Paper 308, CCG Annual Report 14, 2012 (© 2012)

Application of MPS Simulation with Multiple Training Image (MultiTI-MPS) to the Red Dog Deposit

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A Multiple Point Statistics simulation based on the mixing of two training images is developed and put into practice. Its applicability is evaluated at characterizing the uncertainty of occurrence for geological units at the Red Dog deposit in Alaska. The mixing process is based on the allocation of weights for each training image, that can be defined by the user according to their knowledge of the deposit. The main task is to extract the high order statistics of each training image properly and consider them in the simulation. A methodology for calibrating the combined training images against the drillholes based on the entropy along the drillholes will be demonstrated. A one dimensional template allows calculating the entropy for both the drillholes and the training images. For the latter, a sampling process that replicates the original orientation of the drillholes measures the entropy of the training images. A comparison between the entropy of the mixing training image with the entropy of the drillholes allows calibrating the continuity in order to reproduce the high order statistics from both training images and the behavior of the boundaries between the geological units.

Introduction

The assessment of uncertainty in geological units is important. The use of two-statistics techniques has been widely developed and implemented to quantify the uncertainty of categorical and continuous variables. However, multiple point statistics are being used increasingly in order to reproduce the complexity of its geological shapes. The Multiple Point Statistics (MPS) simulation paradigm depends on the use of training images that contain the relationship of more than two points at a time. The selection of the right training images is critical. There are few training images available to the mining industry. Boisvert (2007) proposed a pseudo-genetically methodology for constructing training images for vein type and weathered deposits. Our proposal focuses on using the drillhole data themselves to generate a training image. An application to the stratiform massive sulfide Red Dog deposit will be shown.

The methodology consists of generating a training image that takes into account the continuity of the geological units. The use of entropy as a statistic of the spatial disorder was introduced for measuring the continuity of boundaries. We start constructing two different training images by using deterministic and randomized approaches: 1) the distance function modeling with multiple rock type has showed a capacity of generating adequate geological models with less time consuming requirements, see Silva and Deutsch (2012a), and 2) a relatively fast variogram based technique namely Sequential Indicator Simulation, are capable to construct a training image with a random component along the boundaries. These two training images are mixed according to the drillhole continuity using an entropy measure of the samples (Silva and Deutsch, 2012c).

Case of Study: Red Dog Mine

Teck Resources Inc. has provided an extensive drillhole dataset of the Red Dog mine in Alaska, which is the second largest producer of zinc and lead. The geological-genetic model of the deposit comprises a sedimentary exhalative and replacement origin. The mineralizing process is contained within three exhalative rock types: silica, barite and sulphide rocks. In turn, the deposit can be divided into four mineralized plates according to structural, exhalite and sedimentary characteristics: upper, median, lower and sub-lower. Figure 1 shows an isometric view of the plates. Particularly, two areas were considered for evaluating the proposed approach called the Northern and Southern.

The drillholes of the Northern sector confirm the presence of median and lower plates, the remainder of the rocks are not classified as a mineralized unit and are considered a waste-rock and denominated “other”. The upper plate is added in the southern area. The drillholes are sampled on a regular grid of 100x100 feet. The volumes of the Northern and Southern areas correspond exactly to the size where the training images are defined see Figure (2).

In general, there are two different ways to obtain a reliable training image for simulating a mineral deposit. The first is generating a schematic geological outline, which can be based on the knowledge of the deposit by the geologist. A scheme might be understood as a cross-section interpretation, simulations of categorical variables or pre-established training images based on its metallogenic origin. The second approach considers using the drillholes directly as a training image; however, in this case appears a series of problems conditioned by the lack of a regular grid and the spacing between the training images. Despite the different approaches, the drillholes are still the most reliable source for the inference of multiple point statistics due to its exhaustively sampling process over the deposit. Thus, the use of training images conditioned to an exploratory drilling campaign on a producer mine must be subordinated to similar areas where the drillholes have been previously drilled. In the case of a new deposit, the decision of using a training image should be strongly supported by any previous project under production such that its similarities make the decision justifiable.

The current work proposes to generate a simulated model for the plates units in the Red Dog deposit using a variant of Multiple Point Statistics that mixes two training images. In addition, the simulation is calibrated with the drillholes in order to reflect the grade of continuity along the boundaries at deeming the entropy as its measure. For that, it combines two training images, which were previously generated. These training images represent opposite extremes in terms of continuity. On the one side, we have a smoothed training image constructed at applying the distance function technique for multiple rock types. On the other side, we generate a randomized training image by, for example, implementing the Sequential Indicator Simulation. Such for both northern and southern areas, the resulting training images are presented on Figure (3) and Figure (4).

The drillholes that will be tuned against the training images are those inside the volume defined by the Northern and Southern areas. The first step is to calculate the entropy along the selected drillholes using a one dimensional template, for further reference see Silva and Deutsch (2012b). A template with four locations for both northern and southern sectors was chose. In the case of the first, we have three codes which make a total of 3^4 possible templates' configurations. For the southern, there are four rock codes increasing the total number of configurations up to 4^4. The entropy was performed by calculating the probabilities of occurrence of each configuration over the total of replicates found in the selected drillholes, see equation (1).

$$H_{drillhole} = -\frac{1}{nd}\sum_{i=1}^{nd}\sum_{j=1}^{k} p_{i,k} ln\left(p_{i,k}\right) \tag{1}$$

The second step consists in measuring the entropy of the training images. In order to make comparable the entropy of the drillholes performed with a one dimensional template against the entropy of the training image on 3D, we proposed a sampling procedure over the training image - see Figure (5) and Figure (6) - for each selected drillholes which replicates the same orientation on a regular grid (Silva and Deutsch, 2012b). Firstly, the entropy for each replicate is calculated using equation (1). Secondly, the entropy of the drillhole which is being replicated is the average entropy of all its replicates. Finally, the entropy of the training images is the average of the entropy of all selected drillholes.

The third and last step entails calibrating the entropy of the drillholes with the entropy of the training image that was obtained by combining and weighting the smoothed and randomized training images.

Calibration of Continuity

The calibration process between the training images is a critical step. It allows us to tune the continuity of boundaries of the geological units with the appropriate selection of the weights to the training images. Comparing the entropy of the drillholes we are able to determine the right proportion of continuity at mixing the training images derived from the distance function and sequential indicator simulation. A total of 99 training images were generated from the original two. Each training image is an output of mixing the original two training images with different proportion. Thus for example, the first training image starts with a proportion of 99% from the original SIS training image and 1% of the DF training image; on the contrary, the last training image poses the inverse proportions.

Using the sampling process described previously and one dimensional template with four locations, the entropy of each training image was assessed and plotted against its mixing proportion for both Northern and Southern sectors such as is presented on Figure (7.A and B). A polynomial regression of third degree over the scatter points allows getting the calibration curve. The entropy of the drillholes in the case of the northern area is 1.34 which leads to a proportion of 40% of the training images from DF and 60% from SIS; while the southern reach 1.07 and the mixing proportion is 86% from DF and 14% for SIS. The process was repeated with a template of five locations and the result of the calibrated curve is equivalent to the case with four locations Figure (8 A and B); however there is one difference, the entropy is greater because the number of configuration due to a bigger template was increased (Larrondo, 2003). The training images produced at combining the proportions established by the calibration curve are showed on Figure (9).

For calibrating the training images a code has been written. On line 7 the number of locations of the one dimensional template is set up. Line 8 and 9 call for the name and columns of the drillhole file. From 10 to 12 are described the parameters of the training images, its origin and dimension. It is realized for sampling purposes. On line 13 is defined the sampled grid over the training image. Lines 14, 15 and 16 put the name for output files. Lines 17 sets up the number of training image for which the entropy will be calculated. Finally, for each training images is added the line with the name of the file and the number of the column for the training image.

```
1                       Parameters for CALITI
2                       *********************
3
4  START OF PARAMETERS:
5  3                                - number of categories
6  2  3  5                          - category codes
7  4                                - 1-D template length
8  redogti.prn                      - file with data
9  1  2  3  4  5                    - columns for DH,X,Y,Z,var
10 40       586469        10        - nx,xmn,xsiz
11 53       144322        10        - ny,ymn,ysiz
12 38          560        10        - nz,zmn,zsiz
13 100 100                          - sampling mesh for training image
14 0                                - export sampling drillholes 0:No/1:Yes
15 sampling.out                     - file with sampling drillholes
16 entropy.out                      - file with entropy of drillhles and TI
17 2                                - number of training images
18 DFZ1.out                         - file for training image
19 1                                - column for training variable
20 SISZ1.out                        - file for training image
21 1                                - column for training variable
```

MPS Simulation with Two Training Images

Even though the training images of the Northern and Southern regions belong to the same deposit, they reflect different local geological conditions, that is, the presence of mineralized units, the proportions between them and the continuity along the boundaries. The main concern lies on the fact of extrapolating the features of the training image properly over areas with similar characteristic. The Multiple Point Simulation must be performed in zones of the deposit that are represented accordingly by the training image. The case of exploratory data is even more delicate, with a gross sampling grid the knowledge of the deposit is scarce and difficulty supported by the data. The construction of the training image must be focus on where the grid makes finer.

In order to apply the Multiple Point Simulation, the implementation of the methodology was focused on the drillholes within the current pit limit. The training images of the southern area appear suitable to simulate the geology basically because it reflects the presence and relationship of all the mineralized units within the pit. A total of 100 simulations were performed with a proportion of 86% from the training image generated by the distance function and 14% for whose training image product of the Sequential Indicator Simulation. On Figure (10) is showed a realization of the simulation process reproducing the different aspects of the training images. Over the 100 realizations, probability maps for each mineralized units were generated, it measures the probability to find out one of the four units (upper, lower, sub-lower and otherwise) at all locations within the pit. Benches and cross sections are presented on Figures (11-12) and Figure (13). It shows the main features of the deposit and its uncertainty.

Conclusions

The paper demonstrates a robust workflow to get training images for a mining deposit. The selection of the training images is based on the multiple modeling distance function approach and any classical stochastic geostatistical simulation technique. The variant of Multiple Point Statistics simulation process rests on the extraction of the high order statistics relationship from two training images. The degree of mixing can be defined subjectively by the user according with his knowledge of the deposit. As an alternative, this work proposes to calibrate the continuity of the drillholes with the training images by the use of the measure of entropy. The degree of disorder is determined along the drillholes with a one dimensional template. A sampling process allows assessing the entropy of the training images. A simulated model was plotted on different benches inside the pit of the mine to reflect the main features inferred from both the smoothed and randomized training image. The mixing was determined by the calibration curve in a proportion of 86% against 14%, respectively. Probability maps were created on benches and cross sections along North-South direction to reveal different aspects of the uncertainty between the mineralized geological units.

Acknowledgments

The authors thank to Teck Resources Inc. and especially to the Red Dog Mine for providing the dataset used on the implementation of the methodology.

References

Boisvert, J. (2007). Mineral Deposit Modeling with Pseudo-Genetically Constructed Training Images

Silva D.A. and Deutsch, C.V., 2012a. Modeling Multiple Rock Types with Distance Functions: Methodology and Software in Geostatistics Technical Report, Centre for Computational Geostatistics, University of Alberta. September 2012.

Silva D.A., 2012b. Multiple Point Statistics with Multiple Training Images in Geostatistics Technical Report, Centre for Computational Geostatistics, University of Alberta. September 2012.

Silva D.A., 2012c. An Entropy-Based Measure of Continuity for Weighting Multiple Training Images in Geostatistics Technical Report, Centre for Computational Geostatistics, University of Alberta. September 2012.

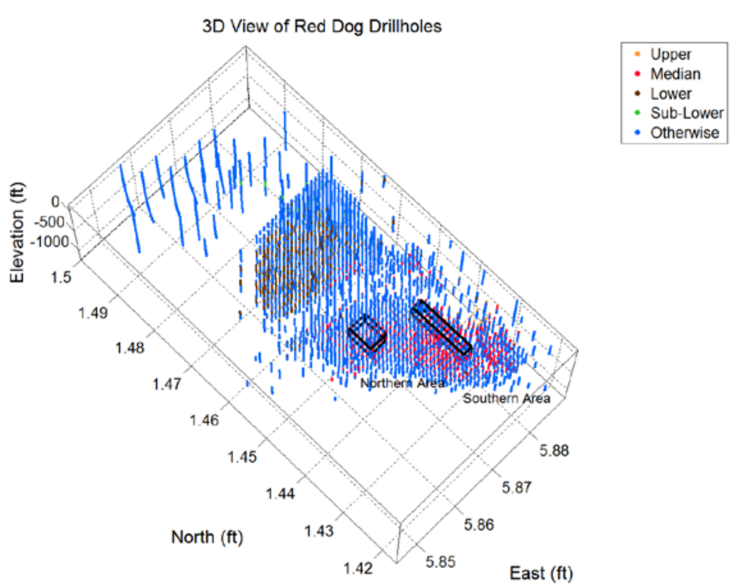

Figure 1: Isometric View of Drillholes in Red Dog mine. Both Northern and Southern sectors are considered in the evaluation of the methodology.

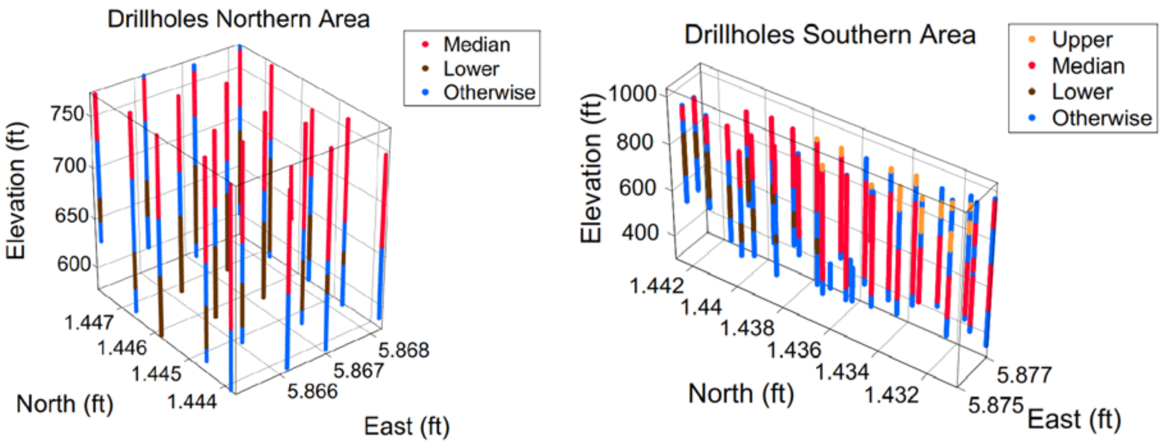

Figure 2: Drillholes with its mineralized geological units within the Northern and Southern areas.

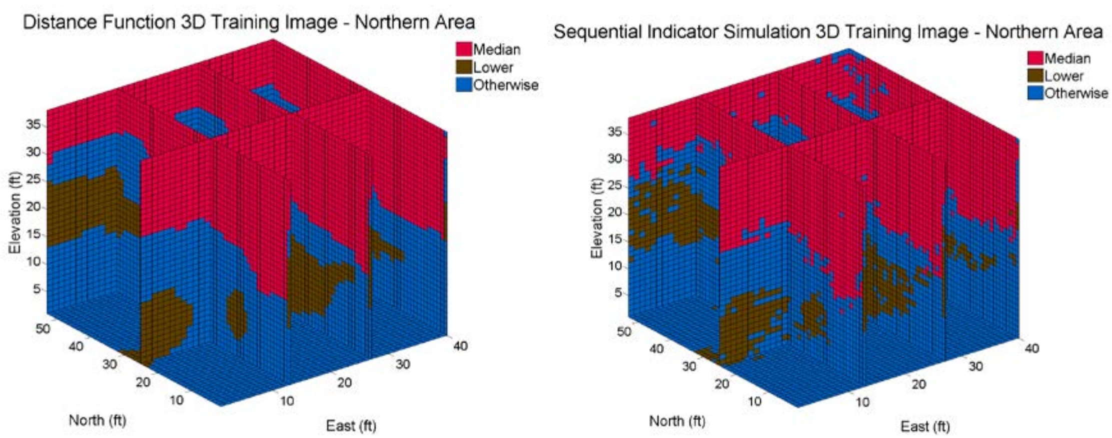

Figure 3: Smoothed and randomized training images for Northern area. The training images are based on distance function technique and Sequential Gaussian Simulation respectively.

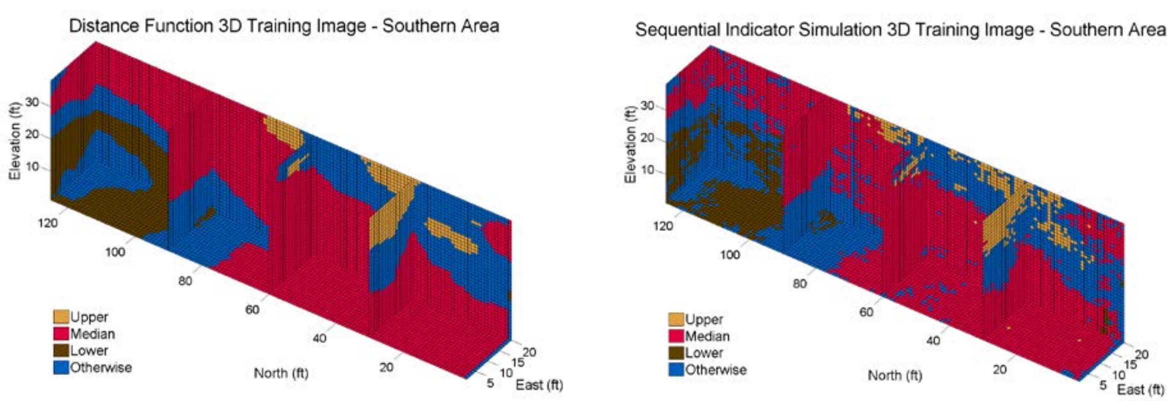

Figure 4: Smoothed and randomized training images for Southern area. The training images are based on distance function technique and Sequential Gaussian Simulation respectively.

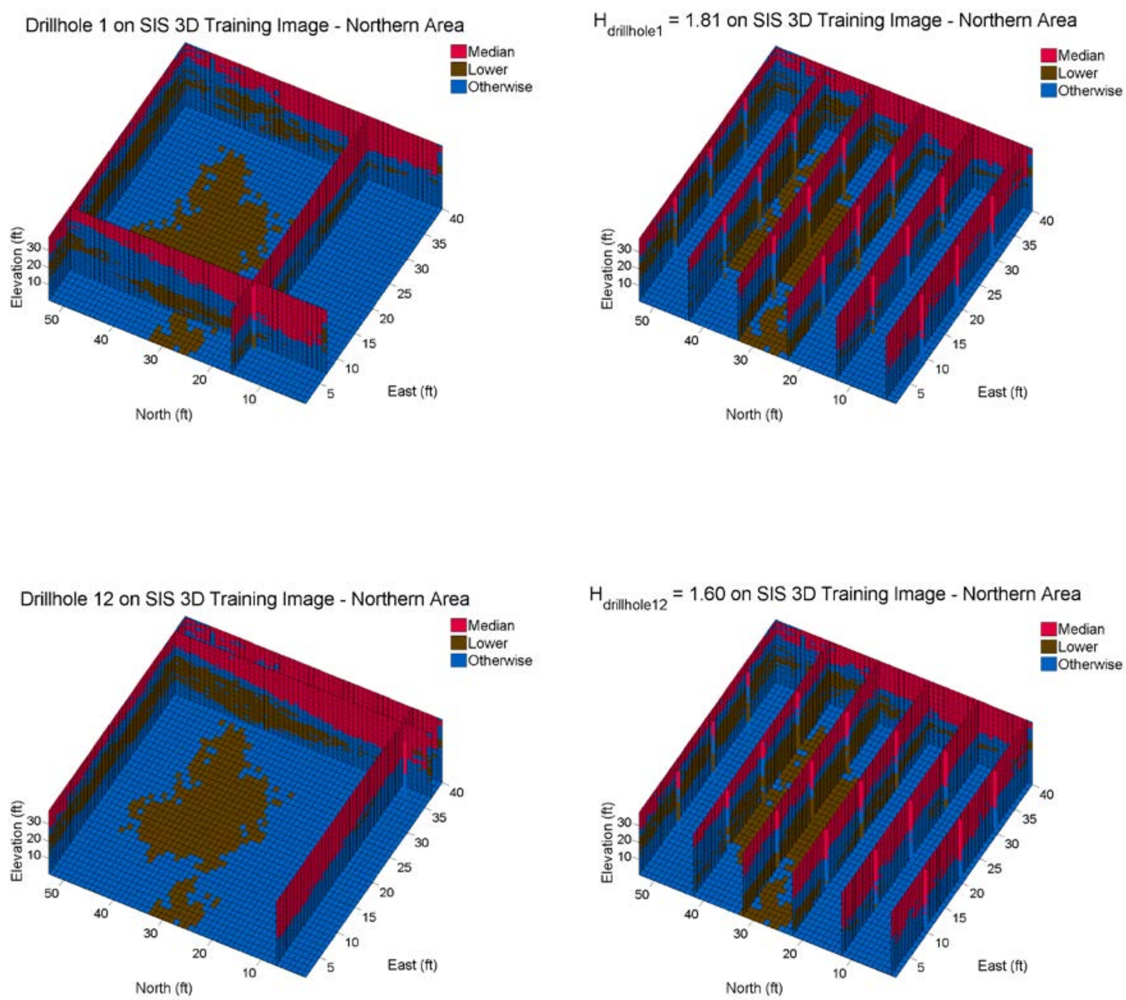

Figure 5: Sampling process on a grid mesh of 100x100 over a Northern training image

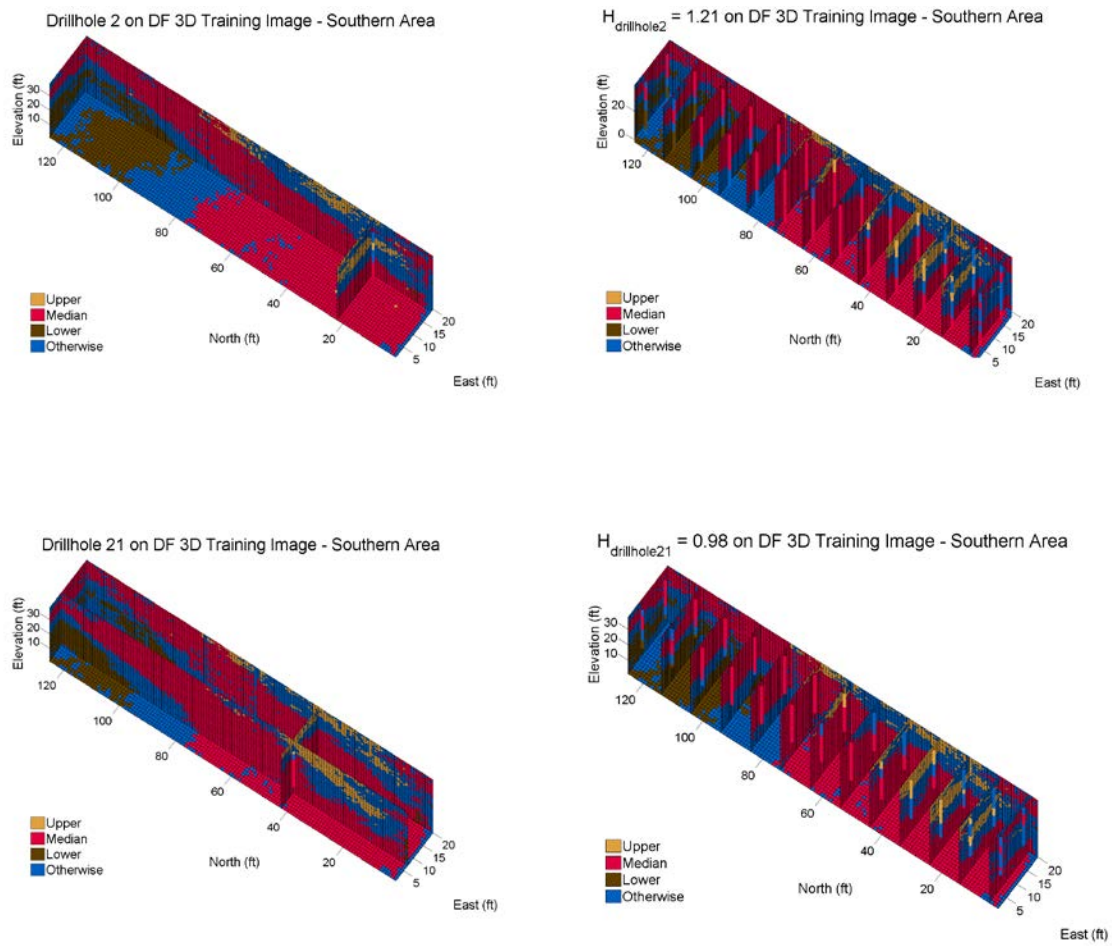

Figure 6: Sampling process on a grid mesh of 10 over a Southern training image

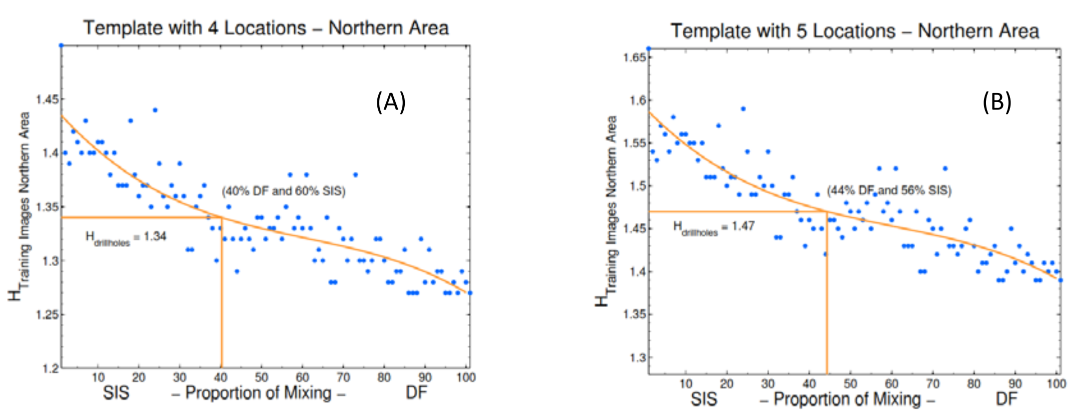

Figure 7: Calibration curve for a template with four and five locations in the Northern area.

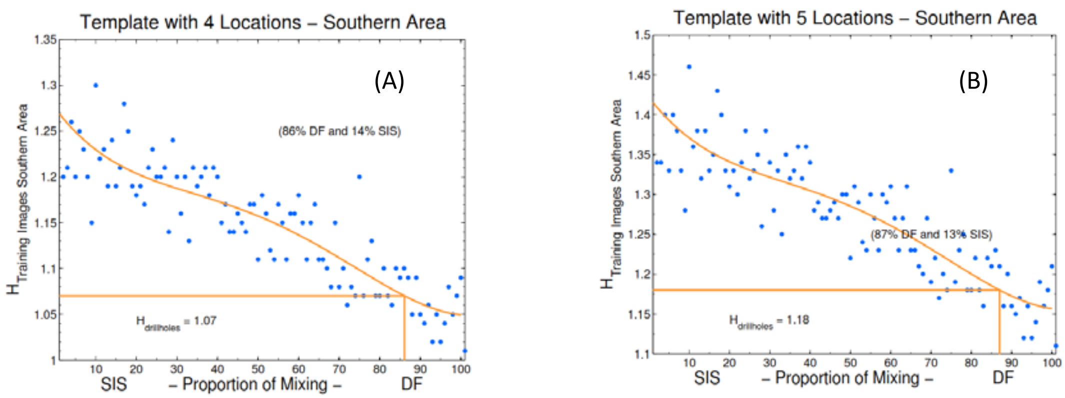

Figure 8: Calibration curve for a template with four and five locations in the Southern area.

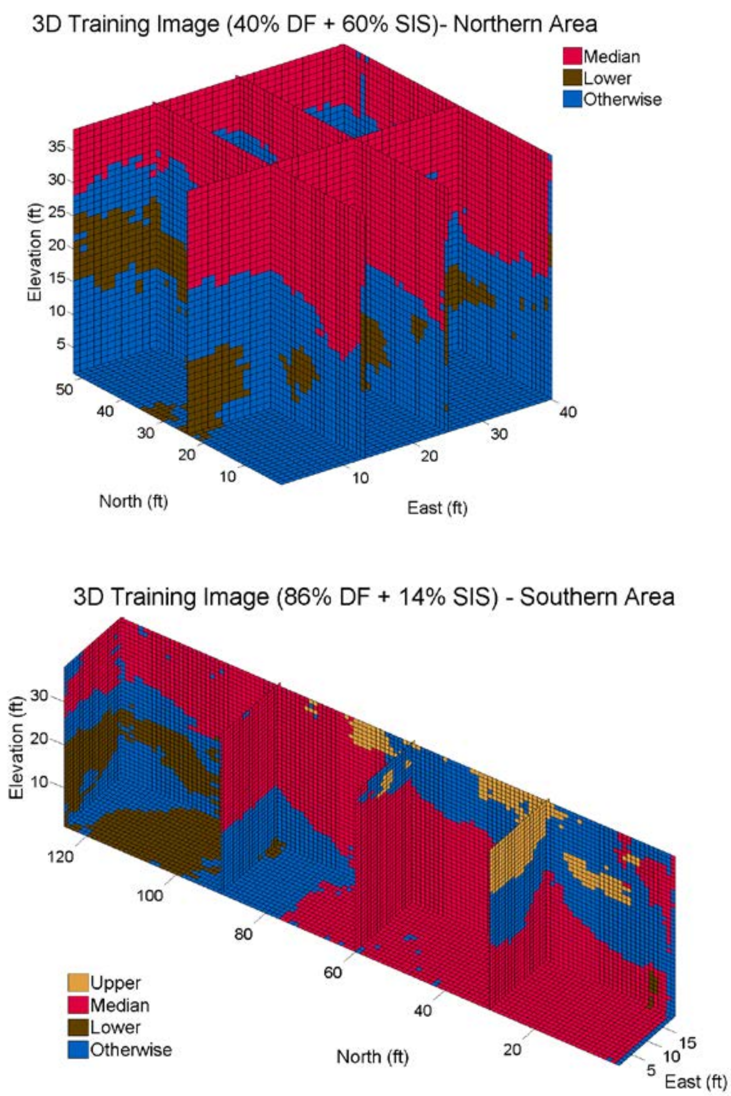

Figure 9: Training images produced at combining the DF and SIS training images with different proportions

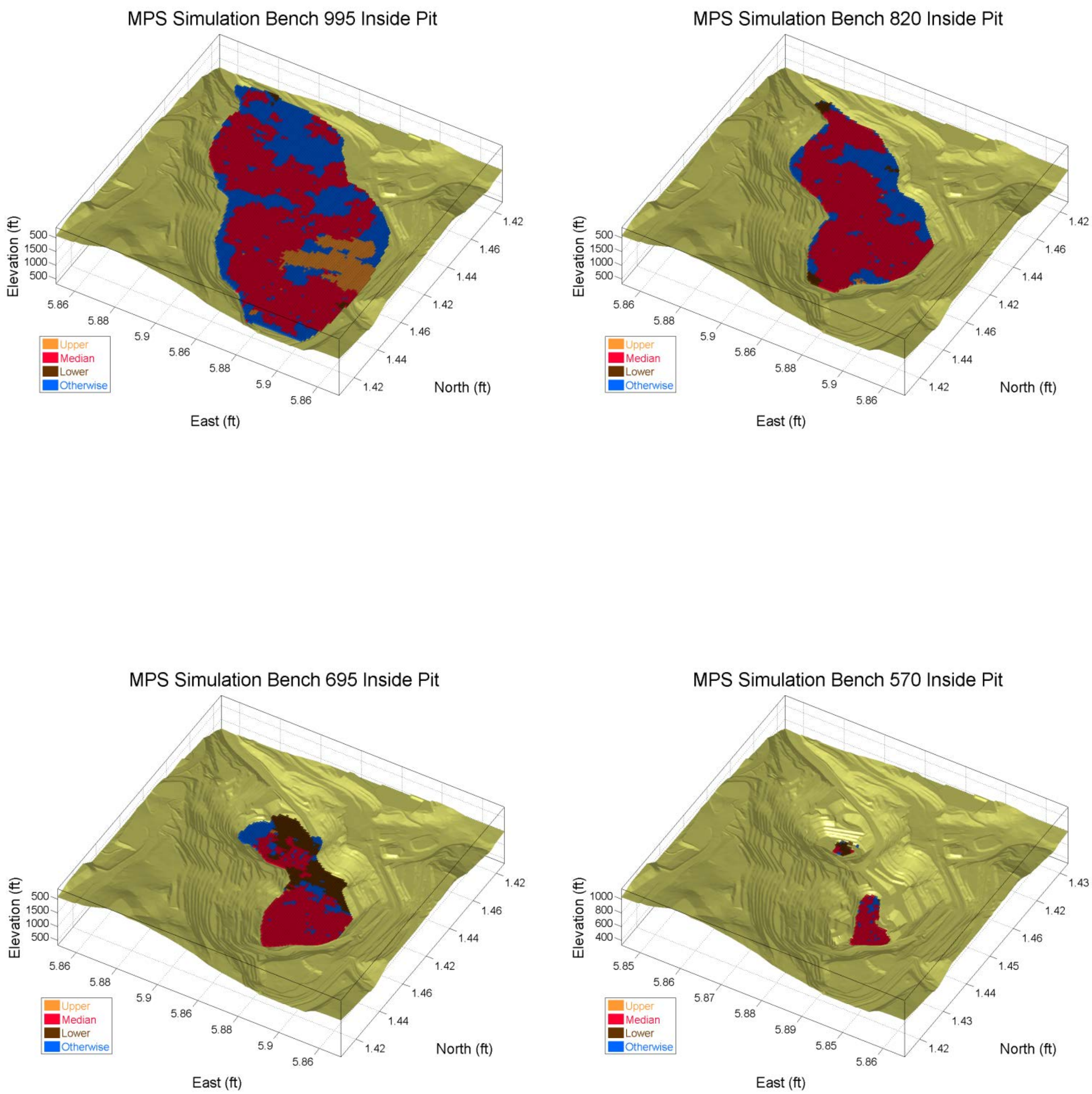

Figure 10: One MPS realization mixing the training images of DF and SIS with proportions of 86% and 14% respectively

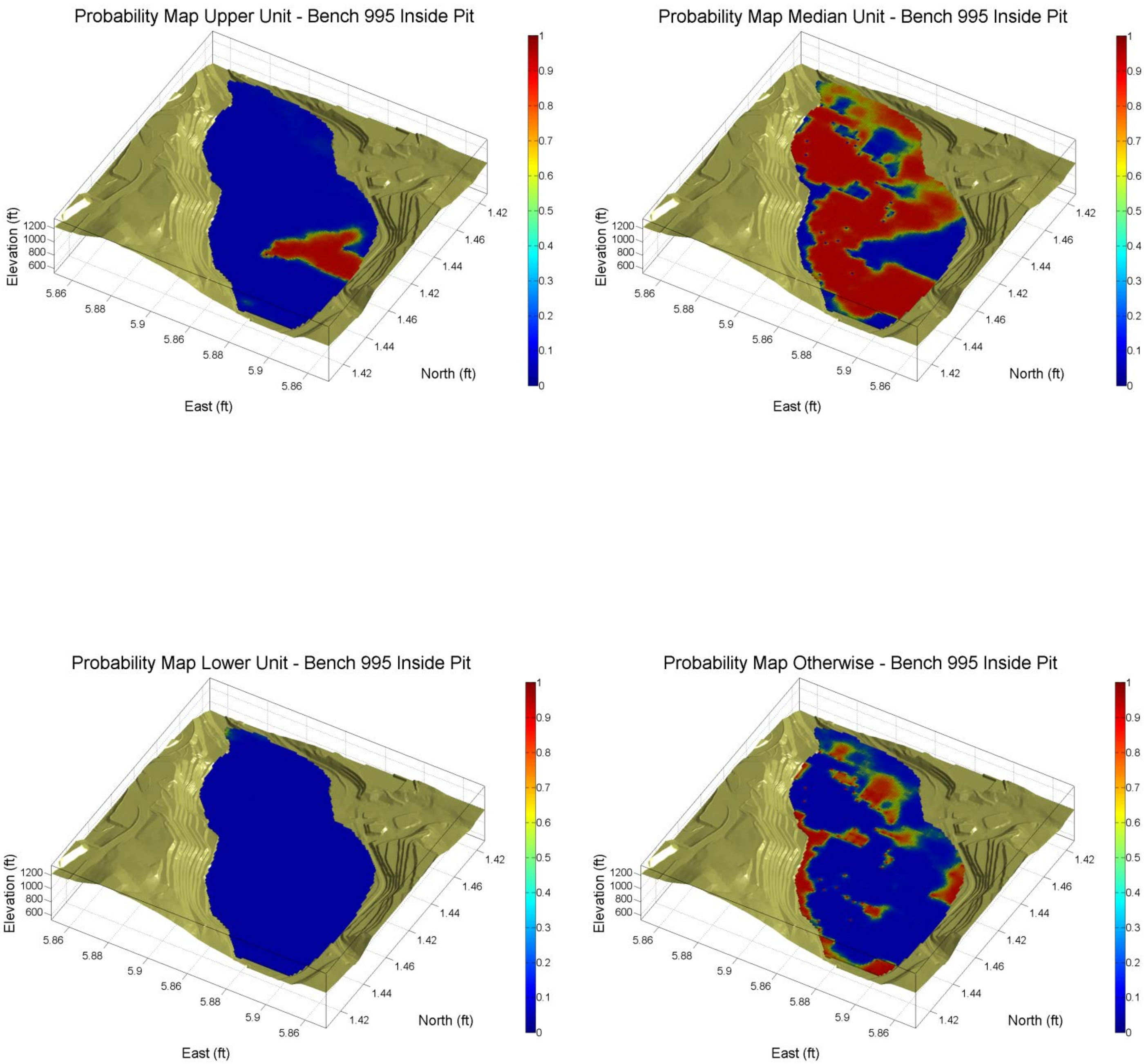

Figure 11: Probability maps on bench 995 for Upper, Median, Lower and Otherwise units

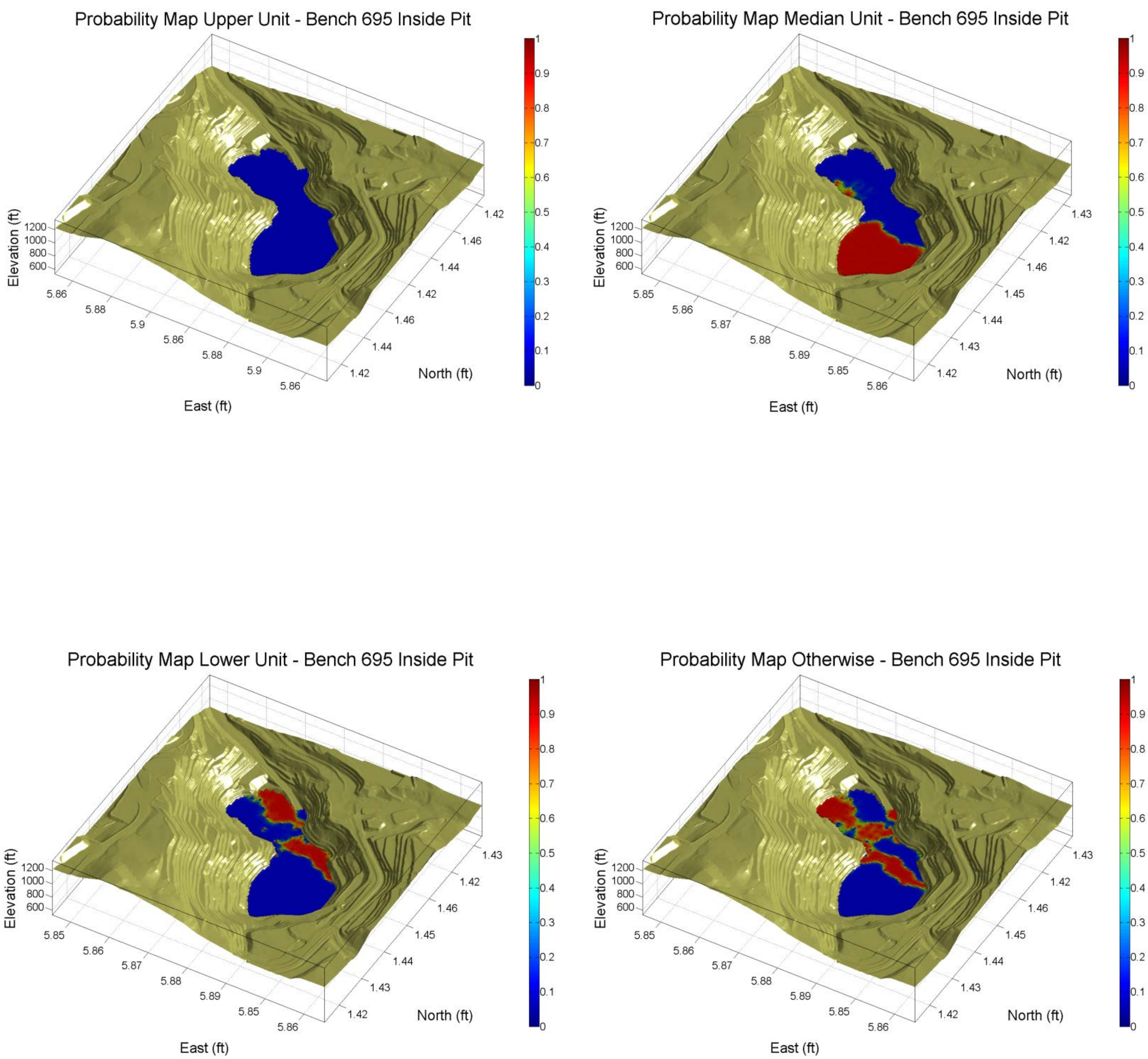

Figure 12: Probability maps on bench 695 for Upper, Median, Lower and Otherwise units

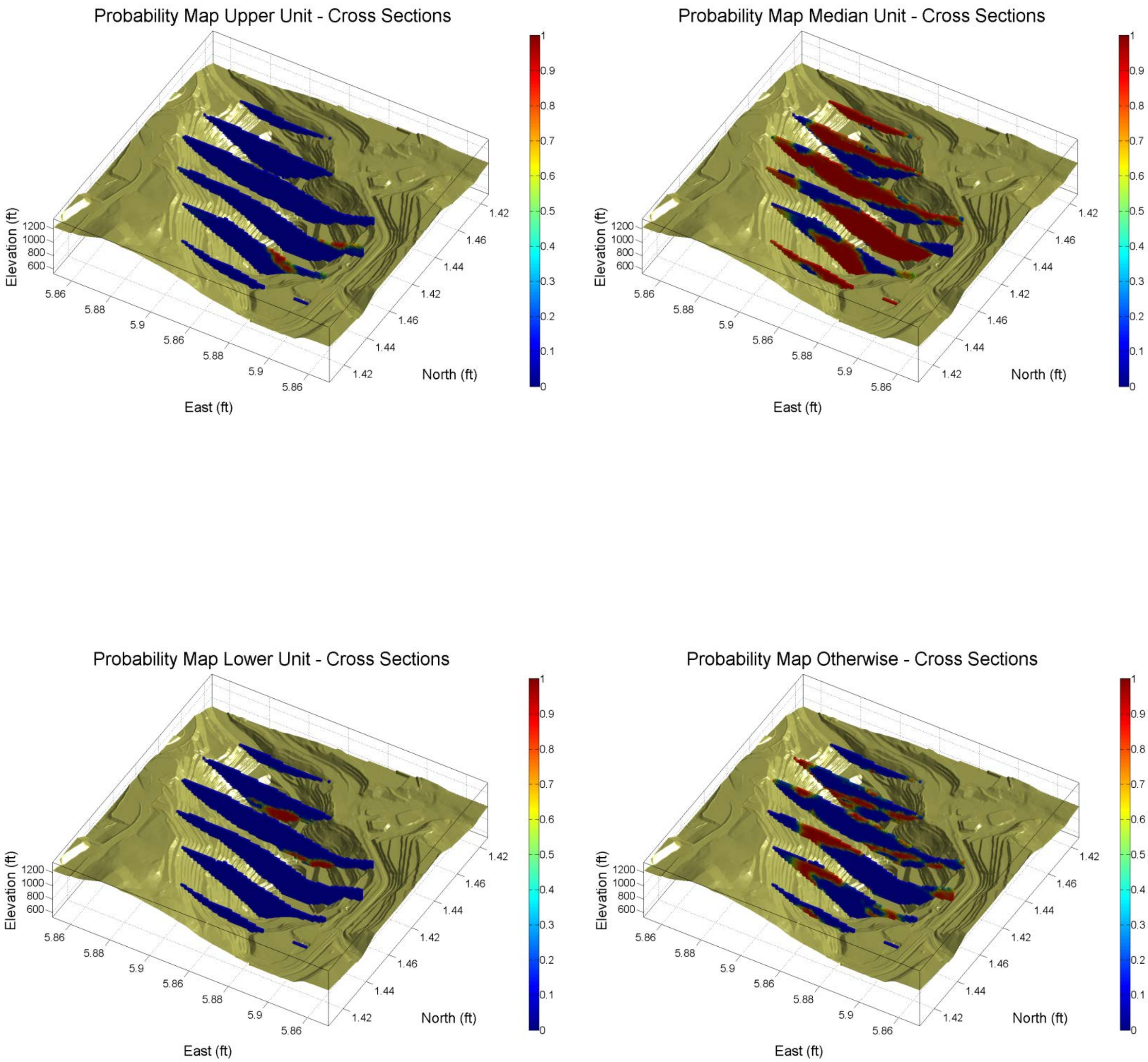

Figure 13: Probability maps on cross sections along North-South direction or Upper, Median, Lower and Otherwise units