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Insights into the dynamics of planetary interiors obtained through the study of global distribution of volcanoes I: Empirical calibration on Earth

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ABSTRACT

The distribution of volcanic features is ultimately controlled by processes taking place beneath the surface of a planet. For this reason, characterization of volcano distribution at a global scale can be used to obtain insights concerning dynamic aspects of planetary interiors. Until present, studies of this type have focused on volcanic features of a specific type, or have concentrated on relatively small regions. In this paper, (the first of a series of three papers) we describe the distribution of volcanic features observed over the entire surface of the Earth, combining an extensive database of submarine and subaerial volcanoes. The analysis is based on spatial density contours obtained with the Fisher kernel. Based on an empirical approach that makes no a priori assumptions concerning the number of modes that should characterize the density distribution of volcanism we identified the most significant modes. Using those modes as a base, the relevant distance for the formation of clusters of volcanoes is constrained to be on the order of 100 to 200 km. In addition, it is noted that the most significant modes lead to the identification of clusters that outline the most important tectonic margins on Earth without the need of making any ad hoc assumptions. Consequently, we suggest that this method has the potential of yielding insights about the probable occurrence of tectonic features within other planets.

1. Introduction

Over the past three decades, it has been increasingly recognized that the spatial distribution of volcanoes might provide insights concerning the size and shape of the magma source, the mechanisms of magma production, and the state of stress in the crust at specific locations on Earth and other planets. Earlier studies focused on the detection of vent alignments within a volcanic field (e.g., Lutz, 1986; Wadge and Cross, 1988; Connor, 1990), later including also descriptions of the degree of clustering displayed by the vents (e.g., Connor and Hill, 1995; Lutz and Gutmann, 1995; Martin et al., 2004; Weller et al., 2006; Kiyosugi et al., 2010; Capello et al., 2012; Connor et al., 2012). Many studies of this type have focused on determining the distribution of volcanic vents over a single volcanic field at a time (e.g., Lutz, 1986; Connor, 1990; Connor and Hill, 1995; Bernhard Spörli and Eastwood, 1997; Weller et al., 2006; Kiyosugi et al., 2010; Mazzarini et al., 2010; Negrete-Aranda et al., 2010; Cebriá et al., 2011), but others have examined the spatial distribution of vents over larger areas, always constrained by specific tectonic features such as one oceanic plate (Conrad et al., 2011) or a particular type of plate tectonic boundary (de Bremond d'Ars et al., 1995; Favela and Anderson, 1999). At a still larger scale, a few descriptions of the distribution of volcanoes over the entire planetary surface have been made, although in those cases attention has been selectively addressed to larger volcanic edifices, or to other types of structures assumed to be the surface expression of specific tectonic features such as mantle plumes (e.g., Crumpler, 1993; Crumpler et al., 1993; Crumpler and Revenaugh, 1997; Magee and Head, 2001), or involving bodies with special constraints concerning the mechanisms of magma production (Kirchoff et al., 2011; Hamilton et al., 2013).

The diversity on the aim of studies devoted to explore the characteristics of the spatial distribution of volcanic centers or vents, is also found in relation to the tools that have been used with such a purpose. Among the various tools that have been used to study the spatial distribution of volcanism, one of the most versatile is the kernel estimation of spatial density contours (Diggle, 1985; Silverman, 1986; Tsybakov, 2009). Unlike other methods aiming to detect alignments within a distribution of volcanoes (Kear, 1964; Ancochea and Brändle, 1982; Lutz, 1986; Wadge and Cross, 1988; Ancochea et al., 1995; Hammer, 2009; Negrete-Aranda et al., 2010), kernel functions are useful in the context of statistical exploratory analysis because they provide a fast and efficient form to assess the degree of skewness and multimodality of the data. Nevertheless, kernel functions have been limited until now to study the distribution of volcanoes within the boundaries of a specific monogenetic volcanic field, and the kernel functions used on those studies (Cauchy, Epanechnikov and Gaussian) have been taken among kernels originally designed to explore the characteristics of data distributions over planar surfaces. Very recently, Cañón-Tapia (2013) extended the list of usable kernel functions to include one specifically

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designed to study distributions of objects found over the surface of spheres, known as the Fisher kernel. More importantly, Cañón-Tapia (2013) showed that it is possible to take advantage of the characteristics of the kernel method to assess the occurrence of clusters that might have physical (geological) significance at various spatial scales, an approach that hitherto has remained almost unexplored in the volcanic context.

In a series of three papers, we explore the spatial patterns that might be defined by the distribution of volcanic activity over the entire surface of three bodies on our solar system (Earth, Venus and Io) by adopting the Fisher kernel. Although the three papers adopt the same approach to study spatial distribution patterns of volcanism at a global scale, each of the two planets and moon presents individual challenges and provides different insights into the dynamics of planetary interiors that need to be addressed separately.

In this paper (the first of the series) we expand the exploratory method described by Cañón-Tapia (2013) formalizing a methodology that can be used in other planets to establish a hierarchy of volcano clusters. The use of the methodology is illustrated by applying it to characterize the global distribution of volcanoes around the Earth where it is shown that clusters identified with this method have direct tectonic interpretations that do not require the introduction of any type of ad hoc geological or tectonic inputs during data analysis. In the second paper (Cañón-Tapia, 2014, Insights into the dynamics of planetary interiors obtained through the study of global distribution of volcanoes II: Tectonic implications from Venus. Submitted to JVGR), the methodology developed here is applied to explore patterns in the volcanism of Venus. Both similarities and differences on the volcano distributions of the twin planets are discussed on that paper, and implications of the global volcano distribution concerning resurfacing models on that planet are also presented there. On the third paper (Cañón-Tapia et al., 2014, Insights into the dynamics of planetary interiors obtained through the study of global distribution of volcanoes III: Implications from Io. In preparation), attention is focused on the study of volcano distribution and mechanisms of magma generation on Io.

2. Basic principles of spatial density estimations

2.1. Probability density functions and multimodality

Probability density functions (PDFs) are mathematical abstractions that can be used to make predictions about the future outcome of a repetitive event for which past outcomes have been documented. From a mathematical point of view, PDFs have well defined characteristics, and can be represented by a formula that associates a unique output with a unique value of a continuous variable that is used as input. The formula might include one or more parameters that determine the general shape and other characteristics of the PDF. The most popular PDFs are characterized for having only one maximum value, or peak. In these cases, the PDF is said to be unimodal, and its peak is associated to the most probable value that a variable can take. The most familiar example of this type of functions is the Gaussian distribution.

In many cases the PDF might seem to have more than one peak, in which case the function is said to be multimodal (bimodality is a special case of multimodality in which the number of modes is equal to two). Multimodality on a PDF might arise due to a combination of several statistical subpopulations, clustering of data, or even non-linear diffusion processes (Comparini and Gori, 1986). Alternatively, it also can be attributable to some undetected bias on the sampling or as an artifact of data processing. Nevertheless, regardless of its origin, the identification and correct interpretation of multimodality always represents a dilemma.

On the one hand it is desirable to identify multimodality when it exists, but on the other hand it is unwise to give too much importance to apparent modes that might be caused merely by random fluctuations in the data, or as an artifact of the sampling used to construct the PDF (Minnotte, 1997). For this reason, different techniques have been devised to test for the multimodality of a data set (e.g., Good and Gaskins, 1980; Hartigan and Hartigan, 1985; Izenman and Sommer, 1988; Davies and Kovac, 2004). Unfortunately, tests of this type have been designed for univariate data sets, and do not avoid entirely the problems associated with the determination of multimodality in multivariate situations (Ahmed and Walther, 2012).

For complex situations where there are few clues concerning the number of modes expected from the distribution, it is preferably to adopt an empirical approach in which no previous assumptions concerning the number of modes is made. Actually, it is in those situations where an exploratory method based on kernel functions can become particularly useful. Thus, to fully understand the form in which kernel functions should be applied in those cases it is convenient to examine their properties in some detail, as done in the next section.

2.2. Basic principles of Kernel functions

A kernel function is defined to include two parts: One is an ordinary single peaked PDF (herein called the PDF generator) and the other is a parameter that has been variously called “weight function”, “window width”, “bandwidth”, “smoothing parameter” or “smoothing factor” (Silverman, 1986). Although the PDF generator of most kernel functions is symmetrical around its peak, the final description of the observations might be a non-symmetrical, multimodal PDF. The reasons for the apparent independence between the PDF that describes the observations and the shape of the PDF selected as the generator of the kernel function reside on the procedure followed to obtain the final description of the observations. Such a procedure consists of two main stages.

First, a “partial” PDF is associated to each and every observation forming the original data base. Each partial PDF has the same form than the PDF generator, it is centered at one of the observations, and has a width determined by the specific value of the smoothing parameter that has been selected by the operator. For example, if the PDF generator is the Gaussian distribution, each of the partial PDFs centered at each of the observations in a given data set has its maximum value at the observation point, and it has a width that can be described by resorting to the levels of confidence marked by one or two standard deviations. Nevertheless, it must be remarked that the standard deviation in this case does not apply to the whole collection of observations, and in fact, there is no simple relationship between this measure of scale and the dispersion of the data set. Thus, in order to estimate the latter, it is necessary to find the PDF that describes the whole collection of data first. This type of PDF is called here “the resulting” PDF (RPDF) to distinguish it from the PDF generator and each of the individual PDFs.

The second stage on the analysis therefore consists in adding together all the individual partial PDFs associated to each of the observations in the data set. The sum of all the partial PDFs defines the resulting PDF, or RPDF. The RPDF therefore depends on several parameters including the number of observations forming the database, its dispersion, and the value of the smoothing parameter that was used to modulate the relative contribution of each observation within the kernel generator. The last of these parameters is responsible for a characteristic of all kernel functions: The same set of observations can be described by an infinite number of RPDFs, each of which is created by a single value of the smoothing parameter.

Although at first sight the multitude of RPDFs associated to a single data set might seem a disadvantage of the method, it is actually this characteristic of kernel functions that allows us to identify multimodality without making ad hoc assumptions about the real distribution. To appreciate this aspect of kernel functions it is necessary to consider that it is possible to create a series of RPDFs between two given values of the smoothing parameter, and that each of the RPDFs on that series might yield a different number of modes. Commonly, at one extreme of the values of the smoothing parameter the RPDF will have a maximum of modes equal to the number of data. At the other