ASSESSMENT OF SPATIAL CORRELATION STRUCTURE OF PENETRATION RESISTANCE OF SNOW LAYERS USING RANDOM FIELD THEORY AND ITS IMPLICATION FOR SNOW STABILITY

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ABSTRACT: Avalanche researchers have long recognized that stability information from specific snow pits may or may not represent the stability conditions on the entire slope. Although considerable theory exists for the probabilistic treatment of geo-technical materials, there has been little effort into identifying the nature of spatial stochastic variation in snow properties. A few years ago the mean and variance was sufficient but snow researchers are now becoming interested in rational snow correlation structures. This paper compares the spatial correlation structure of penetration resistance of two different snow layers, in layer perpendicular direction, using random field theory. Our data come from SnowMicroPen (SMP) measurements at Patsio in Greater Himalayas, India. Knowing that snow properties are spatially correlated, what is a reasonable correlation model? Are snow best represented using fractal models or finite scale models? These are questions that this paper addresses by examining a large number of Equi-Temperature (ET) fine grain and depth hoar snow signatures from SMP soundings.

Analysis shows that one dimensional vertical penetration resistance may exhibit different spatial variability characteristics depending on the length of sampling window. The spectral density analyses of SMP data demonstrate that fractal behavior is present for ET fine grain snow, but is unlikely to be a typical feature of temperature gradient metamorphosed snow. Further we assumed that shear strength of a snow layer would have similar spatial structure in horizontal and vertical direction as that of penetration resistance. The spatially varying shear strength field of the weak layer with desired correlation structure is then generated and a two-dimensional cellular automata model is used to evaluate the extent to which the spatial correlation length in shear strength affects the snow stability. Our simulation results are consistent with recent work relating spatial variability to snow stability, where spatial structure has been quantified using geo-statistical techniques.

Keywords: Spatial correlation structure, SnowMicroPen, Cellular automata.

1. Introduction

Almost all natural snow covers are highly variable in their properties and rarely homogeneous. Snow heterogeneity can be classified into two main categories. The first is the litho-logical heterogeneity in slope perpendicular direction, which can be manifested in the form of different layering within the snow pack. The second source of heterogeneity can be attributed to inherent spatial snow variability within a layer, i.e. variation of snow properties from one point to another in space (both in slope perpendicular as well as in slope parallel direction) due to different deposition conditions and different loading histories. Since snow avalanches release from zones of localized weakness, understanding the spatial variations of snow properties at the slope scale is important for determining slope stability.

Most of the previous studies on snow cover spatial variability have described the heterogeneity of snow properties in slope parallel direction within a specific snow layer. Conway and Abrahamson (1984; 1988) quantified stability variations by making measurements using modified shear frame tests adjacent to recently avalanched slopes. Föhn (1988) conducted similar work using a different shear frame test and found somewhat less variability. Subsequent studies have employed rutschblock tests (Jamieson, 1995), drop hammer, stuffblock, quantified loaded column tests and various penetrometers (Stewart, 2002; Kronholm and others, 2001; Campbell and

Jamieson, 2003; Kronholm and Schweizer, 2003; Birkeland and others, 1995; Kronholm and others, 2004) to assess variations in stability, penetration resistance, and structure of individual layers.

Recently numerical experiments such as cellular automaton (CA) models have been used to investigate the effect of spatial variability on snowpack stability (Fyffe and Zaiser, 2004; Kronholm and Birkeland, 2005). Spatial structure was quantified using nugget to sill ratio of the semivariogram (Kronholm and Birkeland, 2005). These studies demonstrated that shear strength variations both in terms of standard deviation and spatial structure might be critically important for avalanche fracture propagation.

To investigate the vertical spatial variability of penetration resistance in snow layers, we took measurements with SMP and identified individual layers (Equi-temperature fine grain and depth hoar layer) in the snow cover. The vertical spatial structure of each layer was described using classical statistics and scale of fluctuation, δ_v (Vanmarcke, 1983). The penetration resistance data exhibits different spatial variability characteristics depending on the size of the sampling window. We expect that this behavior is due to snow having a fractal nature at many scales. The spectral density analyses demonstrate that fractal behavior is present for Equi-temperature (ET) fine grain snow, but is unlikely to be a typical feature of temperature gradient metamorphosed snow. The spatial structure of depth hoar layer can therefore be well modeled using a finite correlation function such as the Markov correlation function. Further we assumed that shear strength of a weak layer would have similar spatial varying structure in horizontal and vertical direction as that of penetration resistance. The spatially varying shear strength field of the weak layer with desired correlation structure is then generated and a two-dimensional CA model is used to evaluate the extent to which the spatial correlation length in shear strength affects the snow stability.

2. Methods

2.1 Field Measurements

Satyawali and others (2004) used the SMP measurements in estimating snow layers in Himalayan snow packs. The SMP (Johnson and Schneebeli, 1999) is a motor-driven, constant speed micropenetrometer, which generates high-resolution data, sampling approximately 250 measurements of hardness (penetration resistance) per mm. Measurements were taken in the field at Patsio (3800 m) research station on level ground as well as on several small slopes. Snow pit data was also taken along with the SMP profile, which helped in finding the layer interface and the layer type.

2.2 Delineation of snow layers

We first generated sets of SMP signatures corresponding to ET fine grain and depth hoar snow layers to find out the spatial structure of penetration resistance in vertical direction. The desired snow layers were delineated utilizing the SMP data, supplemented with manual snow pit profiles. Apart from the general trend of strength for each layer, sub layers were also noticed frequently within the ET fine grain layers. Most of the ET fine grain layers were actually part of wind slab layers found in majority of SMP profiles. Altogether 100 signatures of ET fine grain snow and 80 signatures of depth hoar snow of varying lengths were extracted from different SMP profiles.

2.3 Vertical spatial variability analysis – Random Field Modeling

In this work we have used random field theory, to find out the statistics relating to the spatial correlation structure of penetration resistance of a layer in vertical direction. Here interest was specifically focus on whether the snow is best modeled by a finite scale stochastic model having limited spatial correlation, or by a fractal model having significant lingering correlation over very large distances. It is assumed that a specific snow layer is spatially statistically homogeneous with respect to penetration process and that the SMP signatures represent an ensemble of largely independent realizations of the same 1-D random process.

Vanmarcke (1983), who pioneered random field theory stated that, in order to describe a property, ν, stochastically, three parameters are needed: (i) the mean, μ; (ii) the standard deviation, σ (or the variance, σ^2, or the coefficient of variation, CV); and (iii) the scale of fluctuation, δ_ν. Central to estimation of scale of fluctuation is the autocovariance function, c_k, or the autocorrelation, ρ_k, at lag k, which are defined, respectively, as:

$$c_k = Cov(X_i, X_{i+k}) = E[(X_i - \mu)(X_{i+k} - \mu)] \qquad (1)$$

$$\rho_k = \frac{c_k}{c_o}$$

Where X_i = value of property X at location i; μ = mean of the property X; E[…] = expected value; c_o = autocovariance at lag 0; $c_k = c_{-k}$ and $\rho_k = \rho_{-k}$.

The sample autocorrelation function (ACF) is the graph of r_k for lags k = 0, 1, 2 … K, where K is the maximum number of lags allowable – generally, K = N/4 (Box and Jenkins, 1970), where N is the total number of data points. The sample ACF at lag k, r_k, is evaluated using:

$$r_k = \frac{\sum_{i=1}^{N-k}(X_i - \mu)(X_{i+k} - \mu)}{\sum_{i=1}^{N}(X_i - \mu)^2} \qquad (2)$$

In the field of time series analysis, the correlation distance determined from sample ACF is known as Bartlett's approximation and corresponds to two standard errors of the estimates i.e. $r_k = \pm 1.96/\sqrt{N}$.

Vanmarcke (1983) suggested that δ_v can be determined by fitting one of the models to the sample ACF, as given in table 1, where Δz is the depth interval. The scale of fluctuation, δ_v, is defined such that it is equal to the area under the correlation function and represents a distance over which the parameter exhibits autocorrelation. These models are considered to be finite scale models because the correlation dies out very rapidly for separation distances Δz greater than δ_v - in particular, the area under ACF function is finite. Such models are also called *short-memory.*

An alternative model, which is rapidly gaining acceptance in a wide variety of geotechnical applications (Fenton, 1999), is the fractal model, also known as statistically self-similar, long-memory and 1/f noise. It is yet to be seen if this idea of long memory behaviour in snow properties holds for natural snow covers both in the horizontal and vertical direction, there perhaps less reason to believe so in vertical direction. Nevertheless, it is worth investigating if statistical evidence supports a fractal model in the vertical direction since this possibility cannot be ruled out. Fractal processes have an infinite scale of fluctuation and correlations remain significant over very large distances. Fenton (1999) suggested that probably the simplest way to determine whether the SMP data are fractal in nature or not, is to examine the sample spectral density function (SDF). Fractal processes have SDFs of the form $G(\omega) \propto \omega^{-\gamma}$ for $\gamma > 0$. Thus, $\log_e\{G(\omega)\} = c - \gamma \log_e \omega$, for some constant c, so that a log-log plot of the sample spectral density function of a fractal process will be a straight line with slope $-\gamma$.

Table 1. Theoretical autocorrelation functions used to determine the scale of fluctuation δ_v (Vanmarcke, 1983; Li and White, 1987)

Model No.	Autocorrelation Function	δ_v
1	$\rho_{\Delta z} = 1 - \frac{\lvert\Delta z\rvert}{a}\ for \lvert\Delta z\rvert \le a$ $\rho_{\Delta z} = 0\ for \lvert\Delta z\rvert \ge a$	a
2	$\rho_{\Delta z} = e^{-\lvert\Delta z\rvert/b}$	2b
3	$\rho_{\Delta z} = e^{-(\lvert\Delta z\rvert/c)^2}$	$\sqrt{\pi}$ c
4	$\rho_{\Delta z} = e^{-\lvert\Delta z\rvert/d}\left(1 + \frac{\lvert\Delta z\rvert}{d}\right)$	4d

2.4 Cellular Automaton Simulation Technique

The physically based cellular automaton model used in this work is similar to models described by Fyffe and Zaiser (2004) and Kronholm and Birkland (2005). The CA model consists of a two-dimensional grid of 100 x 100 cells, which represents the weak layer interface loaded in shear by the slab weight. Each cell is assigned an initial shear stress value $\tau_{x,y}^{int}$, and a shear strength value $\Sigma_{x,y}$ so that its static stability is calculated as $S_{x,y} = \Sigma_{x,y} / \tau_{x,y}^{int}$. A modified version of sequential indicator simulator method (Bellin and Rubin, 1996) is used to generate grids of initial shear strength values with known statistical properties and spatial structures. The initial stress field is globally constant, such that $\tau_{x,y}^{int}$ is constant over the grid and $\tau_{x,y}^{int}$ = min ($\Sigma_{x,y}$). After fracture of a cell the stress on that cell is transferred to any non-fractured neighbouring cells within a certain distance. This stress redistribution may cause some of the neighbour cells to fracture, resulting in fracture propagation through the model domain, but alternatively only one cell may fracture. A detailed discussion on CA model and the local stress transfer scheme can be found in Kronholm and Birkland (2005).

Following Kronholm and Birkeland (2005), we examined the size of the fracture (i.e. number of fractured cells) caused by the initial cell fracture and refer to as 'model avalanche size'. All model avalanches that covered > 9000 cells (90%) in the model were considered 'large'. We investigate the effect of standard deviation and spatial structure on model avalanche size by running the model 1000 times for each defined shear strength field, every time with a different realization having the same statistical distribution and correlation structure. A computer program in C-language is written to implement the simulation process.

3.0 Results and Discussions

3.1 Vertical spatial variability

The extracted force-depth signatures of ET fine grain snow and depth hoar were of varying sample lengths. A truncation length of 200 mm (~50000 data points) for ET fine grain data sets and that of 150 mm (~37500 data points) for depth hoar was selected. The length selected is a tradeoff between the desire to obtain as many contributing records (encouraging a short truncation length) and the need to investigate larger lags to ascertain fractal behaviour (encouraging longer truncation lengths). Apart from these data sets smaller subsets of length 10 mm, 20 mm, 50 mm and 100 mm were also created to find out the effect of varying sampling window. Typical force-depth signatures representing the variations in penetration force values corresponding to ET fine grain and depth hoar data sets are shown in figure 1 a and 1b. For each data set the following steps were carried out:

a. Linear or quadratic trends were evaluated using the method of ordinary least squares (OLS) and removed from the SMP data.
b. The residuals were then converted into a normal distribution using normal score transformation.
c. The sample autocorrelation function (ACF) was evaluated.
d. Vannarckes's simple exponential and squared exponential models (Models 2 and 3 respectively in Table 1) were fitted to the ACF using the method of OLS.
e. Bartlett's limits were calculated using : $|r_k| = \frac{2}{\sqrt{n}}\left(1+2\sum_{i=1}^{k-l} r_i^{\,2}\right)^{1/2} \approx \frac{1.96}{\sqrt{n}}$
f. The scale of fluctuation, δ_v, was evaluated using the relationships given in Table 1.

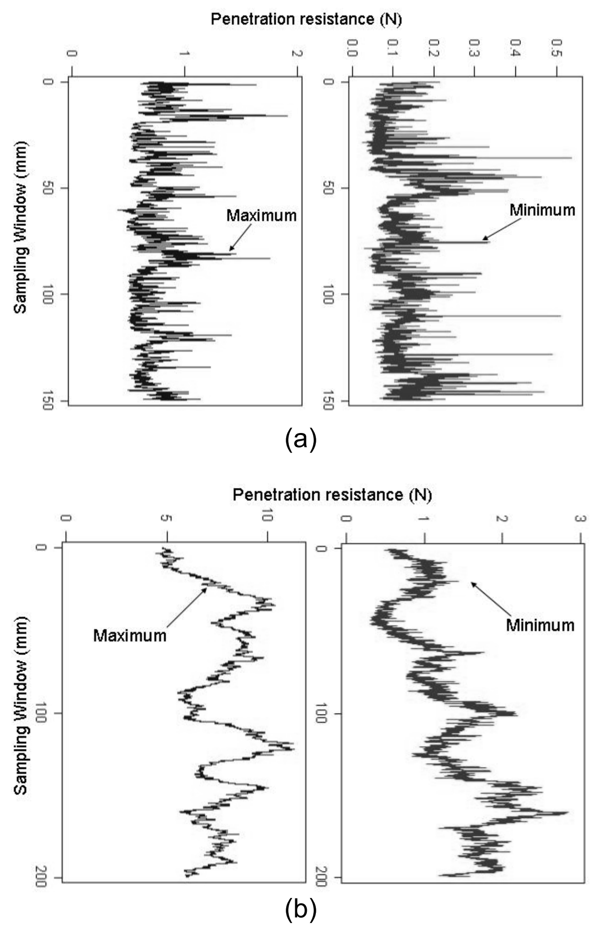


Figure 1: Typical force-depth signatures representing the variations in penetration force values corresponding to (a) Depth hoar and (b) ET fine grain and data sets.

In order to illustrate the evaluation process, a typical ET fine grain record TILA001-EN-720:920mm is used. The sample ACF is shown in Figure 2. Superimposed on the sample ACF are the Markov and squared exponential models as given in Table 1. The scale of fluctuation, δ_v, corresponding to Markov model is 10.78 mm and for squared exponential model is 12.59 mm. By superimposing Bartlett's limits ($r_B = \pm 0.00874$) on the sample ACF, Bartlett's distance (r_B) is determined. It is evident from Figure 2 that the sample ACF intersects Bartlett's limits at a distance of approximately 11.81 mm, hence r_B = 11.81 mm.

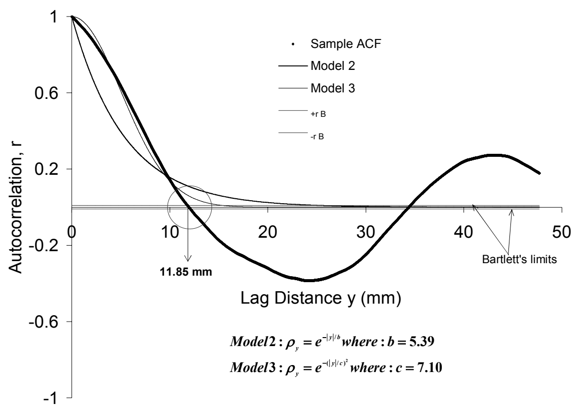


Figure 2: Sample ACF, Bartlett's limit and model ACFs obtained from the normal score transformed residuals of penetration resistance.

The methodology described above was used for each of the analysis performed on SMP signatures corresponding to ET fine grain and depth hoar snow layers. Tables 2 shows the classical statistics and Table 3 the results of ACF analysis for each layer. The mean penetration force for ET fine grain snow vary from 0.76 N to 7.62 N and the CV ranges from 7.8 % to 69.8 %. The vertical scale of fluctuation, δ_v, for ET fine grain varies between 7.9 mm to 25.8 mm, with a mean of 14.7 mm and CV of 26.0 %. Bartlett's distance, on the other hand, varies between 8.9 mm to 24.9 mm, with a mean of 16.1 mm and a CV of 25.7 %. The SMP signatures corresponding to depth hoar layer reveals that mean penetration force vary from 0.12 N to 1.10 N and the CV ranges from 7 % to 67 %. In this case, δ_v is found to vary between 0.34 mm to 4.21 mm, with a mean of 1.54 mm and CV of about 54.9 %, while r_B varies between 0.40 mm to 4.51 mm, with a mean of 1.86 mm and CV of 52.4 %.

One would have confidence in the estimates of δ_v and r_B, as they are based on populations with a large number of data points. Figure 3 shows a plot of δ_v (δ_{v2} & δ_{v3}) against r_B for the ET fine grain datasets examined in detail and shows a strong correlation between these two parameters. In fact, the OLS line of best fit has properties of r^2 = 0.89 for model 2 and r^2 = 0.83 for model 3 and for all practical purposes, one can assume that r_B expresses the same quantity as that given by the scale of fluctuation.

Table 2: Summary of statistics for penetration resistance of ET fine grain and depth hoar layers

Classical Statistics		Min	Max
ET Fine Grain Data Set	Mean Penetration Force (N)	0.76	7.62
	CV (%)	7.8	69.8
Depth Hoar Data Set	Mean Penetration Force (N)	0.12	1.10
	CV (%)	7.0	67

Table 3: Results of random field theory analysis for penetration resistance of ET fine grain and depth hoar layers

ACF (mm)		Min	Max	Mean	CV (%)
ET Fine Grain Data Set Sample size – 200 mm	δ_{V2}	7.9	22.3	13.7	25.9
	δ_{V3}	9.1	25.8	15.7	26.0
	r_B	8.9	24.9	16.1	25.7
Depth Hoar Data Set Sample size – 150 mm	δ_{V2}	0.34	3.66	1.43	51.6
	δ_{V3}	0.41	4.21	1.66	58.3
	r_B	0.40	4.51	1.86	52.4

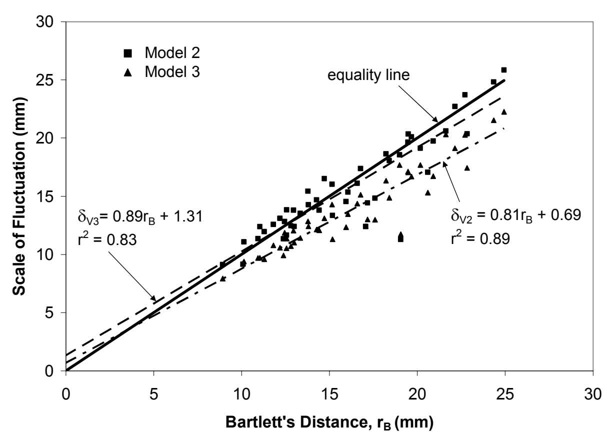
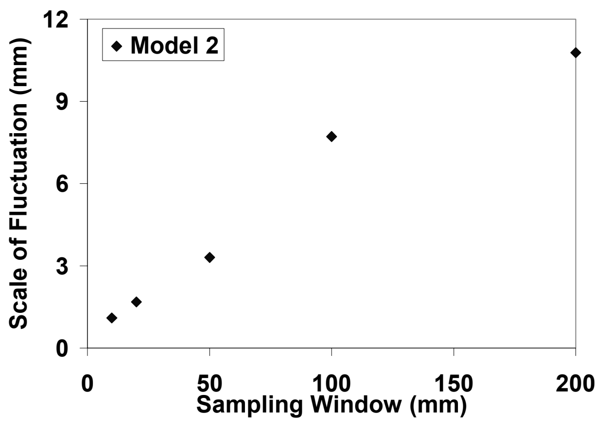
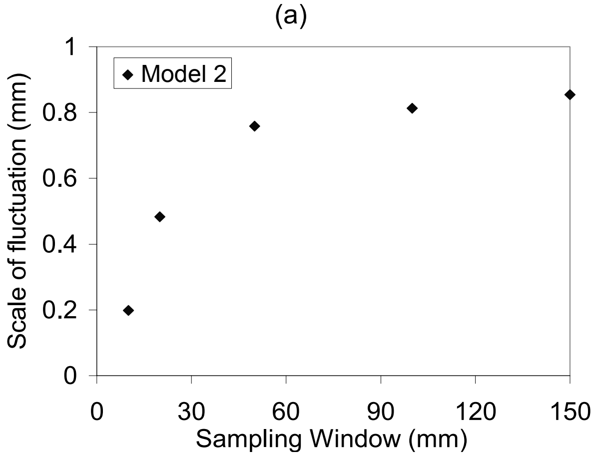


Figure 3: Relationship between scale of fluctuation, δ_v, and Bartlett's distance r_B.

The results on δ_v discussed above were for the sample lengths of 200 mm for ET fine grain layer and 150 mm for depth hoar layer. Attention is now focused towards finding out the effect of varying sample length on the estimates of correlation length. Figure 4a and 4b shows the variation of δ_v with different sampling windows for one of the ET fine grain and depth hoar data set respectively. Figures clearly demonstrate that estimate of the scale of fluctuation increases with the size of the sampling domain for both ET fine grains as well as depth hoar layers; however for the depth hoar, δ_v more or less remains unchanged for sampling windows greater than 50 mm.



(a)



(b)

Figure 4: Variation of scale of fluctuation, δ_v, with different sampling windows for (a) ET fine grain and (b) Depth hoar snow.

Birkeland et al 2004 found each snow layer irrespective of the layer type had unique spatial variability characteristics (both in terms of the linear trends and the semivariogram estimators) and spatial structure of the penetration resistance is strongly influenced by the measurement layout and sampling resolution.

Snow properties exhibit both discreet and continuous spatial variations on a multiplicity of scales (varying from grain scale to slope scale) depending upon interaction among the various external and internal physical processes occurring simultaneously at different length scales. Scale issues related with sampling and measurements also influence the spatial structure. We anticipate that the spatial correlation structure of penetration resistance of a snow layer may include one or a combination of the following dimensions:

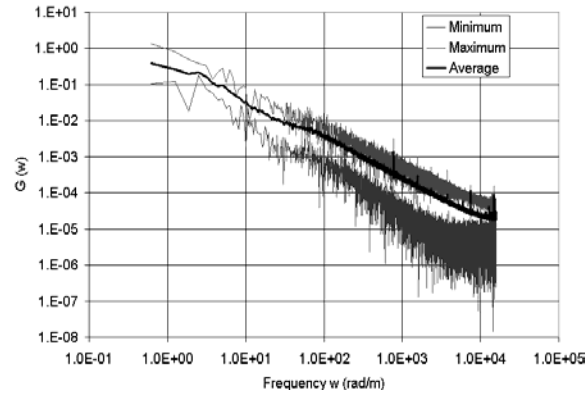
(a) Size of the micro-structural element or the cluster of elements which gives snow its strength during the penetration process
(b) Correlation structure of microclimate (especially horizontal and vertical components of wind) during the formation of a layer and that of internal metamorphic processes when the layer is buried
(c) Horizontal and vertical sampling distances or sampling resolution
(d) Extent of the measurement (sampling domain)
(e) Support volume of the measurement i.e. representative element volume (REV)

We believe that the sampling domain dependence of δ_v as found in present work as well as the sampling resolution dependence of semivariogram estimators as reported previously (Birkland et al 2004) is a manifestation of this multifaceted nature of spatial variability. Though we do not have any conclusive proof, but we expect the estimates of δ_v for 10 mm sampling window size to be related with the dimensions of mechanically significant micro-structural elements, which provide snow its strength. However, as the sampling domain is increased, more than one “nested spatial structures” comes into play which is reflected in variation of δ_v with domain size. Nested structures or sub-layering, which are created by external (e.g dynamic conditions of snow fall and wind) and internal (e.g. temperature gradient driven metamorphism) processes, are sources of variability which come into play simultaneously for all length scales and which are also influenced by the scale of observation.

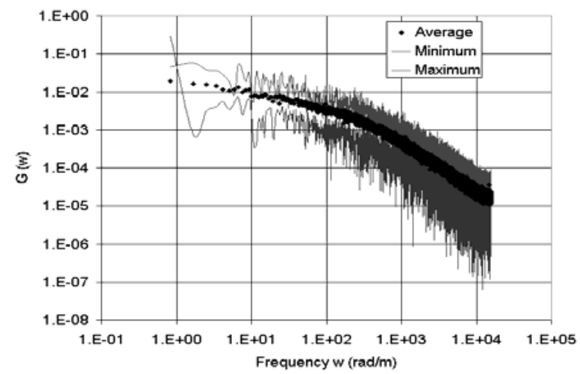
Attention is now turned towards an alternative framework of fractal theory. Fenton (1999) proposed that the variation of spatial variability characteristics with size of the sampling domain is due to material having a self-similar nature at many scales. He showed that this sampling domain dependence is a typical feature of long-memory or fractal processes when characterized by short-memory estimators. Thus, one motivation for the use of the fractal model, if found to be appropriate, instead of an 'equivalent' finite scale model where the scale is adjusted to reflect the domain size, is that the main parameter of the fractal model becomes independent of the domain size.

Figure 5a shows the minimum, maximum and average sample spectral density functions from the ensemble of data sets corresponding to ET fine grain layer. The SDFs in figure 5a appears to demonstrate fractal behaviour due to its near linear nature and constant negative slope. As the curves shown in figures 5a retain a distinct negative slope near the origin, rather than flattening out, the long scale (small frequency) nature of ET fine grain snow clearly shows fractal behaviour. On the basis of these plots, it appears that SMP force data of ET fine grain snow can be modeled by a fractal process with spectral density of the form, $G(\omega) = G_0\omega^{-\gamma}$, where G_0 is the spectral density and γ is the spectral exponent controlling distribution of power from high to low frequencies. The average estimated γ value was 0.9963 ± 0.1559. Over all ET fine grain soundings, the γ estimates ranged from 0.6834 to 1.3640.

Figure 5b shows the, maximum and average sample spectral density functions from the ensemble of data sets corresponding to depth hoar layer. The flattening-out of all the curves at lower frequencies (corresponding to longer scale) clearly indicates absence of long-range correlation and suggests that the fractal behaviour may not be present at large distances. Thus the penetration resistance data of depth hoar layer, where the fractal behaviour is not evident, can be well modeled using a finite scale correlation function, such as the Markov correlation function, which is exponentially decaying with separation distance.



(a)



(b)

Figure 5: Sample Spectral Density Functions averaged over all (a) ET fine grain layer data set (b) Depth hoar layer dataset, with associated minimum and maximum at each frequency.

3.2 Effect of spatial correlation structure on snow stability

Based on previous findings (Jamieson and Johnston, 2001 and Kronholm and Birkeland, 2005), CA model simulations were made with a normally distributed initial shear strength field with a specified mean $\overline{\Sigma}$ = 1500 Pa and standard deviation σ_Σ. Since the shear strength values used in the model represents measurement made with a 250 cm^2 shear frame, each cell of 100 x 100 grid is scaled at roughly 0.15 m x 0.15m, thereby making total size of the model as 15 m x 15 m.

The model avalanche sizes for all model runs showed a tendency to either produce a small fracture (only a few cells) or else nearly the whole grid catastrophically fails. In the first series of model simulations, we did not introduce the spatial autocorrelation in the initial shear strength field and investigated the effect on the proportion of 'large' avalanches that the model run produced at different standard deviations. The proportion of large avalanches appeared very sensitive to the standard deviation of the shear strength distribution (figure 6).

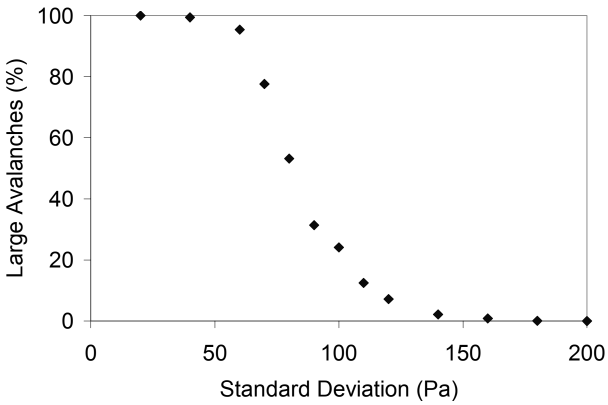


Figure 6: Variation in proportion of large model avalanches (> 90% of the model cells) with standard deviation of shear strength distribution.

In the second series of model simulations, we assumed that the spatial structure in weak layer shear strength field is in the form of a finite scale isotropic Markov correlation function; similar to that of penetration resistance of depth hoar layers. Figure 7 shows an example of weak layer shear strength field with specified mean and standard deviation, but having different correlation structure (δ_v). The spatial structure is quantified with associated ACFs and scale of fluctuations. Figure 8 shows the effect of varying the spatial correlation length on proportion of large avalanches at two different CV's of 10 % and 20 %. The correlation lengths (δ_v) depicted in Figure 8 are scaled to the dimension of a single cell. Given identical mean and standard deviation of shear strength values, initial shear strength field with strong spatial correlation structure (such as Figure 7d) are much more prone to propagating the large fractures than field with weaker spatial correlation structure (such as Figure 7a). Our results are consistent with recent work relating spatial variability to snow stability, where the spatial structure has been quantified using geo-statistical techniques (Kronholm and Birkland 2005).

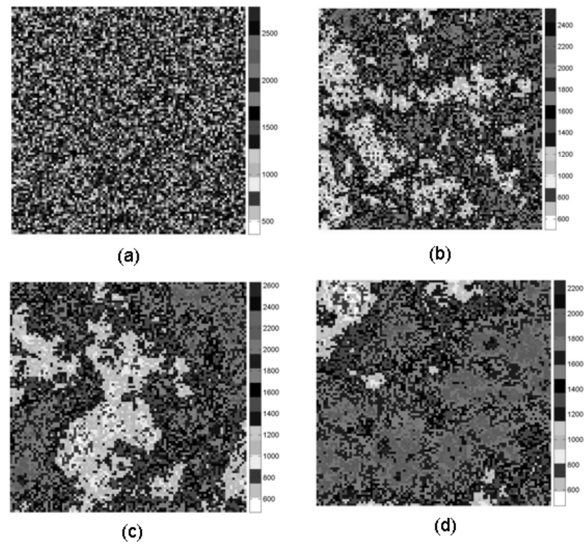


Figure 7: Spatially varying weak layer shear strength fields with mean of 1500 Pa and standard deviation of 300 Pa, having different spatial structure. The spatial structure generated is in the form of Markov correlation function with different correlation lengths of (a) δ_v = 0, (b) δ_v = 10, (c) δ_v = 20 and (d) δ_v = 40

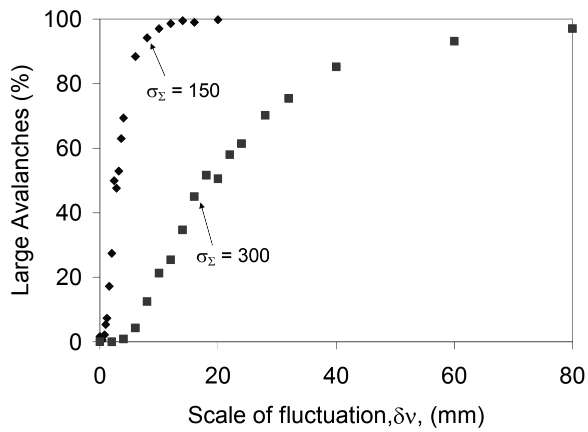


Figure 8: Effect of varying the spatial correlation length on proportion of large avalanches at two different CV's of 10 % and 20 %.

4.0 Conclusion

In this paper, we investigated the vertical spatial correlation structure of penetration resistance in ET fine grain and depth hoar snow layers using random field modeling techniques. The small scale vertical correlation distance (δ_v) of the penetration resistance of ET fine grain (sample size-200 mm) and depth hoar (sample size-150 mm) snow varies between 7.9 mm to 25.8 mm and 0.34 mm to 4.21 mm respectively. Our analysis shows that the vertical spatial variability characteristic, in terms of δ_v, is strongly influenced by the domain of investigation or the sampling window. Estimates of δ_v increases with the size of the sampling domain for both ET fine grains as well as depth hoar layers; however for the depth hoar, δ_v more or less remains unchanged for sampling windows greater than 50 mm. We contend that this sampling domain dependence of δ_v may be due to snow having a fractal or self-similar nature at many scales. The spectral density analysis suggests that fractal behavior is apparent in vertical penetration resistance of ET fine grain layers. The lack of fractal behavior in penetration resistance of depth hoar layers implies that this can be well modeled by finite-scale correlation functions such as Markov correlation function, which are typically easier to use than are fractal models. It should be pointed out, however, that a statistical analysis which does not display fractal behavior does not necessarily imply that the corresponding snow type is non-fractal, just that the particular sample considered lacks the full range of scales of variability, which is particularly true for depth hoar layers in vertical direction. A truly fractal snow layer would exhibit variability at all scales.

Further, a 2-D CA model has been used to investigate the effect of spatial variability on the fracture propagation potential of weak layers. Our analysis shows that the probability of large fractures is strongly dependent on both the spread (standard deviation) and the spatial continuity (correlation length) of the weak layer shear strength field. Fractures through weak snow layers with large correlation length are much more likely to spread over entire model domain than fractures through weak layers with smaller correlation lengths.

The present work is a first step towards analyzing the small-scale vertical spatial variability of snow layers in Himalayan snow cover. Our results are restricted to ET fine grain and depth hoar layers and to reach more general conclusions, additional rigorous laboratory and field studies of penetration resistance of different snow layers are needed. In terms of laboratory investigations, we need to establish the relationship between the correlation length of penetration resistance and dimensions of micro-structural elements (i.e. correlation length obtained from micro-structural analysis) from control snow samples. In addition, analysis of horizontal SMP profiles through a layer will be helpful in comparing the horizontal spatial structure of penetration resistance with the vertical spatial structure.

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