# Volcanic or seismic prediction as an inverse problem

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ABSTRACT. We offer a logical framework for utilizing observations on mutually *dependent* or *independent* precursory phenomena for the purpose of predicting natural hazards. A space is defined whose dimension equals the total number of parameters that may be significant and that we are able to measure. Each set of measurements defines a point in the space, and the smoothed density of points in the space is assumed to be the more general representation of the existing correlations between parameters. The prediction is then made *via* the general theory of inverse problems. The method is numerically illustrated by the prediction of volcanic eruptions, using an actual data set (Krafla volcanic area in Iceland). The output of our algorithm is in that case the density of probability of occurrence of the next volcanic eruption, as a function of time.

*Key words* : Iceland, inverse problem, Krafla, pattern recognizion, prediction.

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## INTRODUCTION

The object of geophysical predictions is to obtain some information about the importance, the place, and the time of occurrence of a future geophysical event (earthquake or volcanic eruption).

The main difficulty for a deterministic prediction is that either, the state of stresses or the geometry (of the system of faults, or of the magmatic reservoir) is poorly known. Moreover, the deterministic relationships (if any) between the measurable geophysical parameters and the main unknowns (importance, place and time of the event) are not well understood.

If we assume that in a given region, the measurable geophysical parameters correlate with the unknowns, we can search for the correlations. Two possibilities arise : *a*) to study the past in the given geographical region; or *b*) to study the present in some regions similar to that under study. The two possibilities being, of course, not exclusive.

In this paper we attempt to define a general prediction of future geophysical events using sets of observed data which (hopefully) correlate with these events.

## PRINCIPLE OF THE METHOD

Let $X^1, ..., X^r$ be the set of parameters to be predicted, and $X^{r+1}, ..., X^n$ the set of observed parameters on which the prediction is to be based. For example, for a volcanic or seismic region under geophysical monitoring, such sets would consist in :

$$\text{To be predicted} \begin{cases} X^1 & : \text{Time to the next event} \\ \dots & \\ X^r & : \text{Importance (Magnitude) of the event} \end{cases} \quad (1)$$

$$\text{To be observed} \begin{cases} X^{r+1} & : \text{Time from last event} \\ \dots & \\ X^n & : \text{Microearthquake activity}. \end{cases}$$

By a capital $X$ with a super index we denote the parameters themselves. Any *general* value that the parameters can take is denoted by a lower case with a super index ($x^i$), and any *particular* value will be denoted by a subindex ($x^i_\alpha$).

Consider some times $t_\alpha$ ($\alpha = 1, ..., N$) *prior* to the last event (in the area under study or in some similar areas). We assume that for these times $t$ the *whole* set of parameters defined in (1) has been observed.

Each measurement gives an experimental point in an $n$-dimensional space $E^n$. We will define a function over $E^n$ :

$$\Theta(\mathbf{x}) = \Theta(x^1, ..., x^r, x^{r+1}, ..., x^n) \quad (2)$$

representing the density of observed points in the neighbourhood of the point $\mathbf{x}$ of the parameter's space.

This function $\Theta(\mathbf{x})$ will contain all the observed correlations (if any) between the parameters. If $\Theta(\mathbf{x})$ has been normalized, then it can be interpreted as the probability density function of the parameters.

Let us now consider how the function $\Theta(\mathbf{x})$ and the present values of the observable parameters $X^{r+1}, ..., X^n$

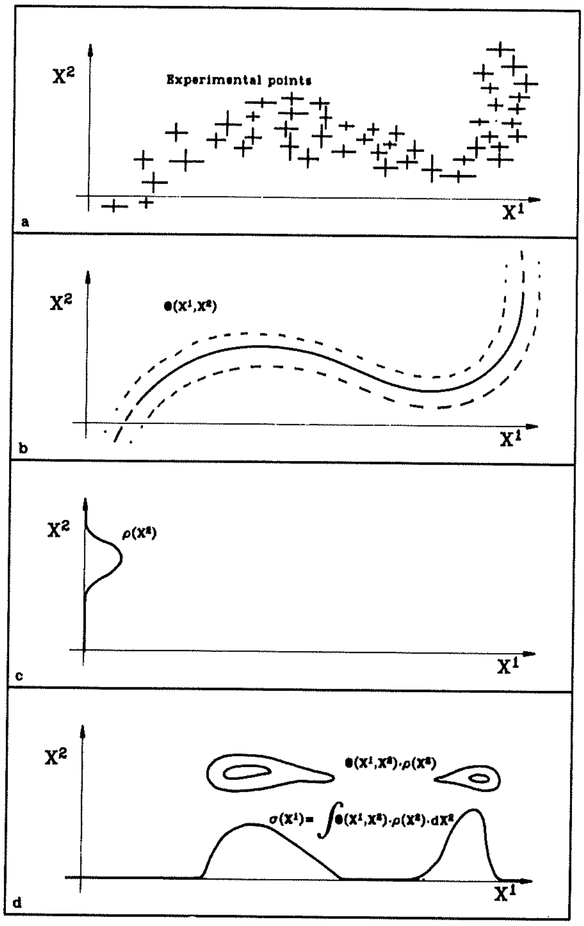


Figure 1
*For the purposes of illustration, we represent in this figure a problem with only two parameters : $x^1$ (to be predicted) and $x^2$ (to be observed). a) the history of the region provides some experimental values of the couple $(x^1, x^2)$, each value defining a point in the parameter space. Error bars are also shown. b) the smoothed density of experimental points, $\Theta(x^1, x^2)$. c) a measurement of the present value of the parameter $x^2$ defines a density probability function on $x^2$. d) the product $\Theta(x^1, x^2).\rho(x^2)$ gives the* a posteriori *density of probability on the parameter space, and the marginal probability density function $\sigma(x^1) = \int \Theta(x^1, x^2).\rho(x^2).dx^2$ gives the most general information on the parameter to be predicted, $x^1$.*

can be used to obtain information on the parameters to be predicted, $X^1, ..., X^r$.

A measurement of the present values of the observable parameters will include estimates of errors; or, more generally, a probability density function :

$$\rho(x^{r+1}, ..., x^n) \tag{3}$$

in the space of observable parameters.

It can be shown from very general arguments of inverse problem theory (Tarantola and Valette, 1982) that the most general information on the values of the parameters to be predicted is given by the probability density function :

$$\sigma(x^1, ..., x^r) = k \cdot \int \Theta(x^1, ..., x^r, x^{r+1}, ..., x^n) \cdot \rho(x^{r+1}, ..., x^n) \cdot dx^{r+1} \cdot ... \cdot dx^n \tag{4}$$

where $k$ is a normalizing factor.

Figure 1 gives a schematical interpretation of this formula.

Many different kinds of information may be extracted from $\sigma(x^1, ..., x^r)$, as for example mean values (or maximum likelihood values), standard deviations, and so on. Nevertheless, for purposes of civil defense, we believe that the most objective response that the scientists can furnish to governmental authorities is in terms of probability rather than in terms of estimators. For example, if we are searching for a prediction of the two parameters

$$\begin{aligned} X^1 &: \text{time to the next event} \\ X^2 &: \text{intensity of the event} \end{aligned} \tag{5}$$

the probability of having an event with *intensity greater than $I_0$ before the time $t_0$* is given by :

$$\int_0^{t_0} dx^1 \int_{y_0}^{\infty} dx^2 \; \sigma(x^1, x^2) \,. \tag{6}$$

## THE PREDICTIVE FORMULA

As stated in the previous section, we assume the existence of a data set consisting in measures of the whole set of parameters $X^i$ ($i = 1, ..., n$). This implies that the measures have been done at different times *before* the last event, and, if possible, for some events. If the area under study has been monitored during a time which is great compared to the time between recurrence of events, all the data will have been obtained in the same area. If the monitoring has not been long enough, the data will have been obtained in some similar areas.

Assume that the data set consist of a list of values of the parameters $X^i$ ($i = 1, ..., n$) measured at different times $t_\alpha$ ($\alpha = 1, ..., N$) :

$$\{ x^i_\alpha, \sigma^i_\alpha \}, \tag{7}$$

where $x^i_\alpha$ are the observed values and $\sigma^i_\alpha$ the estimated errors.

Although it is not necessary, we will assume for simplification, that each datum in (7) can conveniently be described using Gaussian functions, and that the experimental errors are independent. Each datum defines then, in the parameter space, the probability density function

$$\theta_\alpha(\mathbf{x}) = \frac{1}{(2\pi)^{n/2} \prod_{i=1}^{n} \sigma^i_\alpha} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \frac{(x^i - x^i_\alpha)^2}{(\sigma^i_\alpha)^2} \right\} \tag{8}$$

which has been represented by an ellipsoïd (of which the error bars of figure 1*a* are the major axis).
If the ellipsoïds are overlapping enough, the mean :

$$\Theta(\mathbf{x}) = \frac{1}{N} \sum_{\alpha=1}^{N} \theta_\alpha(\mathbf{x}) \tag{9}$$

would be a smooth function representing all the correlations (if any) existing in the data set. If the sum is not smooth because the data are too sparse, we can define $\Theta(\mathbf{x})$ as the mean of (9) *in a neighbourhood of* **x**. Taking for example a Gaussian window

$$S(\mathbf{x}, \mathbf{x}') = \frac{1}{(2\,\pi)^{n/2} \prod_{i=1}^{n} \delta^i} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \frac{(x^i - x'^i)^2}{(\delta^i)^2} \right\} \tag{10}$$

where the $\delta^i$ are some « smoothing lengths », we can define :

$$\Theta(\mathbf{x}) = k \cdot \sum_{\alpha=1}^{N} \int S(\mathbf{x}, \mathbf{x}') \cdot \theta_\alpha(\mathbf{x}') \cdot \mathrm{d}\mathbf{x}' . \tag{11}$$

Using equations (8) and (10) we obtain then, dropping multiplicative constants :

$$\Theta(\mathbf{x}) = k \cdot \sum_{\alpha=1}^{N} \left\{ \prod_{i=1}^{n} \frac{\{ (\sigma_\alpha^i)^2 + (\delta^i)^2 \}^{-1/2}}{\Phi\left(\frac{x_{\text{sup}}^i - x^i}{\delta^i}\right) + \Phi\left(\frac{x^i - x_{\text{inf}}^i}{\delta^i}\right)} \right\} \cdot \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} \frac{(x^i - x_\alpha^i)^2}{(\sigma_\alpha^i)^2 + (\delta^i)^2} \right\} \tag{12}$$

where $\Phi$ is the error function :

$$\Phi(u) = \frac{1}{\sqrt{2\,\pi}} \int_{-\infty}^{u} \exp\left\{ -\frac{1}{2} \cdot t^2 \right\} \cdot \mathrm{d}t . \tag{13}$$

If the present values of measurable parameters are denoted :

$$\{ x_0^i, \sigma_0^i \} \qquad i = r + 1, ..., n \tag{14}$$

the experimental errors being assumed to be independent, then using the Gaussian assumption we can define a density function in the space of observable parameters :

$$\rho(x^{r+1}, ..., x^n) = \frac{1}{(2\,\pi)^{(n-r)/2} \prod_{i=1}^{n-r} \sigma_0^i} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n-r} \frac{(x^i - x_0^i)^2}{(\sigma_0^i)^2} \right\} . \tag{15}$$

The computation of the induced probability density function in the space of unknowns, as defined by equation (4) gives then

$$\sigma(x^1, ..., x^r) = k \cdot \sum_{\alpha=1}^{N} \omega_\alpha \cdot \left\{ \prod_{i=1}^{r} \frac{\{ (\sigma_\alpha^i)^2 + (\delta^i)^2 \}^{-1/2}}{\Phi\left(\frac{x_{\text{sup}}^i - x^i}{\delta^i}\right) + \Phi\left(\frac{x^i - x_{\text{inf}}^i}{\delta^i}\right)} \right\} \cdot \exp\left\{ -\frac{1}{2} \sum_{i=1}^{r} \frac{(x^i - x_\alpha^i)^2}{(\sigma_\alpha^i)^2 + (\delta^i)^2} \right\} \tag{16}$$

where

$$\omega_\alpha = \left\{ \prod_{i=r+1}^{n} \frac{\{ (\sigma_\alpha^i)^2 + (\sigma_0^i)^2 + (\delta^i)^2 \}^{-1/2}}{\Phi\left(\frac{x_{\text{sup}}^i - x_0^i}{\delta^i}\right) + \Phi\left(\frac{x_0^i - x_{\text{inf}}^i}{\delta^i}\right)} \right\} \cdot \exp\left\{ -\frac{1}{2} \sum_{i=r+1}^{n} \frac{(x_0^i - x_\alpha^i)^2}{(\sigma_\alpha^i)^2 + (\sigma_0^i)^2 + (\delta^i)^2} \right\} . \tag{17}$$

Let us recall here the definition of all the symbols appearing in equations (16) and (17) :

| | | |
|---|---|---|
| $X^i$ | $(1 \leqslant i \leqslant r)$ | : Parameters to be predicted |
| $X^i$ | $(r + 1 \leqslant i \leqslant n)$ | : Parameters on whose values the prediction is to be based |
| $x_\alpha^i$ | $(1 \leqslant i \leqslant n)$ | : Observed values in the past |
| $\sigma_\alpha^i$ | $(1 \leqslant i \leqslant n)$ | : Standard errors |
| $\delta^i$ | $(1 \leqslant i \leqslant n)$ | : Smoothing lengths |
| $x_0^i$ | $(r + 1 \leqslant i \leqslant n)$ | : Observed values at present |
| $\sigma_0^i$ | $(r + 1 \leqslant i \leqslant n)$ | : Standard errors. |

(18)

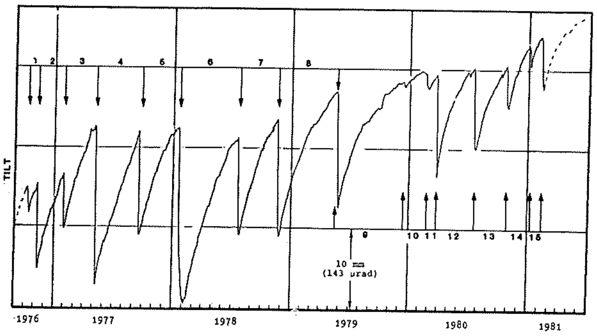


Figure 2

*Tilt data in the Krafla area (from Tryggvasson, 1980). The instrument is a water tube tiltmeter 70 m long. We see several periods of increasing tilt (inflation of the magmatic chamber) followed by sudden deflations (corresponding to sudden injections of magma into the rift system). Arrows show the 15 periods that we have arbitrarily defined and used to define the points in the parameter space. For each day of each one of the periods we have « measured » the following parameters :*

$x^1$ : *Time to the next deflation event.*

$x^2$ : *Time elapsed from the last deflation event.*

$x^3$ : *Tilt level.*

$x^4$ : *Tilt rate.*

$x^5$ : *Tilt drop of the last deflation event.*

## THE KRAFLA DATA SET

In order to test our formulas with actual data we have chosen the Krafla volcanic area in Iceland.

Figure 2 shows a record of a water tube tiltmeter installed in the Krafla area (Tryggvasson, 1980). The slowly increasing tilt corresponds to an influx of magna into the Krafla reservoir, at an estimated rate of 5 $m^3/s$ (Björnsson *et al.*, 1979). The inflow of magma, causes increase of pressure in the reservoir, and when this pressure attains a certain threshold, a sudden extrusion of magma into the rift system occurs, producing a sudden decrease of tilt.

These extrusions take the form of dykes, that may extend some tens of km away from the Krafla zone (Einarsson, (1979) and can, eventually, reach the surface, as a volcanic eruption. In this example we are interested in the prediction of the time of occurrence of a deflation event, regardless of the magma reaching the surface or not.

We have identified 15 periods of inflation, followed by a deflation event, as indicated on figure 2. Let us consider a particular day of one of the periods of inflation. We wish to make a prediction of the value of the parameter :

$X^1$ : Time to the next deflation event (TIMENEXT). (19*a*)

By inspection of the figure, it seems that some parameters that may be relevant for the prediction (at a given day) of the time of occurrence of the next deflation event are :

$X^2$ : Time elapsed from last deflation event (TIMELAST)
$X^3$ : Tilt level (TILT)
$X^4$ : Tilt rate (TILTRATE). (19*b*)
$X^5$ : Tilt drop of last deflation event (TILTDROP).

As the measures of the water tube tiltmeter are normally made daily, each day during the past 15 periods of figure 2 can provide us with the values of these five parameters. Each day then defines a point in the five-dimensional space of parameters. To represent graphically these points in the parameter space, we have projected the points onto some coordinate planes, as shown in figure 3. As the parameter $X^1$ (TIMENEXT) has been chosen common for all the projections, a rapid inspection of figures 3 gives a rough idea of the predictive power of each parameter.

Let us make two remarks about these points :

The first remark is that in at least 3 deflation events, there has been an injection of dykes very close to the tiltmeter site. In that case, the tilt drop reflects the combination of the deflation of the reservoir and the local deformation at the tiltmeter site. To empirically correct our data set for these effects, we have assumed that only 80 % of the observed tilt drop at the end of the third period was deflation related. Similarly, we assume that at the end of the fourth period only 50 % was deflation related. On the contrary, we have assumed that the deflation-related tilt drop for the event at the end of the twelfth period, was about 200 % of the measured tilt drop (the injection of the dyke was produced at the side opposite to the tilt-site). These estimates are based on observations not included in this present study.

The second remark is that the tilt rate has not been defined as the actual slope of the curve of figure 2, which is somewhat erratic, but as the slope of a least-squares parabola fitting the tilt curve from the first day of the period to the day of the measurement. Furthermore, for the first 15 days of a period, even the slope of the parabola is too erratic, and is not computed but it is just extrapolated from the 15th day to the first day of each period. This procedure is questionable and can certainly be changed, but for the present study, it serves its purpose.

We estimate the experimental error on the measurement of each parameter to be of the following order of magnitude.

$$\begin{aligned} \sigma_\alpha^2 &\approx \sigma_\alpha^2 \approx \quad 1 \text{ day} \\ \sigma_\alpha^3 &\approx 0.01 \text{ mm} \\ \sigma_\alpha^4 &\approx 0.01 \text{ mm/day} \\ \sigma_\alpha^5 &\approx 0.01 \text{ mm} \end{aligned} \quad (\text{for all } \alpha). \qquad (20)$$

Although errors in the parameters $X^4$ and $X^5$ are clearly not independent of errors in $X^3$, we will neglect these correlations. In fact, we will see later that the smoothing lengths are great compared with the errors (20) so not only the correlations, but also the observational errors could be neglected.

Figure 4 represents the marginal probability density functions obtained from the function $\Theta(\mathbf{x})$ defined by equation (9). Roughly speaking, this figure represents the projections onto the coordinate lines of the experimental points (or, more precisely, of the experimental gaussian ellipsoids). If we accept that the curves shown in that figure show a general trend and that the high frequencies are mainly due to the sparsity of data, we can apply the gaussian window defined in equation (10) in order to smooth these curves. Using equation (12) we

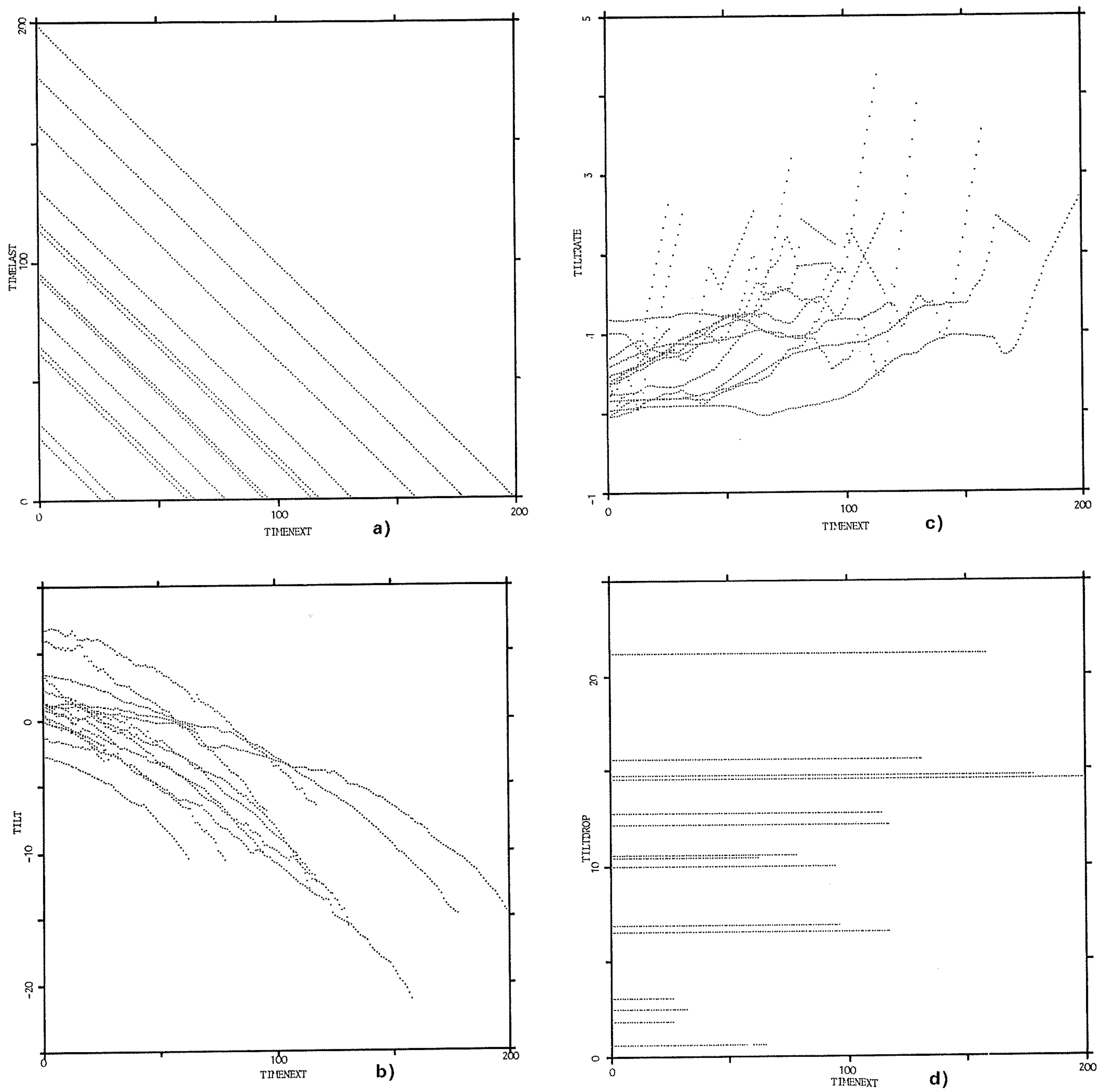


Figure 3

*Graphic representation of the experimental points of the parameter space, by projection of the points onto some coordinate planes. The parameter to be predicted ($x^1$ : Time to the next deflation event) is common to all projections, in order to graphically show the predictive power of each one of the parameters, taken alone.*

*a) TIMELAST-TIMENEXT.* *b) TILT -TIMENEXT.* *c) TILTRATE-TIMENEXT.* *d) TILTDROP-TIMENEXT.*

obtain then a probability density function $\Theta(\mathbf{x})$ whose marginal densities are shown in figure 5. As all the marginal probability density functions of $\Theta(\mathbf{x})$ are smooth, we can hope that the function $\Theta(\mathbf{x})$ is also smooth, which would mean that the gaussian window used acts as an *interpolator* of the experimental points.

In this example we have used the following values for the smoothing lengths.

$$\begin{aligned} \delta^2 &= \delta^2 = 15 \text{ days} \\ \delta^3 &= 2 \text{ mm} \\ \delta^4 &= 0.05 \text{ mm/day} \\ \delta^5 &= 6 \text{ mm}. \end{aligned} \tag{21}$$

It is not very obvious how to choose these values. The larger these values are chosen, the more the smoothed curves will be independent on eventual erratic data. This means that the final prediction will be more *robust.* But of course, the range of significant probability will increase, i.e., the final prediction will be less *precise.* We see thus that there is a trade-off between robustness and precision of the prediction.

The choice made in (21) corresponds to the smaller values that make the curves in figure 5 look smooth. This choice corresponds to the *hypothesis* that if we had more experimental points, the curves of figure 4 will tend to resemble those of figure 5.

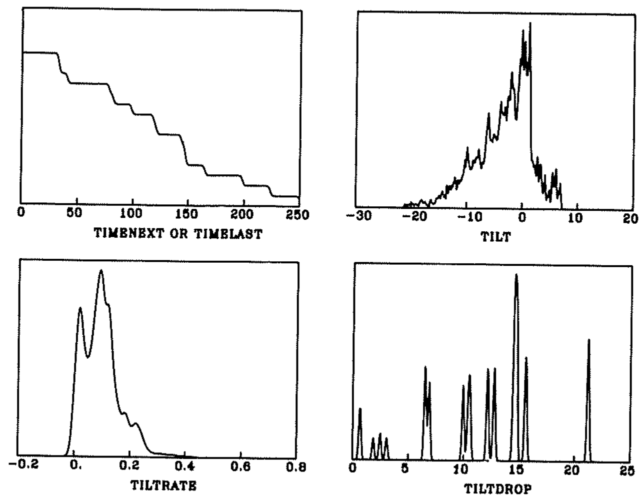


Figure 4
*The* a priori *marginal density functions before smoothing.*

## AN EXAMPLE OF PREDICTION

An adequate way for testing the applicability of the method, is to completely suppress one of the periods from the data set, and to try the prediction of the time of occurrence of the following deflation event (TIMENEXT), using for all the days of the period the current values of the parameters TIMELAST, TILT, TILTRATE, and TILTDROP (which is constant for a given period).

We have arbitrarily chosen to present here the results for the prediction corresponding to the suppression of the 7th period (the conclusions obtained using any other period are similar).

Figures 6 through 10 show the prediction made 21, 42, 63, 84 and 105 days after the end of the previous deflation event. We display both the density of probability and the cumulated probability.

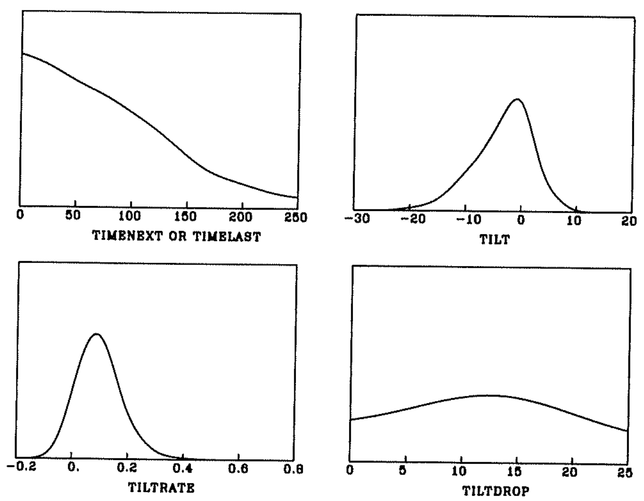


Figure 5
*The* a priori *marginal density functions after smoothing.*

Let us start by the discussion of figure 6. As indicated at the top of the figure, on the 6th day of August 1978, 21 days had elapsed from the last deflation event, the tilt level was – 8.137 mm, the tilt rate was 0.121 mm/day, and the tilt drop in the last event was 12.122 mm (the estimated errors are given by equation (20)). We will try to answer the following question : when will the next deflation event occur ? The results of figure 6 show that the first answer to the question is that the deflation event can occur *any day* between the present and the 225th day from the present. We see that the density of probability is bimodal. We do not recommend the extraction of estimators from the density of probability curve (as the mean, the median, or the maximum likelihood points). Instead we recommend the use of the cumulated probability curve. We believe that the most unambiguous and objective prediction that could be done on August 6th, was of the following type :

*a*) The probability of having a deflation event in the following 30 days is less than 5 %.
*b*) There is a probability of 50 % of having a deflation event before 94 days have elapsed.

*c*) The probability of a deflation event within 180 days is greater than 95 %.

The deflation event took place on November 10, 1978, that is 96 days after August 6th.

Figures 7, 8, 9 and 10 show the evolution of the prediction when the time elapses without occurrence of a deflation event. In particular, figure 10 shows the prediction as it could be done on October 29th, i.e. 12 days before the deflation event. We see that the probability of having a deflation event within 30 days was about 50 %.

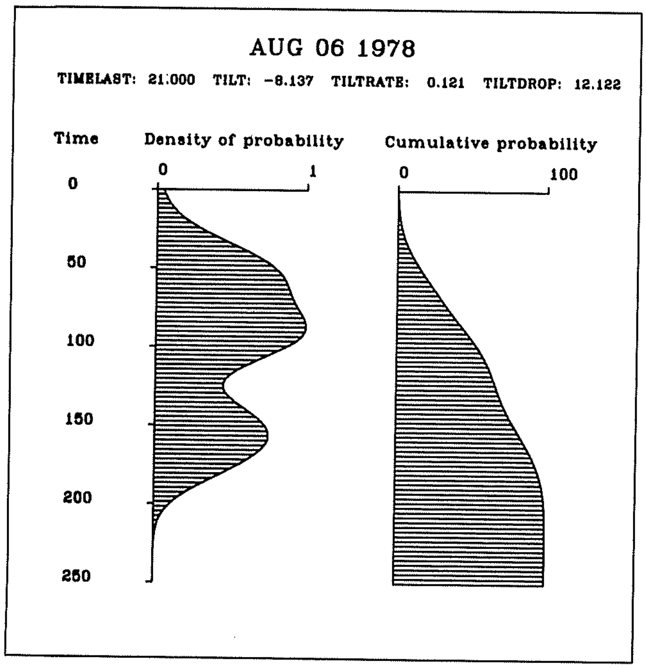


Figure 6
*The prediction as could be done on August* 6, 1978 (*if all periods except the current period were known*).

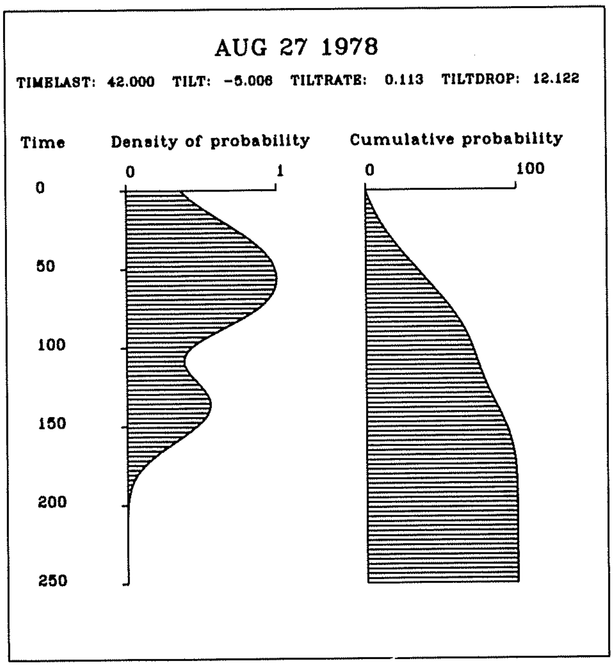


Figure 7
*Same as figure* 6, 21 *days later.*

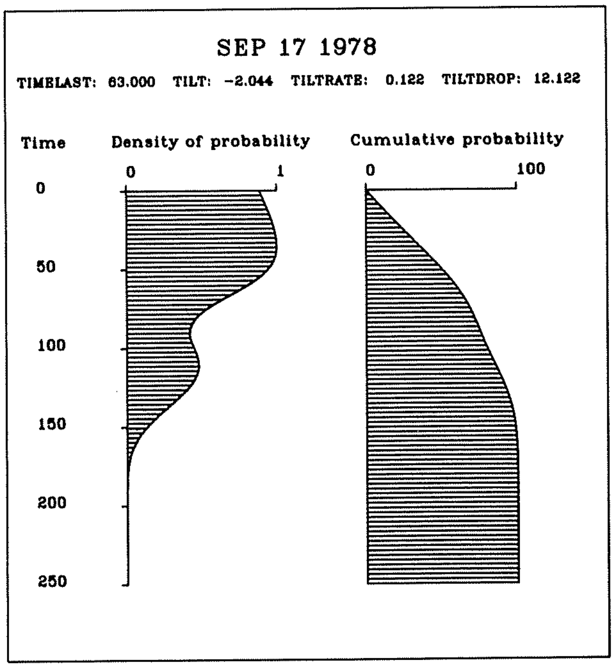


Figure 8
*Same as figure* 7, 21 *days later.*

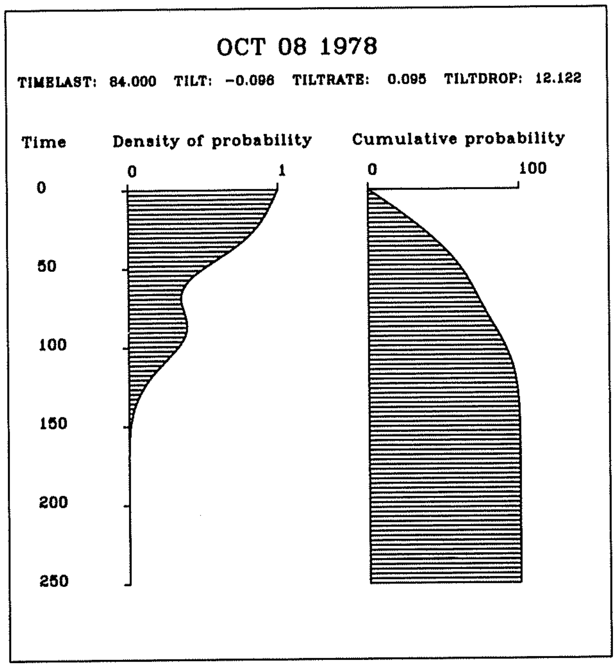


Figure 9
*Same as figure* 8, 21 *days later.*

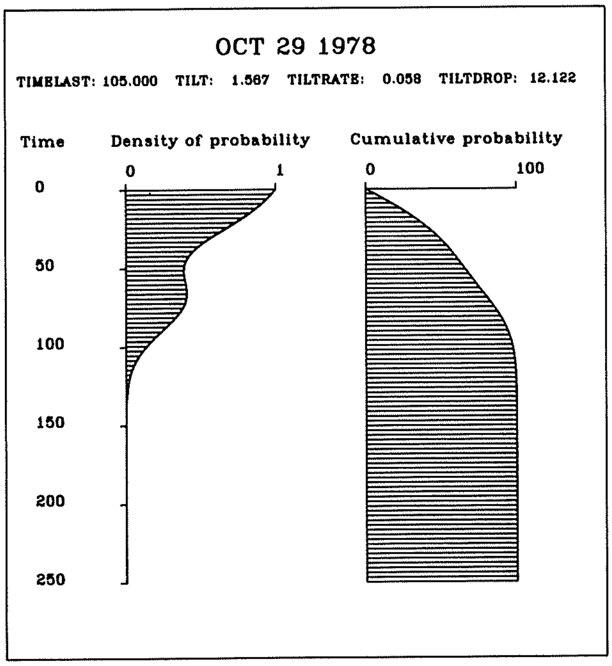


Figure 10
*Same as figure* 9, 21 *days later.*

## REMARKS AND CONCLUSION

In all our runs of the Krafla data set with the above described method, the prediction never contradicted the actual date of the next deflation event. However, the next event frequently occurred outside the period of predicted maximum likelihood, and the non-zero probability extended over a disappointingly long period. We have hoped for a better result but the data of figure 2 is apparently not sufficient for good prediction. Furthermore, the treatment of the data, especially the method used to calculate the tilt rate, may be improved on. Also the division of the Krafla record into periods of increasing tilt is questionable, as small subsidence events are sometimes included (early December, 1979; late December, 1980), but only slightly smaller events are ignored (early November, 1977; late June, 1980; early October, 1980), and still smaller subsidence events are recognized on the original tilt record. Therefore, it is quite possible that better predictions can be made by using the same method on the Krafla data set, if the data set is carefully structurized before application, especially the problem of which size subsidence events should suffice in dividing the data set into periods of inflation.

We recognize that several observed parameters, other than those represented in figure 2, could possibly improve the prediction of events in Krafla. These include tilt observations at other localities, precise distance measurements of a number of lines crossing the inflation area, spatial and temporal distribution of micro-earthquake activity, gas composition in fumaroles width of fissures, absolute ground elevations, gravity observations etc... (Tryggvason, 1980; Johnsen *et al.*, 1980; Einarsson, 1978; Möller and Ritter, 1980).

The smoothing lengths as defined in this paper, need not be constant for each parameter, but may vary in the $n$-dimensional space for best result. In particular, if we use simultaneously small and large events to divide the time series (fig. 2) into periods, we probably need different values for the smoothing length in different regions of the space.

The Krafla volcano has exibited quite regular activity since 1975, and therefore serves well as an example for testing the prediction method. However, any prediction of a future event must be based on the dubious assumption that the character of events does not change with time. This assumption is certainly not true for Krafla, as the past history of the volcano shows (Björnsson *et al.*, 1977 see note added in proof).

The application of the present prediction method to other volcanoes or to seismic regions, needs a selection of parameters which fit each case, but nothing seems to indicate that it will not work, providing the observational material is sufficient to define correlations between observed parameters and parameters to be predicted.

The method proposed here may be employed in earthquake as well as in volcanic prediction, and, in general, in all problems of pattern recognition.

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Note added in proof : When this paper is ready to go in press, it seems, effectively, that the volcanic crisis in the Krafla area has stopped after the eruption of November 1981. Of course, the assumption that the character of the events has not changed with time is no longer satisfied (see Wood and Whitforf-Stark in *Eos*, **63**, May 18, 1982, and *Eos*, **64**, July 12, 1983).

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