are widespread. Using a combination of THEMIS IR and VIS, MOC, CTX, and HiRISE images, 45 intracrater deposits were identified in an area between 0°-30° N and 330°-30° E. Of these 45 deposits, 31 have exposed layering. Although information on their aerial extent, layering styles, degree of layering, and other characteristics were collected, the focus for this study is on their geographic distribution. Using points to represent deposit locations in 2-D map space, the nearest neighbor distances (NND) were analyzed for each deposit using standard techniques in point pattern analysis (PPA). The goals were to determine deposit distribution style and any apparent localized trends. The results, implications, and what more can be learned from other data are discussed below.

**Methods:** The approximate center locations of each intracrater deposit were first mapped as points using ArcGIS, a commercial GIS software package. The point locations were then transformed to a sinusoidal equal-area projection centered at the prime me-

ridian to placate map distortion issues. These points, along with the study region area and perimeter were ingested into CrimeStat III, a free geostatistical software program with PPA functionality [26]. Two nearest neighbor methods were then applied.

The first method calculates the statistical number  $R$ , the ratio of the observed average NND and the expected average NND (according to pattern theory) [27-28]. Because  $R$  compares the observed against the expected (random), if  $R > 1$ , the pattern is considered dispersed (uniform) and if  $R < 1$ , the pattern is clustered.  $R$  at higher orders was also calculated to assess the areas between second nearest neighbors, third, and so on [28]. This allows for better interpretation of spatial patterns from local to regional scales.

The second method is an extension of higher order NND analysis, which calculates the statistical number  $K$  (also Ripley's  $K$ ) [28-29]. Rather than using the distance between immediate neighbors, counts of the total number of points falling within fixed radial distances out from each point are used. The difference between the observed and expected (theoretically random)  $K$  values is then calculated with positive values (high) indicating dispersion and negative values (low) indicating clustering. For robustness, 500 Monte Carlo runs of random patterns were generated to compare against the observed  $K$ . The principle advantages of  $K$  are the ability to explore spatial patterns at all scales and usage of all available points. Both  $R$  and  $K$  have expected statistical values that fall under the definition of complete spatial randomness (CSR) [28].

Two issues must be considered when using these methods, sample size and boundary effects. For  $K$ , low sample numbers ( $n < 100$ ) may have a negative effect on the precision of the interpretation [29]. But because the goal is to understand the broad distribution style, strict precision is not of great importance. Boundary effects are generally problematic because 1) points near the boundaries often have greater NND due to closer neighbors outside the area being left out and 2) calculations of expected NND assume CSR over an infinite surface. For calculations of  $R$  and  $K$ , a rectangular edge correction was applied [26]. While edge corrections are not always completely satisfactory, if the main purpose is to detect patterns over a broad area, boundary effects are generally inconsequential [29-30].

**Results and Interpretations:**  $R$  statistic. For both 45 and 31 deposits, calculations of  $R$  from nearest neighbor orders one to six all resulted in clustered dis-

tributions with  $R < 1$  (Table 1). For 45 deposits,  $R$  values continually decreased from orders one to four and then increased slightly at five and six. For 31 deposits,  $R$  decreased at each higher order. From a statistical significance standpoint, all orders are significant ( $Z$  value  $> -1.96$ ) except for the first for both 45 and 31 deposits.

**$K$  statistic.** For both 45 and 31 deposits, calculations of  $K$  at radial distances of  $\sim 8.1$  km resulted in clustered distributions. The first several bins for both groups ( $\sim 40$ -60 km radially from point centers) were ignored with  $K=0$ . For 45 deposits, the observed  $K$  difference, when compared against the expected  $K$  at a 99.5% confidence level shows that clustering is not definitive until a radial distance of  $\sim 113$  km. From this point, clustering remains steady up to 130 km, stops between 130 to 250 km, clusters again from 250 to 510 km, and stops again from 510 km onwards. For 31 deposits (using the same comparison at 99.5%), clustering begins at  $\sim 130$  km, remaining steady until  $\sim 154$  km, stopping between 154 and 243 km, clustering again between 243 and 453 km, and stopping from there onwards.

Thus, it appears that clustering for both groups occur in two distinct regional masses with gaps in between where points are either very few in number or not present at all. Points not definitive for clustering fall within the expected  $K$  range for CSR, suggesting that points at short radial distances are spatially random before clustering is apparent. No localized trends are evident. The distance range for both clustering and stoppage for 45 deposits is generally larger than for 31 deposits, an indication that the distance separation between points is generally larger.

**Discussion:** The result of two distinct clustered masses is intriguing and may indicate separate events in time and/or space in the formation of layered deposits. If so, determination if the events are somehow related to specific formation mechanisms or perhaps a combination of mechanisms would be of interest. The next step beyond PPA is spatial autocorrelation where attributes from other data, in combination with point locations, can be used to determine which attributes more likely to correlate with certain points. As an example, recent work on ancient subsurface hydrology covering Arabia Terra indicates that groundwater upwelling was widespread and possibly a root mechanism in layered deposit formation [25]. Using raster maps of this data, standard autocorrelation techniques [28-29] can be applied to test possible links between rates of groundwater flux and the clustered masses. Future work in this area is anticipated.

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**Table 1.** Results for  $R$  statistic (nearest neighbor)

Order	n	R	Z*	Interpretation
1	45	0.9373	-0.8049	Clustered
2	45	0.8769	-2.2754	Clustered
3	45	0.8536	-3.3389	Clustered
4	45	0.8455	-4.0837	Clustered
5	45	0.8669	-3.9460	Clustered
6	45	0.8648	-4.3997	Clustered
1	31	0.9179	-0.8750	Clustered
2	31	0.8697	-1.9991	Clustered
3	31	0.8697	-2.4651	Clustered
4	31	0.8652	-2.9588	Clustered
5	31	0.8605	-3.4316	Clustered
6	31	0.8557	-3.8999	Clustered

\* Z = statistical significance