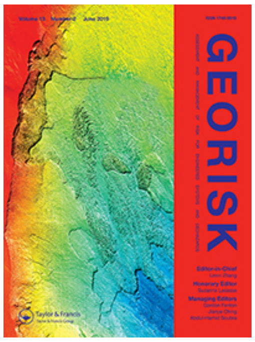

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NOTE

A method for generating virtual soil profiles with complex, multi-layer stratigraphy

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ABSTRACT
This paper presents a framework for generating multi-layer, unconditional soil profiles with complex stratigraphy, which simulates the effects of natural erosion and sedimentation processes. The stratigraphy can have varying degrees of randomness and can include features such as lenses, as well as sloped and undulating layers. The method generates the soil comprising the layers using local average subdivision (LAS), and a random noise component that is added to the layer boundaries. The layers are created by generating coordinates of key points in the simulated ground profile, which are then interpolated with a customised, 2D, linear interpolation algorithm. The resulting simulations facilitate more accurate probabilistic modelling of geotechnical engineering systems because they provide more realistic geologies, such as those usually encountered in the ground. Fortran code implementing this framework is included as supplementary material.

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Spatial variability; layer generation; random field theory

1. Introduction

This paper presents a framework for generating virtual, random, three-dimensional (3D), complex soil profiles by merging multiple, homogenous soils in a process that broadly emulates erosion and deposition. Here, virtual soil profiles are computer-generated representations of a volume of soil property values. The framework focuses on the generation of random stratigraphies, of arbitrary complexity, that define the boundaries between soil layers. While one method of defining layer geology is presented here as an example, a programme, in the form of Fortran source files, is provided as supplementary material, and users may modify the layer generation parameters to suit their own particular circumstances. The code may be added to any number of existing frameworks and software packages that currently work with single-layer soil profiles, as discussed later in this section.

For the purpose of clarity, it is important to note the objectives of the proposed framework, and highlight what it is not intended to achieve. Firstly, the method was designed to model plausible geology, and allow users to investigate the impact of specific geological features. It was not designed as a soil genesis model, which attempts to model physical processes directly, e.g. (Opolot, Yu, and Finke 2015). Secondly, the proposed method cannot currently be used to replicate existing physical soil profiles found in practice. Such simulations are known as conditional, as they are constrained to match the soil properties at their respective physical locations as encountered by soil testing. In contrast, the proposed method involves unconditional simulation, which generates virtual and fictitious soils as specified predominantly by statistical parameters. As such, conditional, multi-layer generation techniques, such as sequential indicator simulation (Bierkens and Weerts 1994) and coupled Markov chain models (Elfeki and Dekking 2001) are not relevant to this work. While it is possible to modify the software accompanying this paper to allow for conditional simulation, it is not the focus of this study.

Virtual soil generation and its use has applications in a range of areas which have pre-existing Fortran software, including settlement modelling (Kuo et al. 2004), optimisation of site investigations (Jaksa et al. 2005), slope stability analysis (Griffiths and Fenton 2004), calibration of reliability-based design (Fenton and Naghibi 2011), modelling groundwater flow (Schlüter et al. 2012), and demonstration in teaching (Kim 2011). Random soils can provide a wealth of statistical information when used within a Monte Carlo (MC) analysis framework (Ang and Tang 2007), where each MC realisation uses an independent random soil. In particular, random soils are often paired with finite element analysis; a

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combination referred to as the random finite element method (RFEM) (Fenton and Griffiths 2008).

While many studies have used various types of virtual soil generating algorithms, they are typically only used to produce profiles that are homogenous or otherwise of simple stratigraphy. Here, homogeneity refers to soils with variable properties that represent a single soil type. In reality, soils contain complex geological features such as faults, lenses and layers of arbitrary boundaries. This complexity is due to the wide variety of natural processes that form and influence the ground and that occur over long periods of time (Skinner and Porter 1987). Soils have a tendency to be eroded and deposited by water, wind or ice. These processes can significantly influence the nature, shape and orientation of soil layers, or even remove them completely. Given the prevalence of these processes and geological features, it is important to have a model that can represent plausible, naturally-occurring soils with this geology.

Virtual soils are generated using random field theory (RFT); a means of creating correlated random values that are representative of realistic geotechnical property spatial variability (Vanmarcke 1983). The product is a random field; a volume of discrete elements, where each element represents a soil property value. In practice, RFT is commonly implemented to generate fields that exhibit second order stationarity (weak stationarity). The soil is described in its entirety by the first and second order moments: The mean (μ) and the standard deviation (SD), as well as the correlation structure. The standard deviation is often standardised by the mean to express the coefficient of variation (COV) where COV $=$ SD/μ. The aforementioned soil correlation structure is needed because soil elements that are in close spatial proximity are expected to have similar properties. This structure is represented by a scale of fluctuation (SOF), which describes the distance over which properties are expected to be correlated. A SOF can be specified for each dimension, and it is often the case that horizontal values are higher than the vertical. The horizontal-vertical SOF ratio is termed anisotropy, and occurs because the effects of gravity and sedimentation frequently result in soil deposits being formed in a series of relatively thin layers, where properties fluctuate more rapidly with depth (Jaksa 1995).

There are two primary reasons why the generation of complex soil profiles has not been widespread. Firstly, as RFT is often implemented with the assumption of weak stationarity, the mean is constant throughout the soil. This theoretically results in soil profiles that are more general, and hence more widely applicable, as opposed to soils with specific geological features with distinct means. However, this simplification is contrary to adopting separate layers, and so the resulting soils cannot reliably be used to represent multiple-layer cases. Secondly, in terms of recreating specific, real-world stratigraphies, layer boundaries are difficult to model as a large, and often impractical, amount of information is required to delineate existing trends with any degree of accuracy (Spry, Kulhawy, and Grigoriu 1988).

A review of existing literature has failed to uncover a flexible, widely-adaptable method of generating multiple soil layers. For example, the soil generation method in (Schlüter et al. 2012) utilises a similar concept to that of the present study, involving the merging of independent homogenous soils to form a multi-layer profile. However, in that study, the layer boundaries were 2D in nature and consisted of simple, idealised layer boundaries. Layer boundaries are rarely perfectly flat or horizontal, and typically incorporate slopes, roughness, and undulations, with the latter describing a wave-like pattern. The method in (Schlüter et al. 2012) attempts to model these features by either a perfect sine wave, or a horizontal boundary with random noise added from a 1D Gaussian random field, which oversimplify the geological components.

On the other hand, Huber, Marconi, and Moscatelli (2015) simulated random multi-layered soils sites by means of a Pluri-Gaussian simulation (Armstrong et al. 2011). The Pluri-Gaussian technique defines layers in 3D by the intersection of multiple, 3D random fields. This method is appropriate for simulating complex random soil profiles, as the process is fully random, and it incorporates spatial correlation as is expected in layer boundaries. However, it does not permit fine control of the layer boundary definition, should it be necessary. For example, when examining the influences of certain aspects of geology, it is often desirable to start with a simplified representation of the geology to determine the effects of individual variables. For this reason, a generalised method for simulating many aspects of geology is required, where the user may specify the level of complexity and degree of randomness required.

The layer-generation algorithm presented in this paper allows for fine control over random layer boundaries, which is absent in Huber, Marconi, and Moscatelli (2015), and allows for greater flexibility and complexity than the method in Schlüter et al. (2012). The algorithm given here is an extension of that presented by Crisp, Jaksa, and Kuo (2017), which utilised the layer generation process described in the present paper to generate 2D soil profiles that consisted of two layers separated by a random, undulating boundary. The main improvements to the algorithm involve its extension from 2D to 3D, and the specification of additional interface options between layers. An example of a semi-random layer boundary is provided in order to demonstrate its use. While the manner of input associated with the example may not be applicable for all geological situations, the underlying process is flexible and can accommodate a far wider range of geology than that shown here, assuming it conforms to the minor constraints described throughout the present study.

2. Methodology

The following sections describe a framework to generate multiple-layer soil profiles. The authors describe a new method of defining geology and producing layer boundaries based on this geology. Recommendations are also given on a means of generating the soil within each layer.

2.1. Description of overall procedure

The framework assembles a soil profile with multiple layers, mimicking the processes of erosion and deposition. Soil layers are added in chronological order: The oldest soil is generated first, and is assumed to completely fill the desired final volume (i.e. ground), as seen in Figure 1 (a). An erosion threshold is then defined in the form of a complex boundary. Above this boundary, the original soil is eroded, and then a newer layer is deposited. This process is repeated until the desired number of layers is obtained. The evolution sequence for generating a four-layer profile is illustrated in Figure 1.

The generation process for each layer can be divided into five stages, as shown in Figure 2:

(1) Soil property generation, to create the soil volume for the present layer (§2.3);
(2) Layer boundary characterisation, comprising user-specified points that spatially define its overall shape (§2.4);
(3) Generation of the mean layer boundary by interpolating the defined points (§2.5);
(4) Addition of random noise to the boundary to represent the chaotic nature of natural processes (§2.6); and
(5) Removal of the soil above the boundary, and replacement with the new soil layer.

These steps are illustrated by the flowchart in Figure 3.

2.2. Description of software

Software, in the form of Fortran code (Rajaraman 1997) has been created to implement this framework, and is available as supplementary material for reference, use, and modification. The code is based on subroutines provided by Fenton and Griffiths (2008), largely updated to Fortran 95 standard, and with new subroutines added to provide multiple-layer functionality. These additional subroutines implement all features described in this paper. Currently, the software generates and outputs multiple-layer soil profiles based on a specified input file. However, it can readily be adapted to replace its single-layer counterpart in software used for purposes described in §1. As such, users should be able to conduct an RFEM analysis by combining existing software with

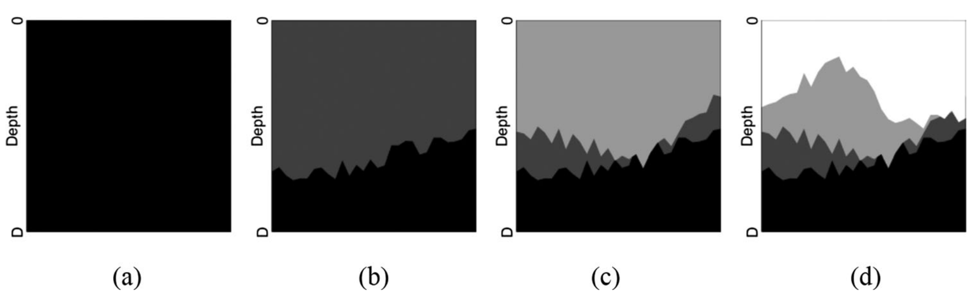

Figure 1. Evolution process of a 4-layer soil profile, in cross section, as each soil layer is added to the profile by erosion and deposition.

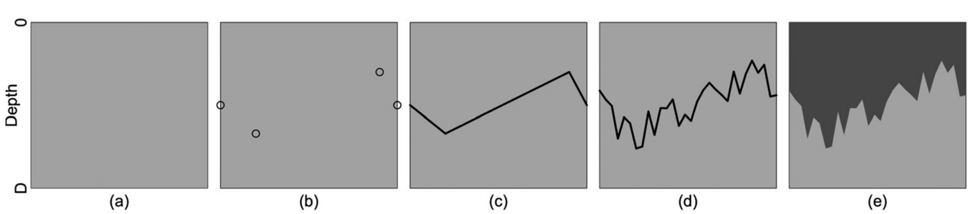

Figure 2. Cross-sectional view of the steps involved [Steps 1–5 (a–e), respectively] of the generation of soil layers and their boundaries.

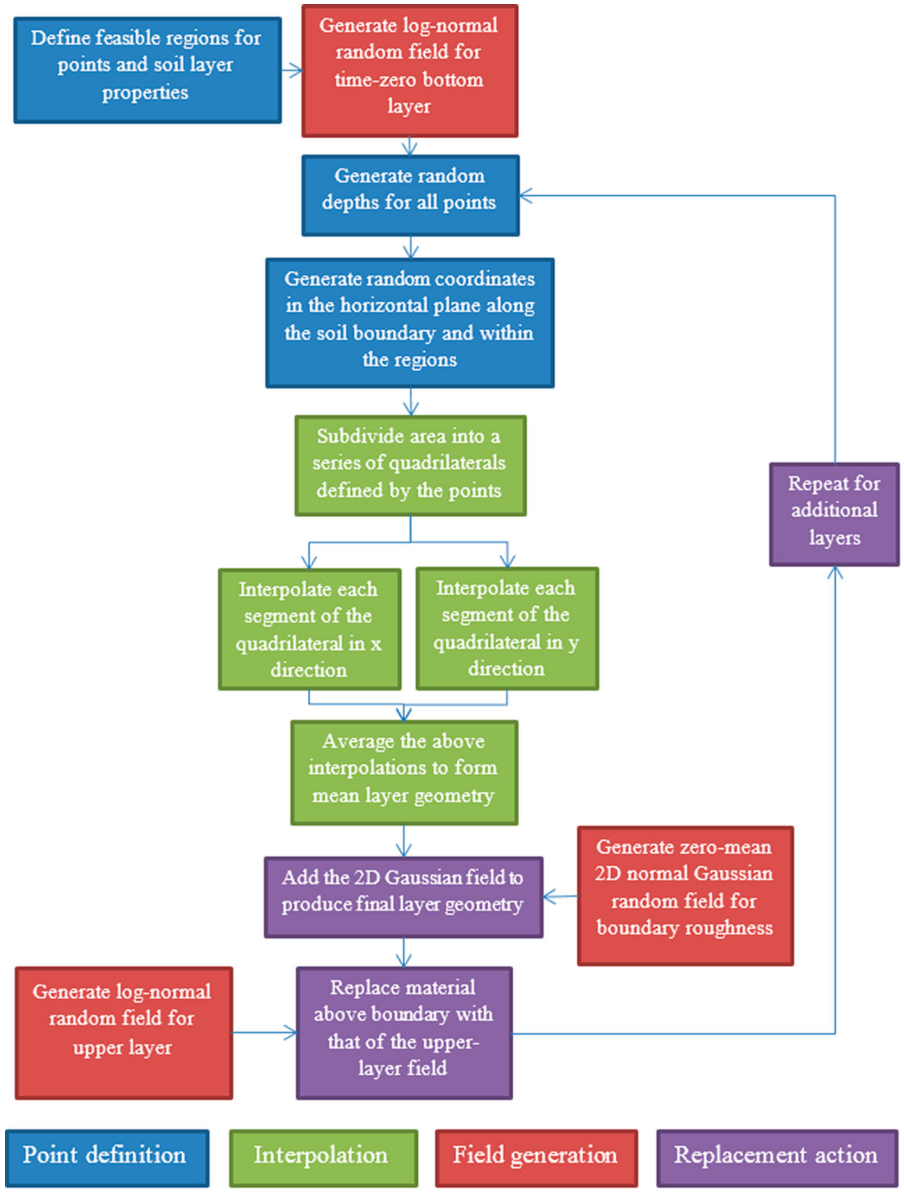

Figure 3. Flowchart describing the process of layer generation, including stratigraphic definition and interpolation.

that provided, as opposed to developing the software themselves.

2.3. Generation of soil by local average subdivision

The proposed framework uses local average subdivision (LAS) (Fenton and Vanmarcke 1990) to generate the random fields that represent the virtual soil within layers. It is a rapid and accurate means of generating random fields that is commonly used to generate single-layer soil profiles, and has numerous advantages over other methods (Fenton and Vanmarcke 1990; Fenton and Griffiths 2008). The authors refer readers to the aforementioned studies for a detailed account of its procedures and assumptions. Nevertheless, a brief overview is provided below to provide a context for the present work.

The provided implementation of LAS operates by first generating a small, stage-zero field of arbitrary size and desired mean using the covariance matrix decomposition method as seen in Figure 4(a). This field is subsequently subdivided across multiple stages, generating new random values at each stage, as demonstrated in Figure 4. Every subdivision results in the soil's resolution doubling in each dimension. When new cells are created by the subdivision of a parent cell, the average of the new cells is equal to the parent's original value. This averaging constraint ensures that the average of the final field is equal to that of the initial stage. Each random value, and hence the field itself, is generated according to the

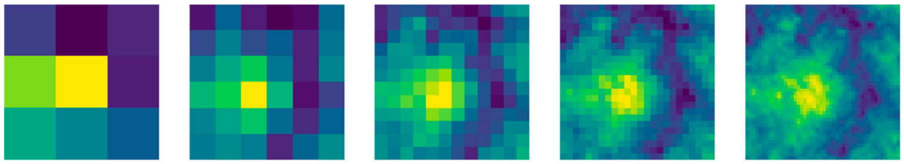
(a) (b) (c) (d) (e)

Figure 4. Demonstration of several stages of soil generation by local average subdivision.

standard normal distribution, with zero mean and unit variance. If other distributions are required, they can be transformed from the standard normal. Therefore, LAS can be used for a large number of property distributions, including lognormal and beta (Ang and Tang 2007).

Overwhelmingly in the literature, the lognormal distribution is used for virtual soils because it ensures that the properties remain non-negative, and because other studies have shown this distribution to be appropriate (Lumb 1966; Hoeksema and Kitanidis 1985). The spatial structure is defined by an exponential Markov correlation, as is common for this application (Fenton, Paice, and Griffiths 1996), and it has been shown to be the most accurate out of a set of alternative options (Cao and Wang 2014).

Local average subdivision has three notable limitations; however, these can be overcome by simple workarounds. Firstly, LAS is restricted to generating soils as discrete volumes of $a2^n \times b2^n \times c2^n$ elements, where a, b, c and n are integers. While this offers a reasonable degree of flexibility, the resulting field size is not completely arbitrary. Secondly, there is a variance reduction effect across parent cell boundaries at each subdivision stage due to correlation approximations (Fenton and Griffiths, 2008). Both of these limitations can be overcome by generating a larger field than required and extracting a randomly-located subset. This subset can be of truly arbitrary size. As the location of the subset is random, so too is the location of the variance reduction, eliminating the resulting bias across realizations. The third restriction is that LAS uses an isotropic correlation structure, as opposed to anisotropy described previously. However, if anisotropy is required, it can be achieved by first generating a deep, isotropic soil, then contracting spatial coordinates in the vertical direction by the desired anisotropic ratio.

The three parameters required for the generation of the soil volume within each layer are the mean, COV and SOF. It is important to choose appropriate values for these properties that correspond to real soils. Several studies have compiled databases of soil properties, including the mean, SOF and COV for various types of soils. These values can be used as guidelines for possible inputs to use in unconditional simulation. A comprehensive investigation of soil property variability was summarised by Phoon (1995). The results are based on the outcome of many years of research on reliability-based design of transmission towers at Cornell University (Filippas, Kulhawy, and Grigoriu 1988; Orchant, Kulhawy, and Trautmann 1988; Spry, Kulhawy, and Grigoriu 1988; Kulhawy, Birgisson, and Grigoriu 1992). Further information on soil properties are provided by (Soulie, Montes, and Silvestri 1990; Jaksa 1995; Phoon and Kulhawy 1999; Akkaya and Vanmarcke 2003; Kulatilake and Um 2003). An over-arching review of these studies, in the context of practical simulation of Young's modulus, was given by (Goldsworthy 2006). Suggested ranges for input values for soil generation by LAS is provided in Table 1 for COV, horizontal and vertical SOFs, mean stiffness, and anisotropy, which is defined as the ratio of the horizontal to vertical SOF in any given soil. Other inputs include the element size, as well as the size of the soil volume in terms of the number of elements in each direction, which may be specified by the user depending on the size of the problem domain.

2.4. Definition of stratigraphy

Our aim with the framework presented here is to be as general and as flexible as possible. This allows one to generate stratigraphies that mimic those observed in nature. In its most general form, the framework defines a boundary by an arbitrary series of points. The point coordinates can be specified exactly or generated randomly in the horizontal and vertical directions. Achieving the desired geological structure then becomes a matter of simply specifying the positions of these points, or the conditions in which the points may randomly occur.

Table 1. Ranges for input parameters for the generation of soil, as used by the 3D LAS algorithm.

Variable	Lower bound	Upper bound
COV (%)	2%	80%
Horizontal SOF (m)	1.5 m	80 m
Vertical SOF (m)	0.1 m	12.7 m
Anisotropy	1	10
Mean (MPa)	5	170

It should be noted that any geology generated by this method must conform to two constraints. Firstly, each layer boundary is defined entirely be a 2D surface of height information. As such, the boundary cannot fold back over itself in the third dimension. Secondly, the overall geology must be defined by a series of points arranged in an arbitrary, and potentially irregular, grid pattern. However, this second constraint may potentially be removed with the implementation of a more sophisticated interpolation algorithm than the one described in the present study.

Admittedly, the current input system is not suitable for all cases of layer boundary definition, as it is deemed impossible to design such a system that satisfies the needs of all users, while maintaining an arbitrary mix of control and randomness. However, besides the input system, the core algorithm is capable of flexible geology definition, subject to the two aforementioned constraints. As such, the user is encouraged to modify the code to extend or replace this input system as desired. For example, 4 points could be defined on an inclined plane, if such an inclined layer is desired. Alternatively, the points may be specified to appear according to a normal distribution to a specified mean and variance in each dimension. However, while the software can be modified to allow this, these examples are not explored in the present study.

For the simplicity of visualisation and definition, the software input is currently coded to produce random, multi-segmented boundaries that are likely to result in an undulating pattern, which in the case of 3 or more layers, may result in the formation of lenses if the layers are allowed to overlap. Such behaviour is desirable, as lenses are a geological feature that may be especially detrimental to the satisfactory performance of foundations (Halim 1991) and so should be present in the analysis of realistic soil profiles.

The segmentation system described above is sufficient for an example of the framework, and functions as follows. The layer boundary is subdivided into a grid of arbitrary quadrilaterals, forming a series of segments in the x- and y- directions. In this case, there are 3 segments in the x-direction and 4 in the y-direction, as illustrated by the black lines in the example in Figure 5. These quadrilaterals are defined by points that are randomly located to appear within certain regions. These feasible regions are defined by the coloured hashed boxes in Figure 5, where each contains one internal point that is randomly located according to a uniform distribution. Where the edges of the box coincide with the edge of the soil, an additional point is created and constrained to that edge, in order to provide boundary conditions. This manner of randomness is reminiscent of a stratified random pattern (Ferguson 1992), albeit with boundary constraints on the edge points. The example in Figure 5 is presented, from a 3D perspective, in Figure 6.

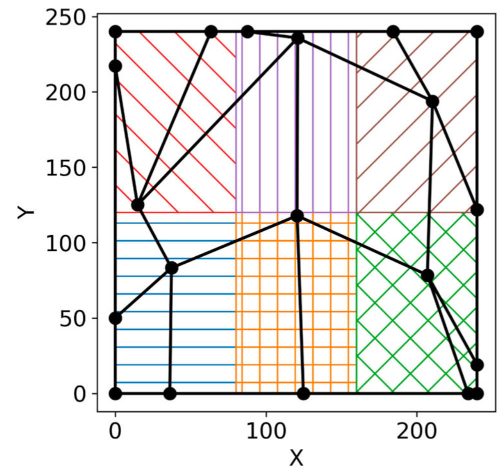

Figure 5. Plan view of feasible regions defined by 2 segments in the y-direction, and 3 segments in the x-direction. A randomly generated realisation of points is superimposed, as well as the boundaries defined by these points.

The parameters required to define a semi-random boundary, in terms of feasible regions in which the points may appear, are the lower bound, b_l, the upper bound b_u, the number of x segments, *nsegx*, and the number of y segments, *nsegy*. Given that the size of the field in the x, y and z directions is D_x, D_y and D_z in terms of the number of elements, and that X is a uniformly distributed random number (between 0–1, inclusive), the coordinates of each randomly-located point within each segment, P_x, P_y, P_z in terms of elements, can be defined as follows:

$$P_z = D_z(X(b_u - b_l) + b_l)$$

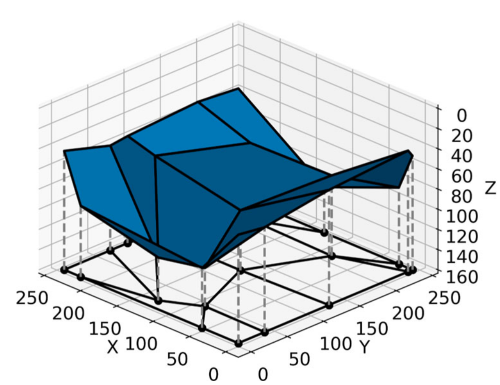

Figure 6. 3D view of the segments shown in Figure 2. In this example, the points are specified to appear vertically between 40% and 60% of the depth of the profile.

Table 2. Parameters for the 2-layer example soil.

Parameter	Unit	Value
D_x	Elements	240
D_y		240
D_z		160
nsegx	Integer	4
nsegy		3
b_l	Proportion	0.25
b_u		0.75
COV	%	80
SOF (isotropic)	m	8
E (layer 1)	MPa	5
E (layer 2)		50
Boundary S.D.	m	1.5
Boundary SOF		15

Similarly, the x and y coordinates for the i^{th} segment are given by:

$$P_y = \frac{(X + i - 1)D_x}{nsegx - 1}$$

$$P_x = \frac{(X + i - 1)D_y}{nsegy - 1}$$

As such, the values of the parameters used for the example soil are given in Table 2.

2.5. Mean layer geometry component

While the overall geometry of a layer boundary is defined by a series of points, the boundary itself must be continuous over the horizontal extent of the soil. Interpolation is used to obtain this continuous profile. As mentioned previously, the soil is represented by a series of discrete elements. As such, the boundary can be considered as a 2D grid, where each grid value represents the height of the boundary at that location.

Linear interpolation was selected, as it is the most fundamental form of interpolation available. This is due to the fact that, with sufficient data resolution, linear interpolation can produce smooth curves. In contrast, smoother interpolation techniques cannot produce sharp edges, which may be desirable. Simple interpolation methods are also frequently used by practicing engineers when attempting to recreate specific geologies found in nature. This simplification is used because there is typically insufficient information available to employ more sophisticated interpolation methods (Baecher and Christian 2005). Instead, the simplest relationship between known layer depths is assumed. The authors designed a piecewise, bilinear algorithm to interpolate a series of arbitrary quadrilaterals, in a domain of discrete elements, as the process involves linearly interpolating across each quadrilateral in the x-direction, then in the y-direction, followed by averaging the two interpolated planes. It is worth noting that a user may wish to adopt their own interpolation algorithm, if desired.

2.6. Layer roughness component

The final stage of the boundary definition process involves the generation and superposition of a continuous, zero-mean, normally distributed, 2D random field. This provides the layer boundaries with a degree of roughness, for reasons discussed previously in §1. The authors selected the normal distribution for this noise, because it has been shown to provide a reasonable representation of boundary depth variation in (Vanwalleghem et al. 2010). This is likely due to the central limit theorem, which states that Gaussian distributions arise naturally when resulting from the mean of several independent, random variables of arbitrary distribution. In a geotechnical context, the independent, random variables represent the many geological processes involved in soil formation. Furthermore, there is precedent, in that studies by Schlüter et al. (2012) and Crisp, Jaksa, and Kuo (2017) both utilised the Gaussian distribution for random noise. As such, the parameters for the layer roughness component are the standard deviation and SOF of the random noise (m).

Regarding statistical properties of layer boundaries, the variation is poorly documented and even less well understood, with focus given to shallow horizons in agricultural areas (Vanwalleghem et al. 2010). While some studies have attempted to determine layer depth parameters, such as standard deviation and SOF, results must be taken with skepticism as the apparent SOF is heavily influenced by sample spacing (Jaksa, Brooker, and Kaggwa 1997a). For example, (Kempen, Brus, and Stoorvogel 2011; Sarkar, Roy, and Martha 2013) obtained samples at an approximate, average spacing of 1 km, and determined the SOF to generally be in the order of 1–2 km, although the latter found the SOF to be as low as 140 m. On the other hand, (Vanwalleghem et al. 2010) sampled with a separation distance of 30–900 m. Besides one case of an apparent SOF of 100 m, it was generally found that there is no detectable SOF, implying that the SOF is small, in the order of less than 15 m. Note that the studies listed here used geostatistical modelling, where the cited range parameter, a, the range of influence of a spherical semivariogram, is roughly double the SOF parameter in the exponential Markov model used in the present study (Jaksa, Brooker, and Kaggwa 1997b). It is likely that these large SOF values are resulting from variation in the mean soil geology, as opposed to random noise. Therefore, a small SOF of 1–15 m is tentatively recommended.

In terms of standard deviation of layer depth, Vanwalleghem et al. (2010) examined the influence of soil horizon depth in natural loess-derived soils, and found the parameter to range from 0.05–2.21 m. It was noted

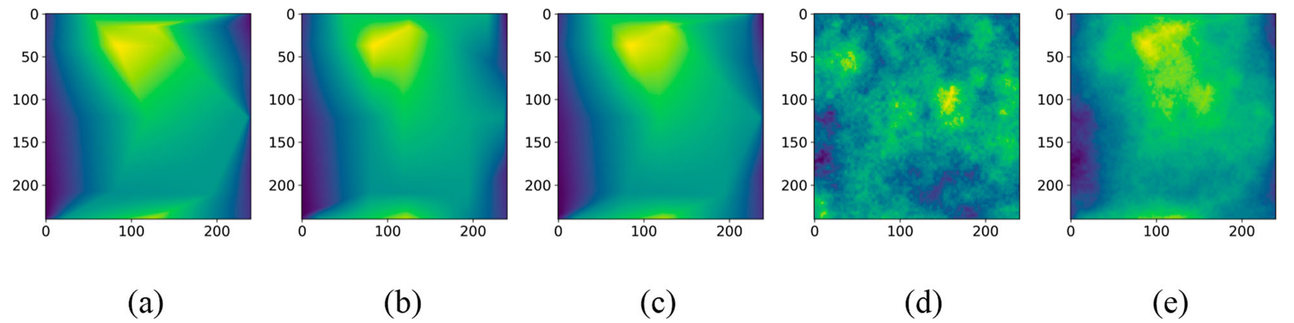

Figure 7. Plan view of the various stages of interpolation of a layer boundary in the: (a) x-direction, (b) y-direction, (c) average of the x and y interpolations, (d) average boundary with random noise, (e) random noise component of the boundary.

that there was a strong, nearly linear ($r^2 = 0.98$) increase in standard deviation with depth. This is understandable, as deeper soils are older, and are therefore likely to have been exposed to a greater number of random processes, hence the increased variation.

2.7. Optional boundary blending and soil trends

There are several additional, optional features available to increase the realism of the virtual soil profiles generated. The first is an option for blending at the layer boundary, to account for cases of two soil layers mixing during the erosion and deposition process. In this study, the simplest form of blending was selected: A linear transition from one layer to the next. This variable is controlled by a smoothing distance parameter between the mean layer boundary (b) and the edge of the linear blending zone. The equation governing the blended soil properties at depth d, P_d, based on a linear transition between the properties of an upper and lower layer, P_1, P_2, is given below for a boundary depth b, and smoothing distance s.

$$P_d = P_1\left(1 - \left(\frac{d + s - b}{2s}\right)\right) + P_2\left(\frac{m + s - b}{2s}\right)$$

The second optional feature is a linear increase in the relevant geotechnical parameter with depth, such as Young's modulus of elasticity. This trend is specified by an initial offset, l_{off}, and gradient, l_{grad}, for each layer. This feature is specifically intended to account for cases where deeper soil has gained stiffness through consolidation. The linear transformation of soil properties at depth d is done according to the following equation.

$$P_d = P_d + (l_{grad} \times d) + l_{off}$$

3. Results

This section demonstrates the generation of a layer boundary in order to produce a two-layer soil profile incorporating complex geology, using components directly from the Fortran software in question. The previously-given example of 3 segments in the x-direction, and 4 in the y-direction is reused. The same mean layer geometry is taken as seen in Figure 6.

The results of interpolating these points individually in the x- and y- directions, as well as the superposition of the two, are shown in Figure 7. As the soil field consists of discrete elements, and the boundary is defined

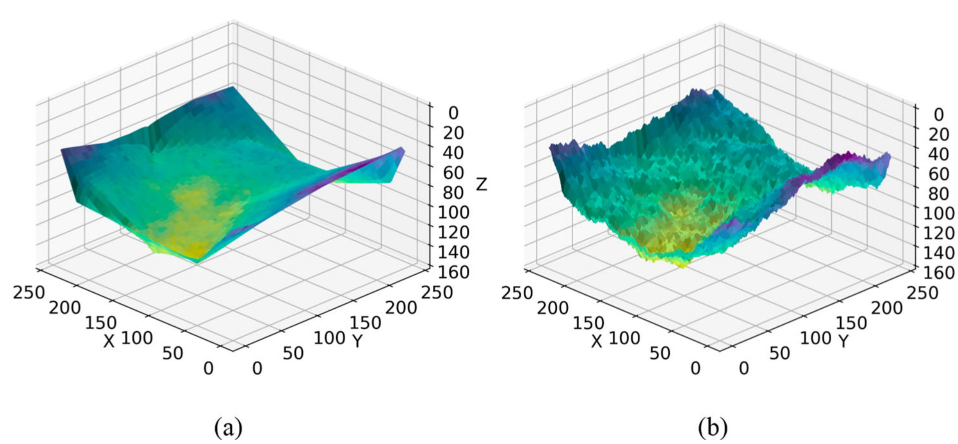

Figure 8. Isometric projection of the (a) mean interpolated layer boundary, (b) final layer boundary incorporating random noise.

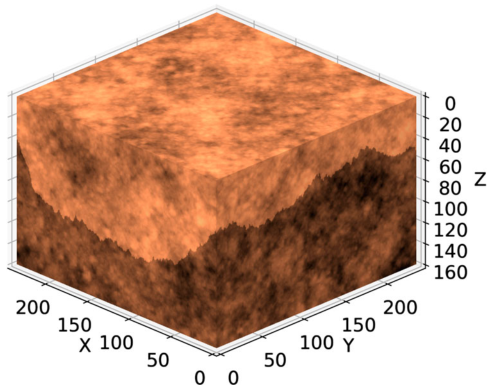

Figure 9. Final virtual soil profile, comprised of 2 layers separated by the generated boundary.

in terms of elements, the values need to be rounded to the nearest integer. The physical size of the soil was specified to comprise 240 × 240 × 160 elements, representing a 60 × 60 × 40 m volume. It can be seen in Figure 7 that the superposition is capable of creating smooth regions between the specified points, as desired. Note that no rounding has been applied to the values shown in Figure 7 in order to demonstrate its smoothness within each segment.

Figure 8 shows an isometric projection of the same field. It can be seen that the random noise succeeds in simulating a realistic layer boundary that might be observed in natural soil deposits. Note that the required rounding to fit the data into a discrete domain has not been implemented. Finally, the complete, simulated 3D soil profile, including the soil volume, is given in Figure 9.

4. Conclusion

This paper proposed a methodology, for generating complex, virtual multi-layer soil profiles that incorporate the spatial variability of geotechnical parameters. The procedure is broadly inspired by the effects of the natural processes of soil erosion and deposition. These effects allow the modelling of complex geological features found in actual ground profiles, such as irregular layer boundaries, lenses, and blending between layers. The method also allows for specific geological features to be modelled, such as slopes and undulations, and allows for the influence of these specific features to be explicitly determined in isolation. A programme, in the form of Fortran source files, has been provided and may be used or modified as desired. Modification of the input components, in particular, is encouraged in order to tailor the manner of layer boundary definition to a bespoke case not achievable with the undulation-like system demonstrated within the present study.

In comparison to previous studies, the framework presented here allows for arbitrary degrees of control and complexity. The combination of both these aspects allows for a wide variety of applications. For example, a layer boundary may have varying levels of randomness, from fully fixed through to completely randomised depth and undulation, across the full width and depth of the profile. Layer boundaries may be as simple as a smooth horizontal plane, or as complex as multi-segmented, rough surfaces. It has been demonstrated that the specification of semi-random conditions allows for the formation of desirable complex geological features, such as lenses. Within a Monte Carlo framework, a boundary may be held constant across the full simulation or randomised on a per-realisation basis.

The method is currently being employed to generate complex soil profiles in a Monte Carlo framework to examine optimal site investigation campaigns. However, the framework and software can equally be adopted to generate complex, multi-layer profiles with which to assess many different aspects of geotechnical engineering design and performance.

Disclosure statement

No potential conflict of interest was reported by the authors.

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