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Impact of DEM uncertainty on TITAN2D flow model output, Galeras Volcano, Colombia

E.R. Stefanescu [a], **M. I. Bursik**[b], **G. Cordoba** [b,c], **A.K. Patra** [a], **D.C. Pieri** [d] **and M.F. Sheridan**[b]

[a]*Department of Mechanical & Aerospace Engineering, University at Buffalo, SUNY, Buffalo,NY 14260 , (ers32@buffalo.edu, abani@buffalo.edu)*

[b]*Dept. of Geology, University at Buffalo, SUNY, Buffalo,NY 14260 , (mib@buffalo.edu, gcordoba@buffalo.edu, mfs@buffalo.edu)*

[c]*Universidad de Nariño, Colombia*

[d]*Jet Propulsion Laboratory, Caltech, Pasadena, CA, 91109 USA, (dave.pieri@jpl.nasa.gov)*

Abstract: In this paper we study the impact of errors and uncertainties in digital elevation models on the analysis of hazardous mass flows at Galeras volcano in Colombia. The increasing use of computer models and software has made it imperative that the effect of errors in digital elevation models which crucially determine the flow characteristics be quantified. We illustrate in this paper the significant effect of such errors and also attempt to correlate these to flow features.

Keywords: granular flow, computer model, TITAN2D, Galeras, Colombia

1 Background and Motivation

Model-based hazard analysis is increasingly the dominant mode of hazard analysis for large classes of hazards where sparse data (large return time of hazard event, etc.) preclude more observation-based methods. Model outputs are unfortunately critically dependent on inputs and parameters. For geophysical flows one critical input to flow models is the digital elevation model (DEM) of the terrain over which the flow needs to be studied. However, terrain is often poorly represented by the DEM with a lot of uncertainty in the elevations which are then magnified in derived quantities like slopes and curvatures.

Building on previous work [Stefanescu et al., 2010a], we focus in this paper on the effect of DEM uncertainty on geophysical mass flow computations using the TITAN2D code [Patra et al., 2005]. Using Galeras volcano as a test case we examine the effect of DEM uncertainty by creating a model of the error and sampling it to create an ensemble of possible terrains (see Stefanescu et al. [2010b] for description of procedure). The flow simulation is then run on every member of this ensemble. Statistics on suitable flow features like maximum flow depth can be used to quantify the effect of errors and uncertainties in DEMs. These can also be compared to terrain features to judge if particular terrain features lead to additional sensitivity in flow computations — thus requiring greater care in model-based hazard analysis.

Computational models, such as TITAN2D are potentially valuable tools for assessing the extent of potential flows and understanding their dynamics at Galeras. There are several towns and villages on the slopes of the volcano that could benefit from a detailed understanding of potential pyroclastic flows and lahar hazards. In the absence of more detailed geological records, this assessment can best be advanced by computational modeling. However, for the outcomes to be sufficiently accurate for public safety applications the models must appropriately represent the physics of the flows, produce robust and accurate solutions of the equations, and the effect of topographic uncertainty on model performance should be evaluated.

1.1 Why Galeras?

Galeras Volcano (elevation 4,276 meters), located in southwestern Colombia (1°13.31' N and 77°21.68' W), is one of the most active volcanoes on the world [Hurtado and Cortes, 1997]. Nearly 400,000 people currently live near the volcano; 10,000 of them reside within the zone of high volcanic hazard (ZAVA abbreviated in Spanish). Pyroclastic flows pose a major hazard for this population. The current period of activity that began in 2004 presents a serious problem for all stakeholders: decision makers, scientists, public safety officials, and general population. Computational modeling has the potential to provide useful information for hazard assessment and risk mitigation. However, there is a need to evaluate the validity of the modeling and the quality of the DEMs available for use in such modeling.

Galeras is an important volcano for computational flow modeling from both risk management and scientific perspectives [Calvache et al., 1997]. Forecasts of volcanic explosions using various geophysical tools [Narvaez et al., 1997] have occasionally brought public warnings to a high level of alert during the past 20 years. When the alert reaches the highest level, the public are urged to evacuate some local areas; this occured as recently as January, 2010. The worst event at Galeras occurred in 1993, when an eruption killed 9 scientists and journalists [Baxter and Gresham, 1997].

The topography of the volcano presents a problem for creation of a good DEM. The irregular morphology on a small scale, with steep slopes, narrow channels, deep gorges and abrupt cliffs poses problems for the creation of accurate GPS and topographic models of the volcano [Ordoñez Villota and Jentzsch, 2000]. In addition, the current flow hazard map at Galeras is mainly based on the sparse geological record [Calvache, 1990]. Dense vegetation, deep erosion, successive deposits of lava and pyroclastic flows hinder the tracing of specific deposits in the field.

The diverse effects of this landscape, as reflected in DEMs created by different processes and of different scales, must be examined and quantified to determine the level of confidence that can be placed in model results. Galeras provides a wide range of topographic features that chalenge the use of computational flow models.

1.2 Why uncertainty in DEM?

Digital elevation models (DEMs) uncertainties can be generated by errors in the acquisition of topographic data and in the interpolation methods used to build the elevation model. Hence, DEMs are representations of topography with inherent errors that constitute uncertainty. Our current work [Stefanescu et al., 2010a, b] and the results of several others [Hebeler and Purves, 2008] show that DEM uncertainty affects the outcome of models using them. However, the effects of DEM error on elevation and derived parameters are often not evaluated by DEM users, and methods to address DEM error have not been integrated with GIS software packages [Wechsler and Kroll, 2006].

Spatial autocorrelation was identified as a significant feature of DEMs, thus conditional simulations based on characterizing the degree of autocorrelation have been used as an approach for error modelling [Goodchild et al., 1992]. To assess the effect of DEM uncertainty on a geophysical model the following procedure was executed: (A) build an elevation uncertainty model, (B) propagate the uncertainty through the geophysical model, (C) perform a visual evaluation of the uncertainties and their impact on the model's output.

2 PROCEDURE FOR EVALUATING IMPACT OF DEM UNCERTAINTY

In a companion paper [Stefanescu et al., 2010b], we discuss the procedure for propagation of uncertainty, including that in DEMs in analyzing hazards at Mammoth Mountain, California, USA. In this paper analyzing DEMs at Galeras volcano, two test DEMs at 30 m spacing were considered for our analysis. The SRTM 30m DEM was derived by spline interpolation from a 90m DEM of southern Colombia using radar data collected in 2000, while the ASTER DEM was calculated at the NASA/USGS Land Processes DAAC using orthorectified imagery from 12 January 2010. The ASTER dataset was used as a surrogate for the "true" elevation while the SRTM dataset was used in creating the error model (Fig. 1 (a), (b)). To find the error in a given DEM dataset the elevation of a DEM may be subtracted from the "true" elevation at a given location. The effect of correlated DEM error was then investigated using stochastic conditional simulation to generate multiple equally likely representations of the actual terrain surface. A raster error surface was then produced for each of the 64 random surfaces. The mean and the standard deviation of model flow depth output determined from randomly drawn, spatially independent points scattered across the surface were taken as being representative of the whole. Finally, the impact of data uncertainty propagation on the flow and the geophysical model are assessed.

3 TITAN2D AND FLOW SIMULATIONS

The TITAN2D code combines numerical simulations of a natural geophysical granular flow with digital data of the natural terrain. It is based on a depth-averaged model for an incompressible granular materia governed by Coulomb-type friction interactions [Savage and Hutter, 1989]. TITAN2D performs flow simulations on a DEM of a desired region, the simulation accuracy being highly dependent on the level of the DEM resolution and quality. The TITAN2D model uses as a driving force the component of gravity along the terrain. Thus, local slopes derived from the DEM elevation data are critical.

In our study of DEM uncertainties using TITAN2D, we drew on four parameters to set the bounds of the computational modeling of pyroclastic flows (PFs): 1) internal friction angle, 2) basal friction angle, 3) maximum volume of the flows, and 4) minimum volume of the flows. We chose parameters for the TITAN flow models to bracket the range of flow volumes and to be representative of the friction angles that have been used by other researchers in their computational models. The internal friction angle has little effect on the output of the flow models [Dalbey et al., 2008; Sheridan et al., 2005]. Many TITAN users have chosen values of internal friction for PFs that range between 15 and 37 degrees with values between 30 and 35 being the most frequent values used [Patra et al., 2005; Murcia et al., 2010]. For our study we used 35 degrees. The choice of a basal friction angle has a large effect on the flow dynamics in the TITAN2D simulations [Patra et al., 2005; Stinton et al., 2006]. Factors that could affect the choice of basal friction include the volume of the flow, the type of the PF, the nature of the substrate and the amount of channelization. Murcia et al. [2010] list the basal friction values chosen by TITAN2D users; they range between 5 and 28 degrees; the mean value being about 15 degrees. For this study we used a basal friction angle of 21 degrees, similar to that for TITAN models of large PFs at Pico de Orizaba, Mexico [Sheridan et al., 2010].

Volumes of pyroclastic flows at stratovolcanoes typically cover a few orders of magnitude. The volume values in this study bracket the range of possible PFs at Galeras. According to Calvache [1990], Galeras volcano produced 5 large pyroclastic flow eruptive episodes; an historic eruption in 1866, and prehistoric events in 1100, 2300, 2900, and 4500 yBP. The total deposit volumes of these episodes range from 1.1×10^6 to 8.9×10^6 m^3. Of course the deposits of each episode could include as few as 1 flow but more likely they contain many flows. Thus, our choice of volumes ranges from 1.6×10^5 to $2.5 \times 10^6 m^3$, because of the high probable likelihood of many small occurring within the studied terrain.

We located the starting point of the flows at 239261 m easting and 132918 m northing based on locations of previous vents. A rectangular area of approximative 40 km^2 was defined around the vent within the available DEMs. The shape of the initial failure is a paraboloid for which the initial thickness is $h_{max} = 10m$ high for the smallest flows and $h_{max} = 100m$ high for the largest flows.

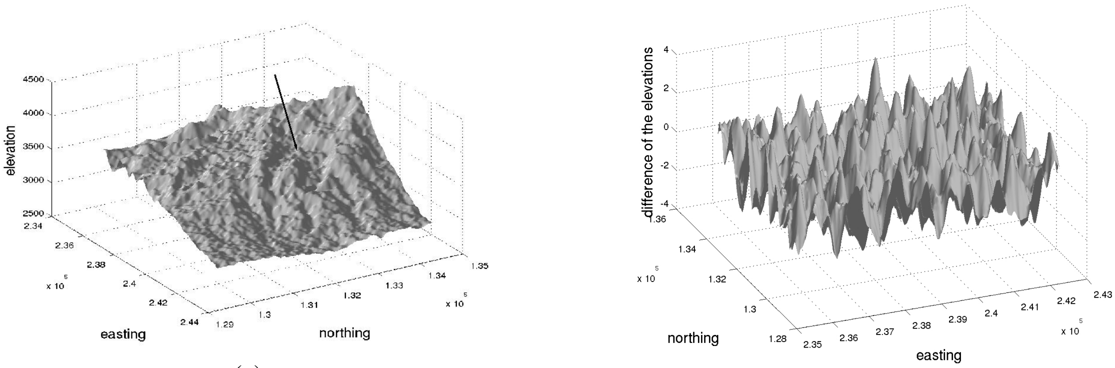
Following the technique outlined in the companion paper [Stefanescu et al., 2010b], realizations of the terrain surfaces were created and used as representations of the topography in the modeling. The correlogram for the data was calculated to determine the range of spatial dependence of elevation points using Grass GIS functions. We found that this spatial dependence persisted to a distance of 2500 meters. To determine the probability distribution function (PDF) for the stochastic simulation, 91 sets of spot locations were selected from the area covered, each set containing 91 points, all pairs of points were separated by more than 2500 meters. For each set, PDF statistics were derived. The random field parameters were chosen after testing more than 400 random field parameters. The combination which resulted in the smallest difference between the error model correlogram and the random field occurs when the minimum distance of spatial independence, $D = 2600$; the distance decay, $E = 0.8$, and the filter parameter, $F = 400$.

4 DISCUSSION AND CONCLUSIONS

One of the output files produced by TITAN2D contains the maximum flow depth over the entire simulated time at each grid point. We use this file in creating flow maps for a single particular run, and the maximum flow depth of all 64 simulations for both low and high volume flows (Fig. 2 (a), (b), Fig. 3 (a), (b)). These figures demonstrate large differences between small and large initial volumes.

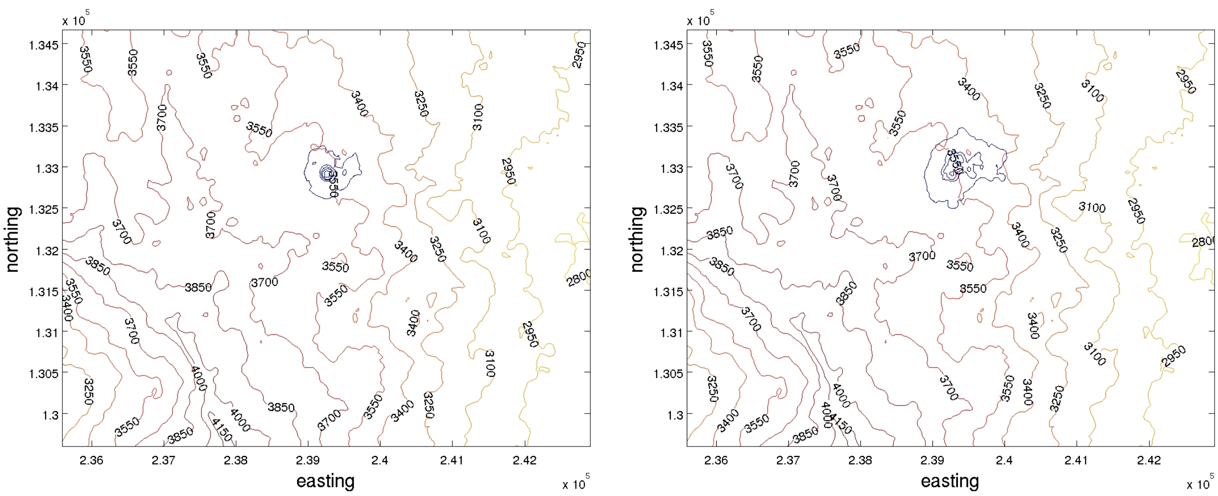
Next, we investigated the best way to specify how the TITAN2D output varies as a function of the DEM input, and if it is possible to predict the flow using only a data-driven statistical model without running the geophysical model. For this, we examinated flow depth at a particular location on the terrain surface for all simulations (Fig. 4 (a), (b)). A visual inspection of Figure 4 shows that a linear or second order (quadratic fit) can not be employed to determine a relation between the terrain (represented as ϵ, corresponding to the random variable with mean 0 and variance 1 used for creating terrain realizations) and the flow. A randomness test with 5% significance level was performed and there was no sufficient evidence to reject the null hypothesis that the maximum pile heights are random. The role of the fundamental physics based model is thus affirmed. Furthermore, it is clear that the flow computations are very sensitive to DEM errors and any attempt at model-based hazard analysis must include consideration of these errors.

It was demonstrated both analytically and empirically by Hunter and Goodchild [1997] that errors in slope and aspect depend on the structure of the spatial dependence. In this study the dependence of the flow output on the (spatially dependent) slope and curvature is investigated. In Fig. 3 (a), (b) the slope and the curvature of the ASTER DEM are presented, with a range of 0°to 70°and -0.045 to 0.045 m^{-1}, respectively. It appears from Figure 4 (a), (b) that low-volume flows are more "stable" relative to perturbations and irregularities in topography than are high-volume flows. In addition, at a 20°slope for both high- and low-volume flows, the geophysical model output appears to be most sensitive to terrain changes. However, this effect may be the result of outlier sampling, as a 20°slope is probably close to the most common slope angle on a volcano [Bursik et al., 2005]. Again, the maximum in error at 0 curvature may result from outlier sampling, as on average one may assume that the most frequently occurring curvature is close to zero.



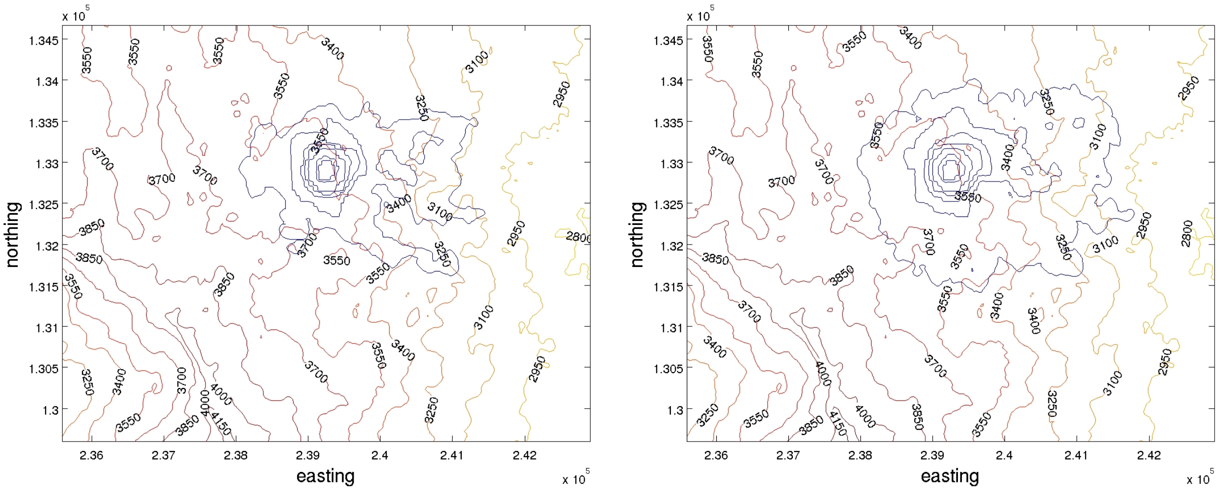
(a) (c)

Figure 1: (a) Aster DEM in easting, northing and elevation coordinates; arrow points to the starting location of the flows. (b) Spatial distribution and magnitude of error



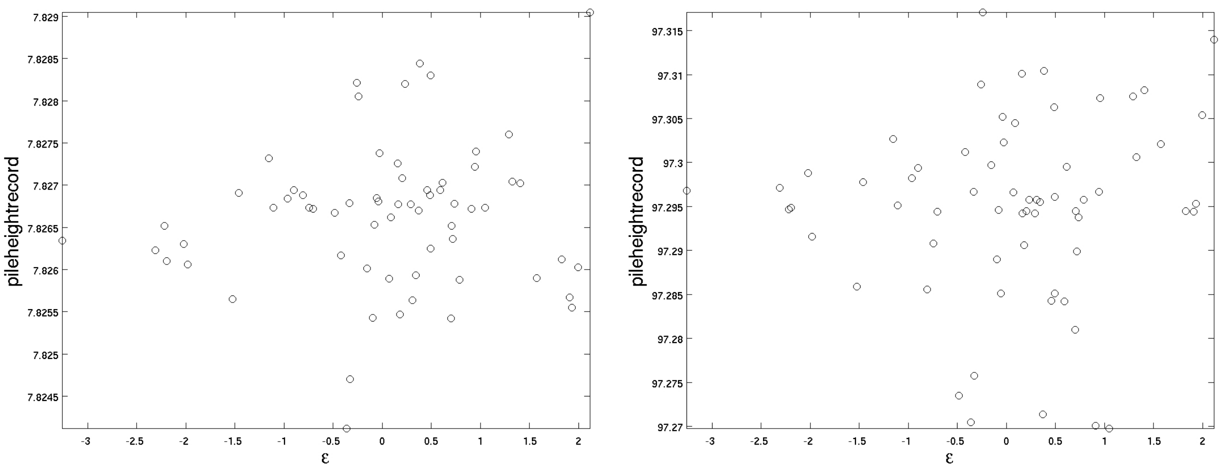
(a) (b)

Figure 2: (a) Flow depth output for a single realization, low volume. (b) Maximum flow depth of all 64 realizations, low volume



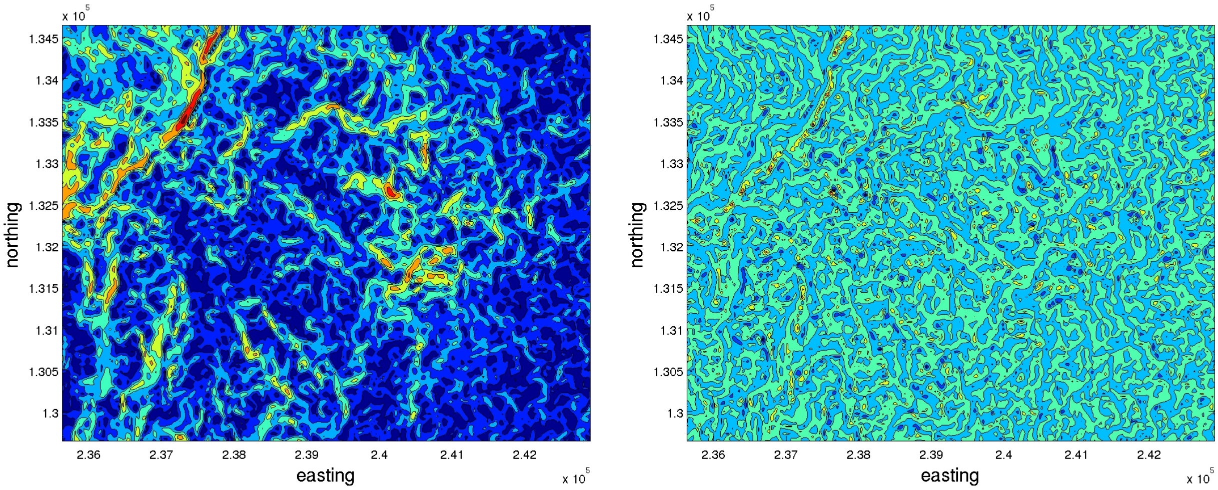
(a) (b)

Figure 3: (a) Flow depth output for a single realization, high volume. (b) Maximum flow depth of all 64 realizations, high volume



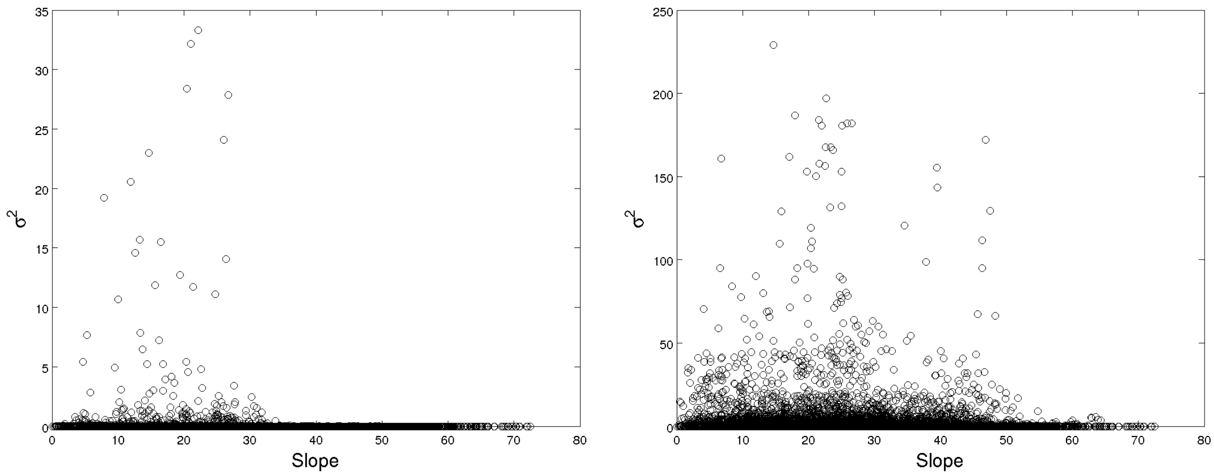
(a) (b)

Figure 4: The dependency of the flow depth on the terrain realizations at a specific location for, (a) low volume and (b) high volume



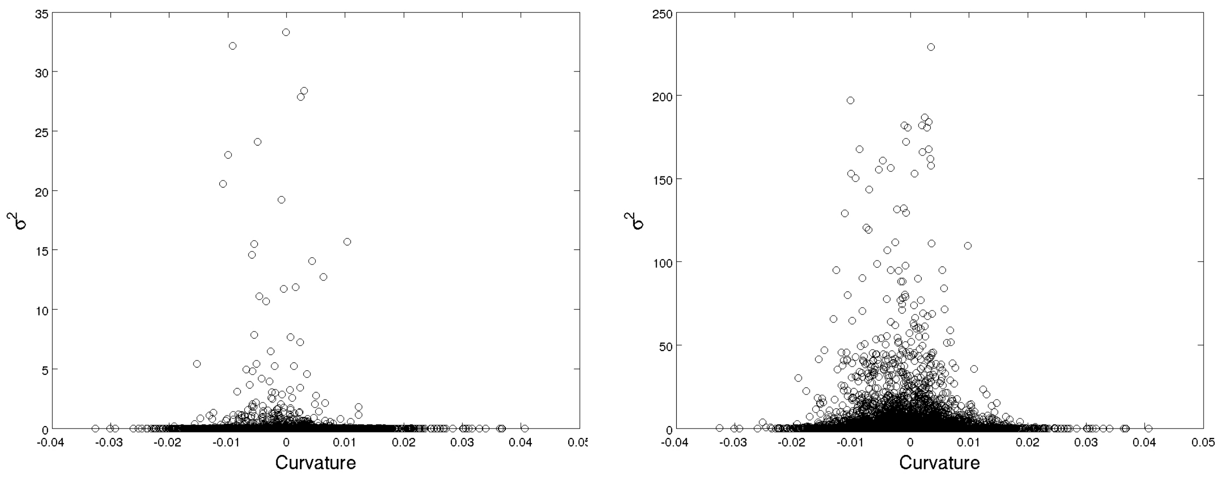
(a) (b)

Figure 5: (a) Slope profile of the ASTER DEM. (b) Curvature profile of ASTER DEM



(a) (b)

Figure 6: Scatter plot showing the correlation of depth flow variance and slope for, (a) low volume and (b) high volume



(a) (b)

Figure 7: Scatter plot showing the correlation of depth flow variance and curvature for, (a) low volume and (b) high volume

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REFERENCES

Baxter, P. and A. Gresham. Deaths and injuries in the eruption of Galeras Volcano, Colombia, 14 January 1993. *Journal of Volcanology and Geothermal Research*, 77:325–338, 1997.

Bursik, M., A. Patra, E. B. Pitman, C. Nichita, J. L. Macias, R. Saucedo, and O. Girina. Advances in studies of dense volcanic granular flows. *Reports on Progress in Physics*, 68:271–301, 2005. doi:10.1088/0034-4885/68/2/R01.

Calvache, M. Geology and volcanology of the recent evolution of Galeras Volcano, Colombia. *Msc. Thesis. Louisiana State University*, page 171, 1990.

Calvache, M., G. Cortes, and S. Williams. Stratigraphy and chronology of the Galeras volcanic complex, Colombia. *Journal of Volcanology and Geothermal Research*, 77:5–19, 1997.

Dalbey, K., A. Patra, E. Pitman, M. Bursik, and M. Sheridan. Input uncertainty propagation methods and hazard mapping of geophysical mass flow. *Journal of Geophysical Research*, 113: 5203–5219, 2008. doi:10.1029/2006JB004471.

Goodchild, M., G. Sun, and S. Yang. Development and test of an error model for categorical data. *International Journal of Geographical Informational Systems*, 6:87–104, 1992.

Hebeler, F. and R. Purves. *Modelling DEM data uncertainties for Monte Carlo Simulations of Ice Sheet Models*, chapter Quality Aspects in spatial Data Mining, pages 175–196. A.Stein, J.Shi &W.Bijker, CRC Press, Boca Raton, 2008.

Hunter, G. and M. Goodchild. Modeling the uncertainty of slope and aspect estimates derived from spatial databases. *Geographical Analysis*, 1:35–49, 1997.

Hurtado, A. and G. Cortes. Third version of the hazard map of Galeras Volcano, Colombia. *Journal of Volcanology and Geothermal Research*, 77:89–100, 1997.

Murcia, H., M. Sheridan, J. Macias, and G. Cortes. TITAN2D simulations of pyroclastic flows at Cerro Machin Volcano, Colombia: Hazard implications. *Journal of South American Earth Sciences*, 29:161–170, 2010.

Narvaez, L., R. Torres, D. Gomez, G. Cortes, H. Cepeda, and J. Stix. Tornillo-type seismic signals at Galeras volcano, Colombia, 1992–1993. *Journal of Volcanology and Geothermal Research*, 77:159–171, 1997.

Ordoñez Villota, M. and G. Jentzsch. Mediciones GPS como topografia basica para el estudio de microgravedad en el Volcán Galeras, Colombia. *Ingeominas Internal Report (in Spanish)*, 2000.

Patra, A., A. Bauer, C. Nichita, E. Pitman, M. F. Sheridan, M. Bursik, B. Rupp, A. Webber, L. Namikawa, and C. Renschler. Parallel adaptive numerical simulation of dry avalanches over natural terrain. *Journal of Volcanology and Geothermal Research*, 139:1–21, 2005.

Savage, S. and K. Hutter. The motion of a finite mass of granular material down a rough incline. *Journal of Fluid Mechanics*, 199:177–215, 1989.

Sheridan, M., A. Patra, K. Dalbey, and B. Hubbard. Probabilistic digital hazard maps for avalanches and massive pyroclastic flows using TITAN2D. *in Groppelli, G., and Viereck-Goette, L., eds., Stratigraphy and Geology of Volcanic Areas: Geological Society of America Special Paper*, 464:In press, 2010.

Sheridan, M., A. Stinton, A. Patra, E. Pitman, A. Bauer, and C. Nichita. Evaluating TITAN2D mass-flow model using the 1963 Little Tahoma Peak avalanches, Mount Rainier, Washington. *Journal of Volcanology and Geothermal Research*, 139:275–308, 2005.

Stefanescu, E. R., M. Bursik, and A. Patra. Effect of digital elevation model on geophysical flow model output. *Natural Hazards*, 2010a.

Stefanescu, E., M. Bursik, K. Dalbey, M. Jones, A. Patra, and E. Pitman. DEM uncertainty and hazard analysis using a geophysical flow model. In *submitted to International Congress on Environmental Modelling and Software*, 2010b.

Stinton, A., M. Sheridan, A. Patra, K. Dalbey, and L. Namikawa. Incorporation of variable bed friction into TITAN2D mass-flow model: Application to Little Tahoma Peak avalanche (Washington). *Acta Vulcanologica*, 16(1-2):153–163, 2006.

Wechsler, S. and C. Kroll. Quantifying DEM uncertainty and its effects on topographic parameters. *Photogrammetric Engineering* & *Remote Sensing*, 72:108–1090, 2006.