On the Sensitivity Analysis of Two Hydrologic Models

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EXTENDED ABSTRACT

The development of new hydrological models and the enhancement of the existing models are needed for water management. For instance, increasing rainfall may accelerate water erosion in watersheds and raise the probability of flooding events in the urban areas. The impacts include environmental and social-economic conditions. The hydrologic models SEADS, a physical process based model and GURUH, an algebraic model based on statistical relationships, are being used to predict the hydrologic impacts of urbanization. These models need to be fully tested so that they can be used with confidence. The implementation of sensitivity analysis to these models is a useful tool in the calibration of the models, in their applications to different catchments, and to urban change in catchments, and also to investigate climate change over the catchments.

This study uses the New Morris Method to conduct the sensitivity analysis (SA) of two hydrological models the SEADS (a soil erosion and deposition model) and GURUH (a rainfall-runoff model) models. The New Morris Method is an extended version of the Morris method that was proposed by Morris (1991). The New Morris Method, in addition to the 'overall' sensitivity measures already provided by the Morris method, offers estimates of the two-factor interaction effects (Campolongo and Braddock 1999). The method retains the computational efficiency of the OAT scheme, applying an efficient sampling strategy in the parameter space. The strategy is based on concepts of graph theory and on the solution of the 'handcuffed' prisoner problem.

The New Morris Method produces sensitivity measures including the mean 'μ', and standard derivation 'σ' for the first order effects. Similar results are obtained for the second order effects where two factors at a time interact. They are the mean 'τ', and standard derivation, 'η' of the second order interaction. The sensitivity outputs are functions of the number of runs (denoted by 'runs') and resolution (denoted by 'res'), which are algorithm parameters of NMM. These parameters govern how many trajectories through parameter space are calculated and at what resolution the parameter space is sampled. The sensitivity measures are obtained with respect to each pair of values of the New Morris Method parameters, runs and res.

In the case of a simple analytic function, the sensitivity may be evaluated by analytical or numerical methods and is called the 'true value'. However, for a complex function (the mathematical hydrologic models), an analytic solution is not available. Consequently a pseudo-analytical solution is obtained with parameter values of runs = 200 and res = 100, and is used in place of the analytic solution. The difference of the SA output measures relative to the 'pseudo-analytical solution' is called the relative error and is examined for various values of runs and res. Each input factor contributes its own relative error. The average of the relative errors due to all factors is called as the average relative error (ARE) with respect to the set of parameters. The values of ARE with respect to the parameters of 'runs' and 'res' can be plotted as a 3D surface.

The roughness of the ARE surfaces reflects the variation of the ARE with respect to the number of runs and resolution. Based on the algorithm derived by Clarke (1986), the fractal dimensions of the ARE surfaces are evaluated and used to describe the overall properties of the highly structured 3D surfaces. This approach obviates the need to use images of the surfaces and avoids making subjective judgements, which may be affected by scale in a diagram.

The results revealed some differences in the fractal dimension of the error surfaces between the types of models, i.e. physically based differential equation model SEADS and the more heavily parameterized compartment model GURUH. The results are not extensive enough to draw definitive conclusions relating to the nature of the models. A great deal more work is required in assembling results across models of different types, before any definitive conclusions can be made. Naturally, there can be "good" and "bad" models of the same physical system, and this will need to be addressed in future work.

1. INTRODUCTION

Hydrology plays a fundamental role in environmental planning, management and restoration (Singh 1995). The rainfall-runoff model typically modeling continuous flow with a long time step is one of the fundamental models used in hydrology. One of its applications is to predict the hydrologic impacts of urbanization such as flooding. Water erosion is the detachment and transport of soil from the land by water, including rainfall and runoff and is the main source of sediment that pollutes streams and fills reservoirs (Ward and Trimble 2004). A soil erosion and deposition model is an important tool to predict the environmental impact due to water erosion.

Sensitivity analysis (SA) is a fundamental tool in the building, use and understanding of models of all forms. Tarantola and Saltelli (2003) concluded that "SA can get useful information regarding the behaviour of the underlying simulated system. This information can range from the identification of calibration variables to model reduction or simplification, better understanding of the model structure for given components of a system, model quality assurance, and model building in general."

The New Morris Method (NMM) is a type of screening method based on the one-at-a-time (OAT) design (Morris 1991). SA techniques also incorporate their own parameters, which govern the accuracy of the analysis (Campolongo and Braddock 1999; Cropp and Braddock 2002). NMM has two important parameters, the number of runs (denoted by 'runs') and resolution (denoted by 'res') that govern how many trajectories through parameter space are calculated and at what resolution the parameter space is sampled.

The difference of the sensitivity measures with respect of runs and res relative to the 'true value' is termed the relative error. The average of the relative errors due to all input factors is the average relative error (ARE). The values of ARE with respect to the parameters of 'runs' and 'res' can be plotted as a 3D surface. The technique of fractal analysis is used to measure the ARE surfaces by a single figure, fractal dimension, in order to describe the overall properties of the highly structured 3D ARE surfaces.

The aim of this work is to investigate possible linkages between the fractal dimension of the average relative error surfaces and the nature of the models in order to determine the optimum values of runs and res. This will be addressed by using the NMM to conduct SA on two different algorithm hydrologic models to construct the ARE (average relative error) surfaces with respect to the NMM parameters; runs and res.

2. THE TWO HYDROLOGIC MODELS

Two hydrologic models were studied. The SEADS (Soil Erosion And Deposition System) model is a mathematical model used to predict soil erosion/deposition (Yu 2003). The Griffith University Representation of Urban Hydrology (GURUH) model is a daily rainfall-runoff model developed by Newton et al. (2003). These models represent very different approaches to the problem as the algorithm of the SEADS model involves the solving of the governing partial differential equations whereas the GURUH model formulates the linear relationship among the parameters. Both the number of input factors and model outputs of the GURUH model are greater than that of the SEADS model.

2.1 GURUH Model

The GURUH model models the relationship between the rainfall and runoff to investigate the impact of urbanization for small urban catchments (Newton et al. 2003). The surface runoff component of the GURUH model is based on the conceptual description of rainfall response given by Boyd et al. (1993).

Table 1. Input parameters and outputs of the GURUH model

Nine input parameters and their ranges:	
1. Capacity of effective impervious store	C_1 ($0 - 4$ mm)
2. Capacity of other impervious store	C_2 ($5 - 100$ mm)
3. Average capacity of pervious stores	C_3 ($15 - 200$ mm)
4. Proportion of effective impervious	A_1 ($0 - 0.67$)
5. Loss factor	F_L ($0.5 - 5$)
6. Proportion of RO to interflow store recharge	R_{IF} ($0 - 1$)
7. Max recharge rate to baseflow store	R_{max} ($0 - 5$ mm.d^{-1})
8. Interflow store linear recession constant	K_{IF} ($0 - 1$ d^{-1})
9. Baseflow store linear recession constant	K_{BF} ($0 - 1$ d^{-1})
Seven outputs:	
1. Median runoff (RO) for days with RO > 0.01	RO_{med}
2. Maximum daily runoff	RO_{max}
3. Coefficient of total runoff to total rainfall	C_{ro}
4. Sum of squares of runoff differences to basecase	SLS
5. Percentage of days on which RO > 10mm	RO_{10}
6. Percentage of days on which RO > 1mm	RO_1
7. Percentage of days on which RO > 0.1mm	$RO_{0.1}$

The catchment is assumed to consist of three types of surfaces with increasing initial loss before runoff commences; effective impervious, other impervious, and pervious surfaces. Effective impervious areas are defined as areas which produce virtually 100% runoff after some small initial loss. The effective impervious area is often similar to the impervious area that is directly connected to the drainage network and may be obtained from examination of the recorded rainfall-runoff response (Boyd et al. 1993). The total impervious area includes the effective impervious area plus other impervious areas which do not contribute immediately to runoff

(Newton, Jenkins et al. 2003). The GURUH model has nine input parameters and seven model outputs. The nine parameters of describe the properties of catchments (Newton, Jenkins et al. 2003). Some assumptions are made so that a linear relationship among the parameters is established. The nine input parameters, with ranges used in the SA, and the seven outputs are presented in Table 1.

2.2 SEADS Model

There are two approaches to mathematical modelling for an erosion/deposition prediction. One is to use a large data base collected from a particular system and to derive an equation empirically (Semple 1991). The second approach is to formulate the model from theoretical relationships to mathematical modelling, although data will be required to determine the value of the parameters (Rose 1985). The SEADS model is the second type and it is based on the concept of simultaneous erosion and deposition (Rose et al. 1983; Rose 1985; Hairsine and Rose 1991; Hairsine and Rose 1992). Yu (2003) pointed out that the framework considers three continuous physical processes of rainfall detachment, flow detachment, and sediment deposition simultaneously. Yu (2003) noted that this approach has received experimental support and is used to model multi-class sediment deposition. The SEADS model has six input factors describing the properties of the soil and returns three outputs (Table 2).

Table 2. Input parameters and outputs of the SEADS model

Six input parameters and their ranges:	
1. sediment wet density	ρ_s :(1500 – 2500 kg/m^3)
2. flow entraiment parameter	F :(0.01 – 0.1)
3. soil erodibility parameter	J :(0.5 - 50 kg/J)
4. soil detachability parameter	E_d :(0.008 – 0.08 kg/m^3)
5. stream power	Ω :(100 – 105 W/m^2)
6. particle size scaling parameter	P_s :(0.2 – 5)
Three outputs:	
1. total erosion	(t/ha) , T_e
2. sediment delivery ratio	Del
3. cumulative sediment distribution at 50%	(mm), C_{sd}

3. METHODOLOGY

3.1 SA Measure

The NMM is used to conduct the sensitivity analysis on the two hydrologic models, SEADS and GURUH. The Morris method provides sensitivity estimates of the 'overall' influence of a factor on the output and is an 'overall' or average sensitivity measure of curvature and interaction between factors where the average is taken over a section of parameter space (Morris 1991; Campolongo and Braddock 1999). The new method, in addition to the 'overall' sensitivity measures already provided by

the Morris method, offers estimates of the two-factor interaction effects (Campolongo and Braddock 1999). The method retains the computational efficiency of the OAT scheme, applying an efficient sampling strategy in the parameter space (Campolongo and Braddock 1999).

The New Morris Method produces sensitivity measures with respect to a specific pair of NMM parameters, runs and res. Higher value of runs means larger sample size and sample space increases with the value of res. Obviously, high value of runs with high value of res returns higher accuracy output (by the Central Limit Theorem). However, it means longer computation time and then higher computation cost. Basically, computation time is a function of number of runs, but is independent of res. While both values of runs and res are low, the output has low accuracy, since both the sample size and sample space is small. In case of low value of runs (small sample size) and high value of res (large sample space), the output can only cover a small area (local effect) of the large parameter space. When using NMM, the determination of the optimum pair of values of runs and res for a specific model is important to improve the efficient.

The NMM produces the sensitivity measures with respect to the NMM parameters, runs and res. They include the mean 'μ', and standard derivation 'σ' for the first order effects and the mean 'τ', and standard derivation, 'η' for the two-factor interaction effects.

3.2 Average Relative Error

In the case of a simple function, the sensitivity measure (first or second order) evaluated by analytical methods is called $\beta_{analytic}$, where β is one of the sensitivity measures 'μ', 'σ' 'τ', and 'η'. The difference of the SA output measures β_{ij} sampled in parameter space, with runs = i and res = j, relative to the $\beta_{analytic}$ is called the relative error (Cropp and Braddock 2002). Each (or each pair) of model input factor(s) contributes to the relative error and the average of the relative errors due to all factors is termed the average relative error (ARE). For example the ARE_{ij} , runs = i and res = j is defined as:

$$ARE_{ij} = \frac{1}{n} \sum_{n=1}^{n} \frac{\beta_{ij} - \beta_{analytic}}{\beta_{analytic}} , \qquad (1)$$

where n is the number of the factors or pairs of two factors (e.g. for the SEADS model, n = 6 and 15 for first order and two-factor interaction respectively).

However, analytical estimates of β are not readily obtained for the SEADS and GURUH models. Instead, Matthews, et al. (Mattrews et al. 2003) proposed the use of a pseudo-analytical solution β_{pseudo} to evaluate the average relative error. The

β_{pseudo} is obtained with parameter values of runs = 200 and res = 100, and replaces $\beta_{analytic}$ in equation (1).

Note that β can be applied to all SA measure: μ, σ, τ, and η, and the corresponding measures are denoted by ARE_μ ; ARE_σ for first order effects, and ARE_τ ; ARE_η for second order interact effects. The values of ARE with respect to the parameters of 'runs' and 'res' can be plotted as a 3D surface.

3.3 Fractal Analysis

The surface roughness reflects the variation of the ARE surfaces with respect to the number of runs and resolution. Fractal dimensions can provide an objective means for comparing surfaces (Barnsley and Rising 1993). The triangular prism surface area method derived by Clarke (1986) was used to calculate the fractal dimension of a geographical surface. He claimed that his method provided a technique with the simplicity of the 'walking dividers', which used geometry alone in the computations. In this study, the geographical elevations were replaced by the ARE with respect to runs and res. The triangular prism surface area was calculated using Heron's Formula.

The values of ARE of the SA measures for runs = 1 to 17 and res = 2 to 18 were computed. The surfaces for 289 ARE of SA (17 x 17 grids) with respect to runs and res were obtained for each model output. The fractal dimension of the surface plots are denoted by

D_μ : fractal dimension of the ARE_μ ,
D_σ : fractal dimension of the ARE_σ ,
D_τ : fractal dimension of the ARE_τ , and
D_η : fractal dimension of the ARE_η .

The values of the fractal dimension were investigated to find the possible linkages between the fractal dimension of the average relative error surfaces and the nature of the models.

4. RESULTS

The results (Ho 2004) shows that the input P_s yields the highest value of either μ or σ for all outputs of the SEADS model for the first order effects of sensitivity measures, while the factor Ω has the greatest value of μ for the output Del and the greatest value of σ for the output C_{sd}. The high ranking of P_s in particular, and Ω in terms of the standard deviation, suggests that these factors are likely to be involved in second order interactions. For the GURUH model, the factor A_1 appears to be the most important factor with a high ranking on μ for five out of seven outputs. However, the factor A_1 is not as highly ranked with respect to σ values, and this an indication that it does not interact significantly with other factors. The factors C_2 and C_3 also have several first rankings with respect to

both u and σ values, and have a first ranking 5 times with respect to σ. This suggests that C_2 and C_3 will participate in significant second order interaction.
For the second order effects, none of 15 pairs of two-factor interactions has a highest ranking for more than one output, thus indicating a more even sensitivity pattern in the SEADS model. However, the factors P_s and Ω, participate in nearly all of the highest ranked interactions. Among the 36 pairs of two-factor interactions, the interacting pair $C_2\_C_3$ is the most outstanding one with a high ranking on both τ and η, and a slightly lower ranking based on η for the median runoff output. The second important interacting pair is $C_1\_C_2$, where it has a high ranking on τ for 5 outputs, and a high ranking on η, for 2 outputs.

The fractal dimensions of the ARE surface plots were evaluated and these are listed in Table 3 and 4. The fractal dimension of the ARE surfaces for the three outputs of the SEADS model are given in Table 3, for both the first order and second order effects. The rank is given according to the fractal dimension of the three outputs, for each of D_μ, D_σ, D_τ and D_η and rank 1 corresponds to the highest value. The output T_e gives the largest fractal dimension, and hence the greatest surface roughness of all the outputs, and this holds for both first and second order effects. The fractal dimension outputs for Del and C_{sd} are significantly less than those for T_e, with the exception of the D_τ for C_{sd}. The fractal dimension D_τ of the ARE_τ surface for the second order is smaller than ARE_μ for first order, except for Del, where the difference is marginal. The fractal dimension of the second orders ARE_η surface is also less than the corresponding first order ARE_σ surface for each output.

Table 3. Summary of Fractal Dimensions for the SEADS model

| output	D_μ	rank	D_τ	rank	D_σ	rank	D_η	rank
T_e	2.0129	1	2.0030	1	2.0219	1	2.0025	1
Del	2.0007	3	2.0009	3	2.0051	2	2.0007	3
C_{sd}	2.0034	2	2.0030	1	2.0026	3	2.0008	2
σ_D	0.00523		0.00099		0.00857		0.00083	

The fractal dimensions of the ARE surfaces for the seven outputs of the GURUH model are given in Table 4. The results for the output RO_{10} are not given as the algorithm returned a complex number. This has no physical meaning as a fractal dimension, and arises from the very high values of ARE_τ or ARE_η on some of the peaks in Figure 1 and 2. The output C_{ro} has the highest fractal dimension for ARE surfaces. The output SLS also shows relatively high rankings for all categories. Generally the values of D_μ are larger than D_τ for each out put, except for R_{max} and C_{ro}. Generally the values of D_σ are greater than the value of D_η with the only exception being for C_{ro}. The results for RO_{10}, RO_1 and $RO_{0.1}$ are similar, showing some evidence of increasing fractal dimension from RO_{10} to $RO_{0.1}$: note the anomalous results for RO_{10}. The difference between RO_1 and

RO$_{0.1}$ are small.

The variation of the fractal dimensions among the outputs can be measured by calculating the standard deviation (σ_D). On the whole, the values of σ_D for the SEADS model are smaller than that of the GURUH model, except for σ_D of D_σ. The values of σ_D are in the range of several thousandths for the SEADS model, while that of the GURUH model can be greater than one tenth. The variance is mainly due to the output C$_{ro}$ having the highest fractal dimension.
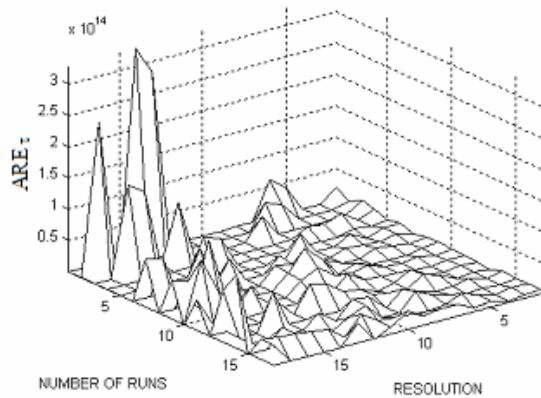
Figure 1. ARE$_\tau$ surface for RO$_{10}$
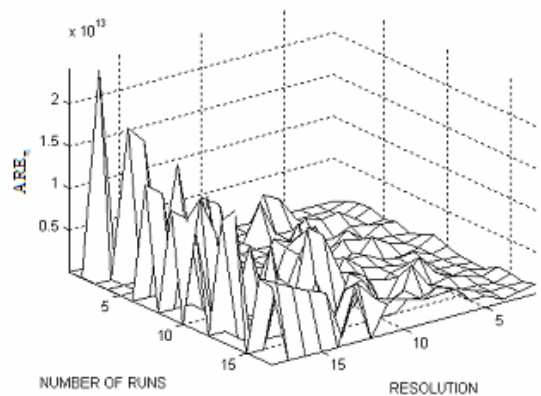
Figure 2. ARE$_\eta$ surface for RO$_{10}$

5. DISCUSSION

The first order sensitivity effect of all the outputs from SEADS, are dominated by the two parameters P$_s$, and Ω. The outputs were less sensitive to the four other parameters of the model. The parameters P$_s$ and Ω also played a major role in the second order sensitivity interactions, with other parameters, and are likely to be involved in third order effects. For the GURUH model, the sensitivity analysis suggests that the seven outputs are sensitive to a range of parameters with F$_L$, C$_3$, C$_2$, A$_1$ and K$_{IF}$ being prominent in providing sensitivity effects to several outputs. These constants all arise in the GURUH model, and are trying to represent the pervious and impervious compartments of the model. These factors are also well represented in the second order interaction and second order sensitivities of the GURUH model.

The SEADS model is based on solving the one dimensional transport equation, that govern the movement of suspended particles. This is a physical process model using a one-dimensional partial differential equation, which incorporates a given hydrological flow. The model incorporates a numerical solution process for the partial differential equation, and it is the most sophisticated of the models, in term of its physics and physical processes. Mathematically it is the more complex model, although its parameterisation is not as extensive as the GURUH model.

The GURUH model is a relatively highly parameterised model based mainly on algebraic functions to model the runoff features in urban areas. GURUH has flow processes incorporated as algebraic models, and based on observation. It is more alike to an observational simulation using statistical relationships, than the physical process modelling incorporated in SEADS model. Thus GURUH model presents complexity in its parameterisation and outputs, rather than in its mathematical sophistication. Boughton (2004) noted that the more parameters used, then the better is the fit to rainfall and runoff data, but the increase in the number of parameters lessens the reliability in the calibration of each parameter. This is because more parameters produce more interactions among parameters and less clarity in the definition of each.

Some of the error surfaces showed the presence of large peaks, and the GURUH output for RO$_{10}$ is a prime example. According to the definition of relative error, there are two possibilities giving rise to the huge number. This is either obtaining an extremely large value of a numerator, or an extremely small value of the denominator. For the output RO$_{10}$, the value of τ for the second order interaction C$_2$_R$_{max}$ is 2.27 x 10^{-15} (which is very insensitive) and this is the result from the pseudo-exact solution and the denominator of the equation (Ho 2004). On the other hand the mean effects of the interacting factors C$_2$_R$_{max}$ for 1runs and 14res is 26.81 returned by NMM. It was found that the location of the peak is at the point of run = 1 and res = 14, the problem must be arisen from this output.

By definition, the mean relative error is:

$$MRE = \frac{\left|26.81 - 2.27^{-15}\right|}{2.27^{-15}},$$

$$= 1.18 \times 10^{16}$$

Compared with this huge value of MRE, the other 35 estimates of MRE are neglected, and thus

$$ARE_\tau = 1.18 \times 10^{16} / 36$$
$$= 3.28 \times 10^{14}$$

which is about the value of the peak as shown in Fig. 1. In the other words, if the output is insensitive to the input factors, the extremely small value of the β_{pseudo}, as a denominator cause the ARE to fail as a metric. Thus the pseudo analytical solution can lead to some difficulties in constructing the error surfaces.

The fractal dimension seeks to compact information about a surface, and reduce it to a roughness measure. It obviates the need to use images of the surfaces and avoids making subjective judgements, which may be affected by scale in a diagram. In the results, two fractal dimensions were not given as the algorithm returned a complex number for the surface area. This requires study to clarify the reliability of the algorithm. The problem is due to the presence of the unacceptable peak in the response surface. As the algorithm includes a square root computation in the iteration, the huge value of the peak and the rounding error involved result in the algorithm attempting to take the square root of a negative number during the iteration. The problem was tested and found it is solely the occurrence of the anomalous peaks, and apart from this, the algorithm is reliable.

Tables 3 and 4 show the fractal dimensions for the SEADS and the GURUH models. The SEADS model has smaller range in roughness than the GURUH model. In fact, it is also reflected by the values of the σ_D. The surface of output C_{ro} is the roughest for all columns. The values D_τ (second order mean effects) are generally less than the values of D_μ, for the SEADS model with the exception of the outputs Del. The same pattern holds for GURUH with the exception of the outputs RO_{max} and C_{ro}. The spread of these fractal dimensions illustrates the difficulty in arriving at values for runs and res to obtain a specified accuracy.

The value of σ_D is a useful indicator. It indicates the variation of ARE among outputs. If the value of the σ_D is small, the ARE for all outputs are likely controlled at an approximate range. On the other hand, the larger the value of σ_D suggests the need to investigate if some outputs are producing unreasonable ARE surface patterns (e.g. the GURUH model). The sensitive measure of that

output should be interpreted with care. A larger value of number of runs (a larger sample size) or higher resolution (the larger sample space) may be required to control the desired level of ARE (i.e. accuracy).

On the whole, the physical models in SEADS are providing a more uniform pattern than the more highly parameterised GURUH. This is perhaps a little surprising given the mathematical complexity of the modelling of the physical processes in SEADS. Moreover, the results are not extensive enough to draw definitive conclusions relating to the nature of the models.

6. CONCLUSION

The SA was conducted on two hydrologic models, SEADS and GURUH models by using NMM. The four sensitivity measures: μ, σ, τ, and η were estimated with respect to the 'runs' and 'res' which are the important parameters of NMM. The concept of a pseudo-exact solution was adapted to calculate relative errors. Average relative errors of all sensitive measures were evaluated and plotted on the surfaces of the 'runs' and 'res'. By means of the fractal technique derived by Clarke (1986), the fractal dimensions of each surface were calculated. The fractal dimensions provide an objective means for comparing the surface plots, and of assessing the model. The results did show some differences in the fractal dimension of the error surfaces between the types of models, i.e. physically based differential equation model SEADS and the more heavily parameterized compartment model GURUH. The results are not extensive enough to draw definitive conclusions relating to the nature of the models. On the other hand, the results, particularly the fractal dimension can help to determine the optimum NMM parameters, runs and res. Here, a great deal more work is required in assembling results across models of different types, before any definitive conclusions can be made. Naturally, there can be "good" and "bad" models of the same physical system, and this will need to be addressed in future work.

7. ACKNOWLEDGMENTS

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