Does the Morphology of Alluvial Fan Drainage Basins Reflect their Climate?: A Case Study of Terrestrial Basaltic Fans.

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Introduction: The global occurrence of alluvial fans on the martian surface suggests that Mars was once a wetter place, at least episodically, into the Amazonian [1]. However, we still lack good constraints on the amount of water that built the martian fans and the climate in which they formed. A terrestrial study by Stepinski and Stepinski (2005) [2] suggests that insights into past climate and formation processes may be constrained from the morphology of drainage basins using the circularity function. However, this study did not investigate drainage basins in basaltic terrains or periglacial environments – which is important as Mars is mostly basaltic and leading hypotheses suggest martian fans likely formed in cold and icy climates. Moreover, this study did not characterize the basins of alluvial fans.

Here we use the circularity function of alluvial fan drainage basins in basaltic terrains and different environments to explore whether climate plays a dominant role in fan basin morphology. We also use new insights and algorithms to test and improve the functionality of the circularity function.

Methodology: The alluvial fans investigated in this study were randomly selected in basaltic terrains that span different latitudes and climatic regimes. In total, 294 basins were collected from Iceland, Greenland, Siberia, the Mojave Desert, and Hawai'i islands. The fans were identified using Landsat images (mosaiced by Google Earth and accessed in QGIS) and the basins of these fans were manually delineated as shapefiles. Each shapefile was then used to extract basin elevation data from high-resolution digital elevation models (DEM). For Arctic basins we used the ArcticDEM 2 m/pixel dataset [3], while for the U.S. basins we used the USGS national ⅓ arc-second DEM dataset [4].

The Circularity Function. The circularity ratio is defined as $C = 4\pi \frac{A}{P^2}$ [2]. The circularity function consists of the planform circularity ratio at equi-partitioned slices of elevation across the basin's elevation range. The basin's relief is normalized to be 1, such that $C(z) = 4\pi \frac{A(z)}{P(z)^2},\ 0 < z \leq 1$. Subsequently, $C(1)$ is the planform circularity of the entire basin. The circularity function for each basin was calculated in MATLAB using the TopoToolbox [6]. The perimeter of each basin slice was calculated using an improved algorithm by Prashker (1999) [7] that approximates the smooth perimeter of a raster image.

Hierarchical Clustering. Hierarchical clustering is an unsupervised technique that groups data into pairs on a dendrogram. Hierarchical clustering makes it possible to see natural divisions within a dataset, after which clusters can be judiciously chosen. Ward's method was used for linkage, and Euclidean distances between circularity functions were used to determine similarity [2].

Climate Data. We used mean annual precipitation as our main climate metric for each basin, due to the inferred influence of available water from precipitation on basin formation and morphology [2]. Mean annual temperature and annual temperature range were also considered. The 30 arc-sec CHELSA dataset [8, spanning 1979-2013] was used to extract climate data due to its high resolution, allowing us to collect data within each basin, rather than using a regional data set.

Results: Figure 1 presents the cluster tree calculated from all 294 basins. The nodes found at the bottom of the tree each correspond to at least one drainage basin. The cluster tree bifurcates into two distinct morphological classes (Fig. 1). A manual examination of the basins in each of these classes shows that the basins in the leftmost major branch tend to be more compact, while the ones on the right tend to be more elongate and dendritic in shape (Fig. 1). There are fewer basins in the rightmost side (65 versus 229), but they exhibit more individual variation in circularity, hence pertaining to more nodes. For classifying the basins further, we found it more useful to run the clustering algorithm on each morphological class separately. A focus was thus placed on the 229 more compact basins, as the longer basins exhibit fewer similarities, as reflected in the dendrogram. Based on Figure 1, four sub-classes exist for the leftmost class.

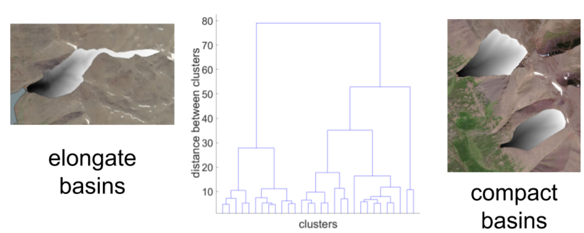

Figure 1: Drainage Catchment Dendrogram with Icelandic Examples

Figure 2 presents each of these subclasses. Basins are colored according to their location. Within each morphological subclass presented above, there is still a large amount of variation. Moreover, it is clear by visual examination that each class itself is somewhat similar, with the circularity of basins in classes 2, 3, and 4, rarely exceeding $\pm 50\%$ of the final basin circularity. It is difficult to visually isolate morphometric classes from these basins and, with the exception of cluster 1, little to distinguish them from one another.

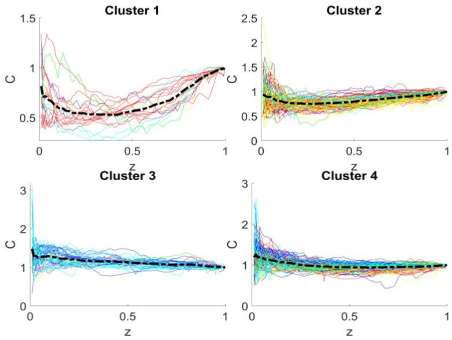

Figure 2: Drainage Basin Clusters

Next, one can compare climate statistics between the clusters. Figure 3 presents these results in boxplot form.

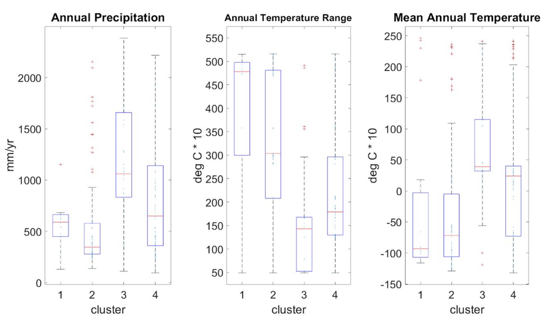

Figure 3: Climate Statistics for Basin Clusters

We then compared climate statistics between the clusters (Fig. 3). As shown in Figure 3, our analysis failed to demonstrate a strong correlation between circularity function and climate within the morphometric sub-classes in Figure 2. An analysis of variance at an α-significance of 0.05 reveals that some clusters in some variables have climate statistics that are different from others. No clusters in any climate variable have different statistics than all others, and the clusters that are different are not consistent across all climate variables.

In order to attempt to reduce dimensionality of the dataset, a principal component analysis was done on the circularity functions. This yielded a primary principal component that explained 86% of the variance, with monotonically decreasing coefficients; clustering basins using only their value on that principal component led to similar results as the clustering from the full dataset. When examining a subset of Andean basins taken from Stepinski and Stepinski (2005) [2] with PCA, the first 3 principal components were necessary to explain the same amount of variance between basins [2].

Discussion: Our results contrast with those presented previously by Stepinski and Stepinski (2005) [2]. In their study larger basins than those explored in our study had circularity functions which visually revealed distinct morphological classes, and typically exhibited distinct variation and features across the basin's elevation range. The PCA and visual examination of the clusters in Figure 2 both suggest that these smaller basins' clusters' greatest variance comes from differences between basins in normalized circularity at low normalized elevations. It is possible that the circularity function is not enough, at least on its own, to connect smaller basins with climate. It is also possible that circularity may relate more directly with the mechanism of formation (e.g., water-carved erosion, frost-cracking, etc.) rather than the climate.

Moreover, while the DEMs used are high resolution, the drainage basins' small size makes the pixel-count of each basin relatively low compared to the basins in Stepinski and Stepinski (2005) [2]. A preliminary analysis of a subset of basins from Stepinski and Stepinski's Andean sample using SRTM 1 arc-second DEMs [9] resampled to various lower resolutions, suggests that lower resolution can lead to significant differences in the calculated normalized circularity function.

Conclusion: Our study suggests that the circularity functions of small drainage basins (~0.1-1.2 km in length), like those of alluvial fans, do not have clear trends with mean annual precipitation. However, it is possible that they instead reflect other environmental conditions or basin formation processes. Future work will focus on expanding our basin database and constraining the minimum DEM resolution and basin size needed for accurate analyses with the circularity function.

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