# An Artificial Stream Network and Its Application on Exploring the Effect of DEM Resolution on Hydrological Parameters

**Haicheng Liu**

**Abstract** Digital elevation models (DEM) are widely used in various distributed hydrological models. The stream network can be extracted from it so that runoff routing can be calculated. With the advent of remote sensing and computing technologies, the computation based on DEM with high resolution becomes possible. However, there still exist regions with poor resolution, particularly in developing countries. Previous work only conducted comparisons between results by implementing hydrological models for specific basins in the real world and resolutions were only assigned to several fixed values, such as 30 and 90 m. So, the results derived were thus not in a general sense. To roughly understand how DEM resolution influences the hydrologic response, in this paper, first an artificial stream network of which the principle is originated from fractal theory is constructed. Then by implementing calculation on such artificial networks in an iterative way and performing aggregation, the influence of DEM resolution on several hydrological parameters, namely, the number of basins, drainage density of all basins, total stream length, average stream slope and average topographic index used to assess the spatial distribution of soil saturation of the largest basin can thus be acquired. It is found that DEMs of low resolution would reduce drainage density, total stream length and average stream slope, but would increase topographic index. But the effect is insignificant regarding the number of basins. In the end, the results of the simulation as well as the quality of the fractal terrain are validated by referencing field data.

**Keywords** Fractal terrain · DEM · Stream network · Hydrological parameter

H. Liu (✉)
Faculty of Architecture, Delft University of Technology, Delft, The Netherlands
e-mail: H.Liu-6@tudelft.nl



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## 1 Introduction

DEM as a common approach to express the topographic information is used as the basis for many fields and applications, for example (Li et al. 2004): determination of hydrological terrain parameters, highway and railway design, orthoimage generation, wind models for environmental study and so on. Widely used distributed hydrological models like TOPMODEL (Beven and Kirkby 1979), SWAT (Arnold et al. 1994) and DHSVM (Wigmosta et al. 1994) are all based on DEMs to calculate stream flow. The effect of DEM resolution on these hydrological models or hydrological parameters has been the focus of many researchers in the past several decades. For example, Wolock and Price (1994) found that degradation of the spatial resolution of the topographic data resulted in higher minimum, mean, variance, and skew values of the TOPMODEL topographic index distribution. Wei et al. (2004) indicated that the decrease of DEM resolution would result in the increase of total stream length and the reduction of average slope of stream flow from a perspective of topographic entropy. Furthermore, this might cause the reduction of both simulated flood peaks and hydrological response time. Similarly, by implementing DHSVM, Kenward et al. (2000) also observed lower predicted peaks and additionally higher base flow for DEMs of lower resolutions. However, all these studies including more recent ones (Sørensen and Seibert 2007; Yang et al. 2014; Jain and Sahoo 2017) share the same methodology, that is, demonstrating the law using data in the real world since it is impossible to collect data of all basins throughout the world to prove the discovery. In other words, whether those results can be applied to other watersheds is still under suspicion. The aim of this paper is to propose a new approach in a generic sense to resolve how the resolution affects hydrological parameters extracted from the DEM. To do so, the simulation on terrains is implemented using principles from fractal theory.

Basically, fractal terrain is originated from Mandelbrot and Pignoni (1983) who came up with fractals could be used as a basis for simulating natural scenes and phenomena. Since then, different algorithms (Saupe 1988) for generating fractal terrains have been proposed and implemented mainly in the field of computer graphics. The quality of fractal terrains is judged by their visual analogy to reality. It is true that self-similarity is the core of the fractal terrain, but in order to assign it more physical meaning, Kelley et al. (1988) first proposed a method in which a stream network was first generated using empirical erosion models and then the terrain was developed according to the channel network. Musgrave et al. (1989) adopted physically based models of hydraulic and thermal erosion and sediment movement to simulate the erosion caused by water flow to modify the fractal terrain. Later Stachniak and Stuerzlinger (2005) employed a stochastic local search to identify a sequence of local modifications. This method deformed the fractal terrain to conform to a set of specified constraints. And it served as a general solution to the modification of a fractal terrain. All these approaches make the fractal terrain realistic in terms of physics.

This paper first introduces the generation of a realistic fractal terrain where empirical statistic recognitions of the stream network are enrolled in a filter to select raw fractal terrains. Then, the qualified terrain is used as a platform to derive some commonly referenced hydrological parameters. This is then followed by a discussion about the effect of resolution of DEM on these parameters by adopting aggregation on the digital terrains. Finally, the comparison between results from field data and experiments on virtual channel networks is performed.

## 2 Artificial Stream Network

The artificial stream network is extracted from a DEM using the D8 algorithm (Tarboton et al. 1991) which assumes the flow direction of one cell can only be one of its eight neighbours. So the DEM, i.e. fractal terrain has to be firstly generated. Here, the diamond-square algorithm which is originated from two-dimensional approximations to fractional Brownian Motion (Fournier et al. 1982) is adopted. The procedure of this algorithm is demonstrated in Fig. 1.

In Fig. 1a, first we choose a common elevation value for four points at the corners on the boundary of the square. But it is also possible to assign random numbers from a normal distribution to the four points. Then, by averaging the elevations of the four points and adding a random number extracted from a normal distribution of which the mean value equals 0 and the standard deviation is a figure which can represent the range of elevation for a certain area, we can get the elevation for the central black point in Fig. 1b. For example, if the minimum height of a particular area is 20 m, and the highest point is 160 m, then it is better to set the standard deviation to 35 m which stands for $\sigma$ for the normal distribution. The same principle goes for black points in Fig. 1c, but this time the mean is derived from the combination of two points at corners with the central point. After this, the whole square is divided into 4 patches and each of them falls into a similar situation of Fig. 1a. However, when calculating the value for a special black point in Fig. 1d, another normal distribution with a different standard deviation from the one used in Fig. 1b is employed and the relationship between them is expressed as Eq. 1. The mean value for the normal distribution remains unchanged, i.e. 0.

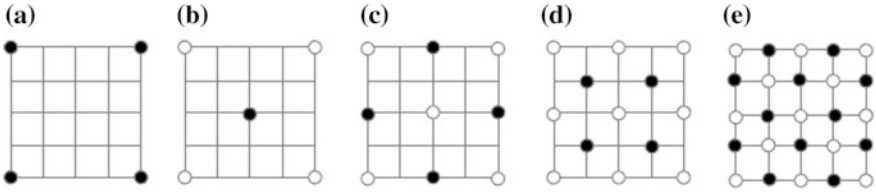


**Fig. 1** Generation of a fractal terrain using the diamond-square method

$$\sigma_n = \frac{\sigma_{n-1}}{2^r} \tag{1}$$

where σ is the standard deviation for the normal distribution, n represents the iterative times, and r is basically a factor describing the roughness of the virtual terrain and actually it determines the fractal dimension of the terrain. It ranges from 0 to positive infinity. Visualizations for some specific r values are provided in Fig. 2. As can be seen from the figure, the terrain generated by a higher roughness parameter tends to be more flat. The reason for successive modification of standard deviation is to guarantee the self-similar principle which means by zooming into a specific segment of the whole terrain, the sub-terrain presents a similar pattern as the whole terrain.

By implementing such a procedure in an iterative way, an elevation dataset can be generated in any dimension required. Of course, horizontal coordinates will be later assigned to form a DEM.

As mentioned earlier, terrains produced this way have weak physical meaning. For example, the number of streams in the first strahler order (Strahler 1957) derived from such a terrain may be equal to that in the second order, which contradicts the fact in the nature. Consequently, either modifications to the generation of the fractal terrain should be implemented, such as embedding an erosion model, or some validations should take place to filter the raw fractal terrains to fulfil physical laws. Here, the second option is adopted, and basically these criteria are originated from the statistical knowledge of stream networks though field surveys (Shreve 1966; Smart 1968). They are:

1. The coefficient of variation of drainage density for different basins derived from the DEM should be no more than 0.5.
2. The average bifurcation ratio of the stream network of the largest basin should be between 2.5 and 5.
3. The average stream length ratio for the largest basin can only range from 1 to 3.
4. The average slope of all first order streams should be larger than that of the maximum order streams in the largest basin.

So the procedure to generate an artificial stream network is as follows,

1. Generate a raw DEM dataset with a specific roughness parameter using the diamond-square algorithm.
2. Extract the statistics of stream networks such as the average bifurcation ratio from the raw DEM.


**Fig. 2** Fractal terrains with different roughness values, $r_a = 0.5$, $r_b = 1.0$, $r_c = 2.0$

3. Judge whether the raw DEM follows all the constraints, and if so, enter the next step. Otherwise, return to the first step.
4. Implement the D8 algorithm on the DEM to derive the stream network.
5. Iterate the whole process until a large number of qualified DEMs are produced for experiments.

## 3 Effect of DEM Resolution

The initial DEM which is acquired by the diamond-square algorithm is assigned 10 m as the resolution. By aggregating the DEM, we can get coarse versions. In addition, as has been explained earlier, the roughness parameter plays a crucial role on the shape of the fractal terrain, so 0.6, 0.8, 1.0 and 1.2 are adopted respectively. Five hydrologic parameters explored are the number of basins of the terrain, drainage density of the terrain, total stream length of the largest basin, average stream slope of the largest basin and average topographic index (Beven and Kirkby 1979) of the largest basin. The specific procedure for the experiment is provided below,

1. Set the initial value of the elevation for the four corner points to 100 and the primary standard deviation to 50. Then 0.6 is chosen as the roughness parameter to generate the fractal terrain in an iterative way for 9 times. The result is an array of the elevation in the size of 513 × 513. This is then followed by the constraints validation. If the constraints are violated, then redo this step, otherwise aggregate the dataset into smaller scales, i.e. 30, 60, 90 m and enter the next step.
2. Derive the stream network from all the DEMs, and then extract the 5 hydrological parameters.
3. Repeat step 1 and 2 1,000 times (Table 1) in order to retrieve the statistical information of the 5 parameters for each resolution, i.e. the distribution of their values.
4. Alter the roughness parameter and repeat step 1 to 3. And after this step, statistics of five hydrological parameters in four terrain shapes can be derived.

Basically, for each parameter, Probability Density Function (PDF) is derived by fitting the data using a specific type of distribution. PDF here is to generalize the

**Table 1** Statistics of experiments on fractal terrains

| Roughness | Total fractal terrain | Qualified fractal terrain | Success rate (%) |
|---|---|---|---|
| 0.6 | 1,000 | 507 | 50.7 |
| 0.8 | 1,000 | 484 | 48.4 |
| 1.0 | 1,000 | 407 | 40.7 |
| 1.2 | 1,000 | 262 | 26.2 |

quantitative findings, e.g. the mode and deviation, which makes analysis conveniently later. Figure 3 demonstrates this. 1.0 is taken as the roughness while 10 m is assigned to the resolution. Since the fractal terrain is generated in random totally, so the first two parameters, i.e. the number of basins and drainage density fit the normal distribution well which is later adopted as the distribution type for these two parameters. However, when it comes to the last three parameters, the target is changed to the basin with the largest area, which means in order to access the values

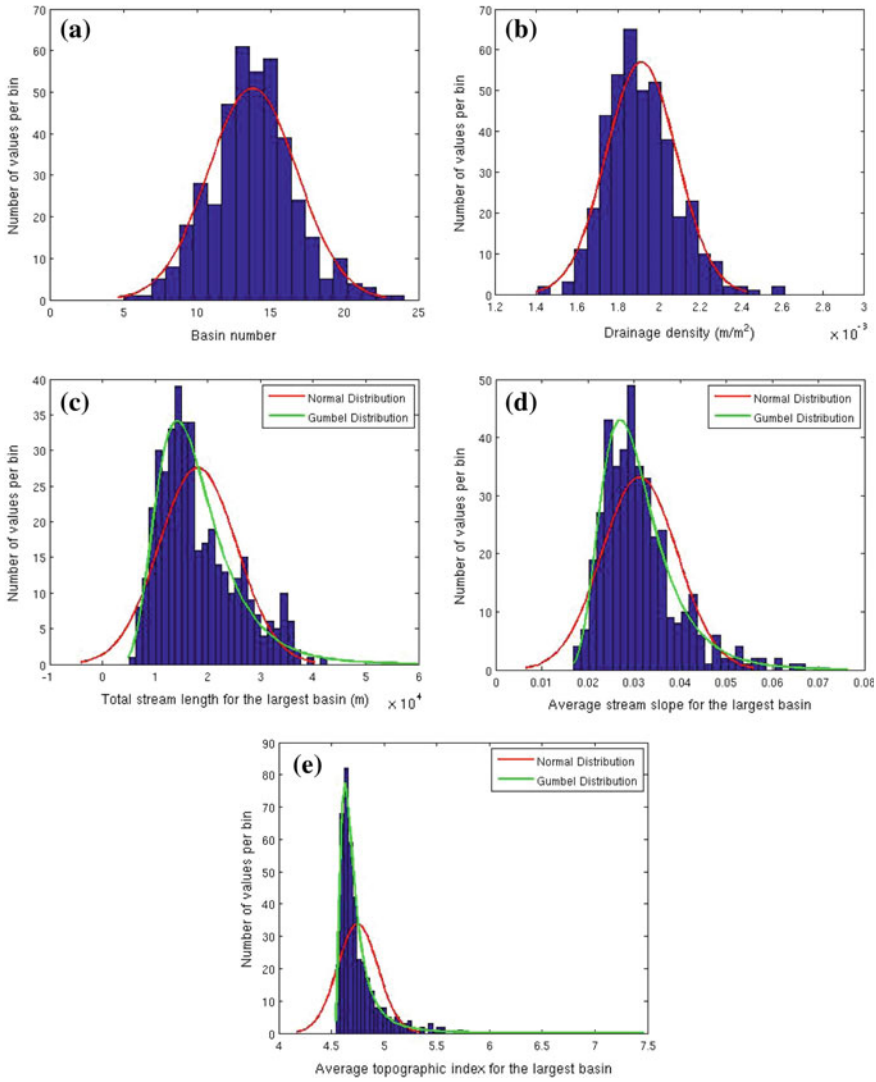


**Fig. 3** Determination of probabilistic distributions of five parameters

of these parameters, first the largest basin in the original DEM has to be selected therefore the whole procedure is concerned with the extreme distribution. In Fig. 3c–e, on the one hand, normal distribution is adopted to fit the histogram, on the other hand, Gumbel distribution which belongs to extreme distribution is tried. Figures clearly show that Gumbel distribution leads to better fitting results. Thus it is utilized to analyse the last three parameters.

## 3.1 The Number of Basins

In Fig. 4, the gaps between the 10 m DEM and the other aggregated DEMs are not large, and the original DEM produces the least basins in general. Actually, in the experiments, there were also results which indicated that aggregation decreased the number of basins.

Additionally, figures also present that the mean value of the number of basins is around 14 and such a large number indicates that the artificial stream network can only be suitable for simulating the head area of rivers where trivial streams are in a large quantity. So the regions of the field data selected later to check the stability of the experiments are also located at source-basin areas of rivers.

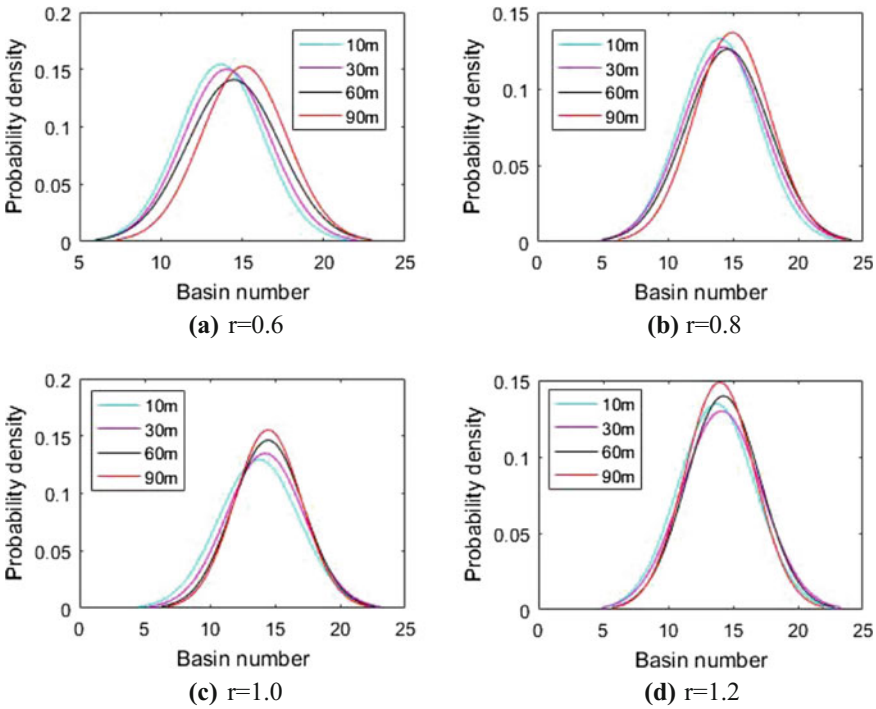


**Fig. 4** PDFs for the number of basins where *r* represents the roughness parameter

## 3.2 Drainage Density

Drainage density is one of the most representative parameters to describe a basin. Former studies have shown that several morphological processes have great correlation with drainage density, such as streamflow (Carlston 1963), sediment yield (Hadley and Schumm 1961), flood (Pallard et al. 2009), etc. It is the sum of channel lengths divided by basin area. Horton (1945) indicated that the drainage density tended to be a constant for all basins within a same region because of the common environment.

Figure 5 Shows that the drainage density of the source DEM can be 1.5 times larger than that of the most coarse DEM. The direct cause can be attributed to the decrease of the total stream length after aggregation since the area is nearly the same for all the DEMs. As can be seen in Fig. 6, for the 90 m DEM, some tributaries disappear, which makes the total stream length decline. A further influence on hydrological response can also be deduced. Basically, runoff process is divided into two parts of which one takes place on the slope, and the other occurs in the channel. It is the fact that the water velocity is higher in the channel than on the slope. Thus a high drainage density implies that the flood can be formed in a short time. On the

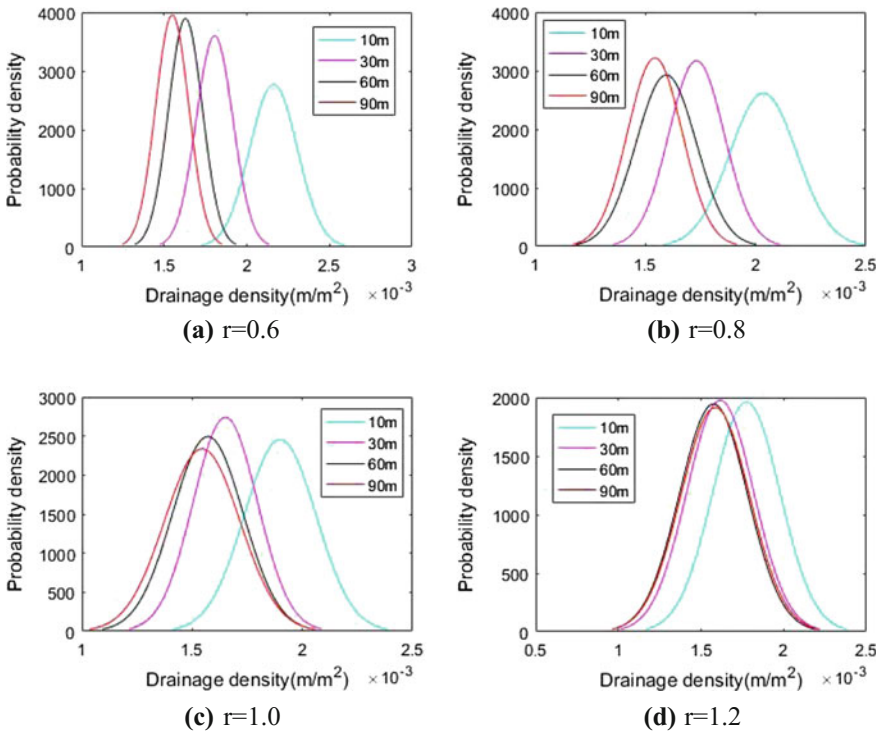


**Fig. 5** PDFs for drainage density

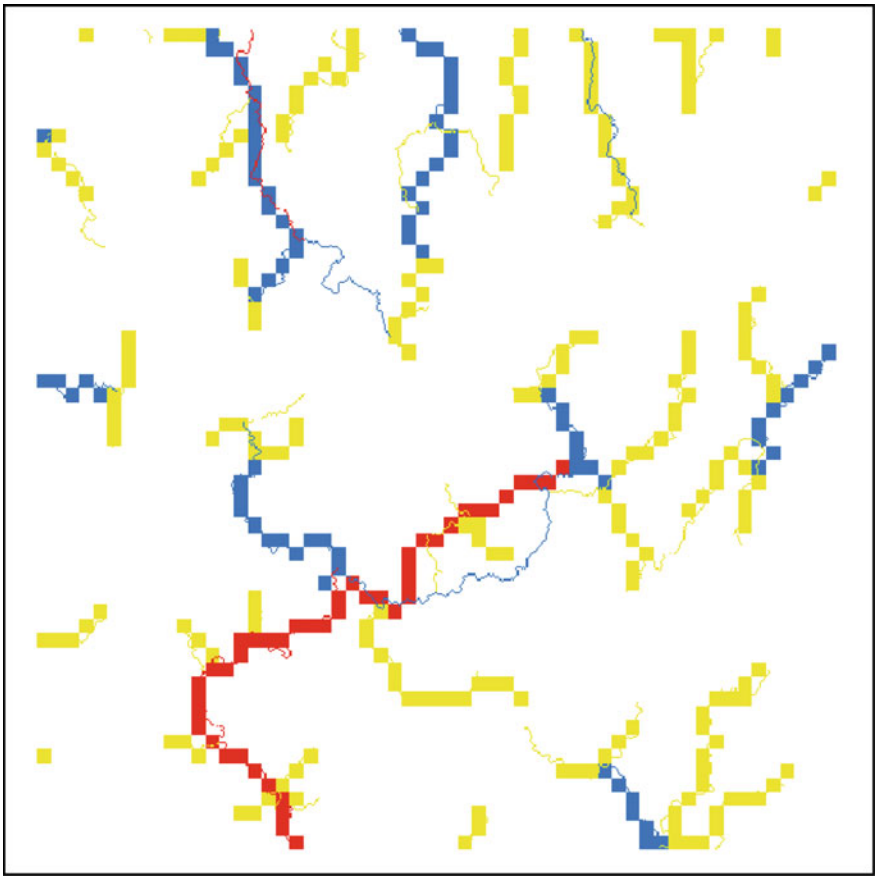

**Fig. 6** Stream network for the original DEM represented by thin lines, and the 90 m DEM represented by thick lines. Each colour refers to a distinctive stream order. For instance, yellow streams are all of the first order. The roughness parameter is 0.6

other hand, less water infiltrates into soil on the slope, which can increase the volume of flood. Pallard et al. (2009) also indicate some indirect effects of the drainage density on flood. For instance, drainage density can be regarded as an index of vegetation cover in semiarid areas where bare soil is much likely to be eroded, which results in high drainage density and high runoff production. This further implies large flood peaks and volume.

Another interesting point is that the flatter the terrain is, the weaker the effect of DEM resolution presents. When the roughness parameter is equal to 1.2, the gap between the aggregated DEMs and the original DEM becomes narrow. This is because the average effect of aggregation is not that strong for plane compared with mountain areas where local elevation change can be very serious, hence aggregation significantly affects the basic shape of a stream.

### 3.3 Total Stream Length of the Largest Basin

Although the effect of DEM resolution on stream networks can be demonstrated in a rectangle place, the widely adopted hydrological research unit is still the basins which is the basic unit for the analysis of hydrological responses.

Analogous to drainage density, with the increase of roughness of the terrain, variations between the original DEM and three coarse DEMs decline. Coarse DEMs have smaller total steam lengths because some tributaries are lost during aggregation (Fig. 6).

### 3.4 Average Stream Slope of the Largest Basin

In Fig. 7, on the whole, due to the averaging effect of the aggregation, the average stream slope of each coarse DEM is lower than that of the original DEM. More specifically, for the rugged terrain, i.e. r = 0.6, the difference can be as large as 2 to 3 times of the average stream slope derived from coarse DEMs. But when the roughness parameter goes up, the average stream slopes retrieved from different DEMs present little gaps. This can be attributed to that in flat areas, the slope can

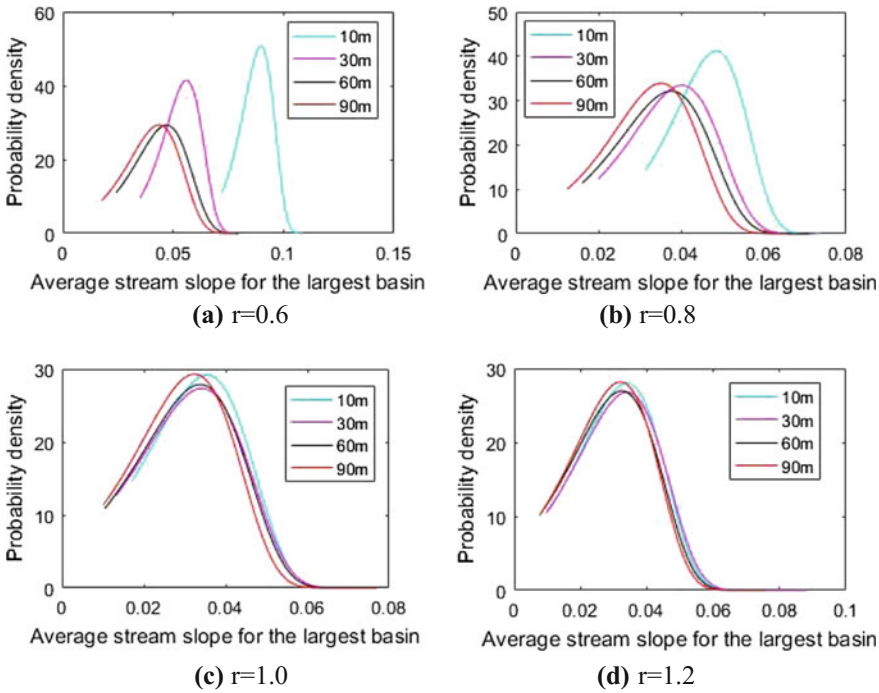


**Fig. 7** PDFs for average stream slope of the largest basin

keep a constant for a wide scope, so the aggregation does not influence the value of slope very much. While in mountain areas, the slope can vary severely in a narrow space and averaging elevation will definitely affect the average stream slope.

The average stream slope is also correlated with hydrological processes. Roughly speaking, the speed at which the water flows in the channel would decrease if the slope descended. We usually take the combination of the average stream slope and the total stream length to analyse composite effect on the hydrological process. So taking consideration of the conclusions from previous section, it can be deduced that the arrival of flood would delay and the flood volume would decline if the coarse DEM was adopted to perform related calculation. The focus here is only the effect caused by the change of stream network, but hydrological process is always concerned with several sub processes, like evapotranspiration, infiltration, etc. More accurate results can be got by running a distributed hydrological model, such as DHSVM, which in turn complexes things since more elements are enrolled in the process.

## *3.5 Average Topographic Index of the Largest Basin*

Topographic index, also known as the wetness index is first introduced in TOPMODEL by Beven and Kirkby (1979) and it is used to assess the spatial distribution of soil saturation. A high value of the topographic index indicates the region has high potential to be saturated. It is defined as the logarithm of the ratio of the upslope area and the local slope for a certain pixel. The upslope area means all the area which contributes flow across a particular pixel. Topographic index is a crucial attribute for hydrological responses since soil moisture is closely related to runoff, soil moisture and the depth of ground water.

As can be seen from Fig. 8, the average topographic index is mostly between 4.5 and 5 for the most accurate DEM, while for the coarse DEMs, the index ranges from 5.5 to 8.5. This is mainly due to the decrease of the average slope of the whole basin which can be roughly reflected by the average stream slope from last section. This is based on two assumptions. First, the basic shape of one basin remains the same after aggregation. Second, the stream location in the coarse DEMs would not shift too much from the original DEM and this can be verified by Fig. 6. Basically, the deviation of the slope of a pixel on the one hand, is caused by the change of flow direction, and on the other hand, it results from the change of relative elevation between the pixel and its target neighbour with respect to the flow direction. These two assumptions imply that the flow directions inside the basin stay the same as the original DEM. So the change of the average stream slope is mainly attributed to the averaging effect of the aggregation which works the same for all pixels inside the basin.

Large gaps between topographic indexes derived from DEMs of different resolution indicate the DEM resolution has profound impact on the calculation of the volume of stream flow by TOPMODEL. In fact, the average topographic index

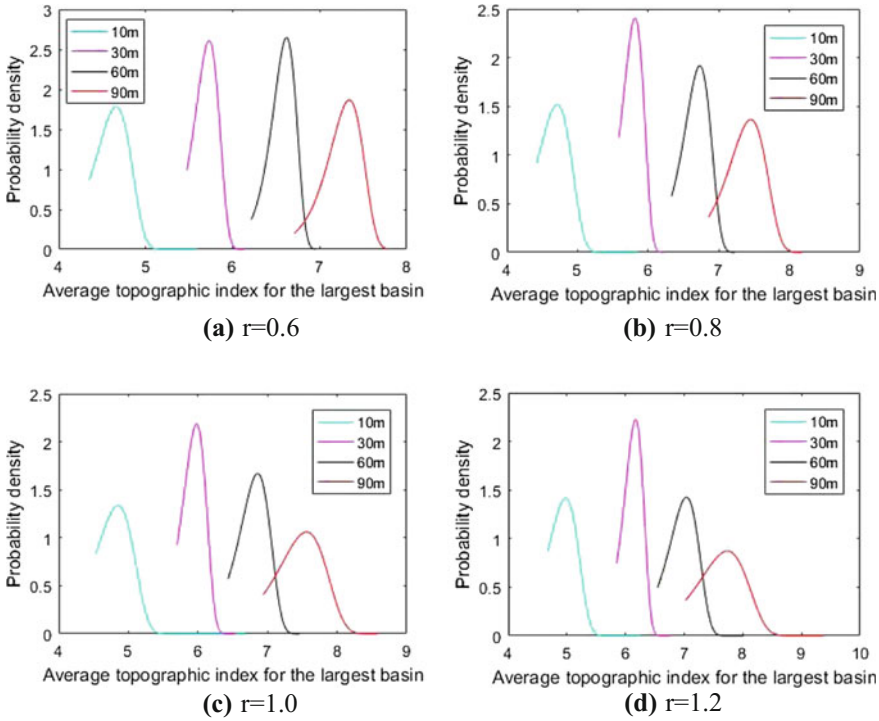


**Fig. 8** PDFs for average topographic index of the largest basin

cannot represent the spatial distribution of soil saturation which may differ from pixel to pixel, instead it can only provide a sense of the overall saturation.

# 4 Validation Against Field Data

## *4.1 Data Description*

The field DEM data all comes from the National Elevation Dataset (NED) of the USA. The NED is a seamless mosaic of best-available elevation data drawn from a variety of sources. Much of the NED is derived from USGS Digital Elevation Models (DEM's) in the 7.5-min series, increasingly large areas are being obtained from active remote sensing technologies, such as LIDAR and IFSAR, and also by digital photogrammetric processes. NED is available in spatial resolutions of 1 arc-s (roughly 30 m), 1/3 arc-s (roughly 10 m), and 1/9 arc-s (roughly 3 m). And the dataset is updated on a two months cycle.

The accuracy of the NED varies spatially because of the variable quality of data sources. An overall vertical accuracy is acquired by comparing it with the geodetic

**Table 2** Error statistics (in meters) of the NED versus 13,305 reference geodetic control points (Gesch 2007)

| Minimum | Maximum | Mean | Standard deviation | RMSE |
|---|---|---|---|---|
| −42.64 | 18.74 | −0.32 | 2.42 | 2.44 |

**Table 3** Primary metadata of field DEM datasets

| Region | Location | Resolution (m) | Minimum value | Maximum value | Rows | Columns | Area ($km^2$) |
|---|---|---|---|---|---|---|---|
| Tennessee | −84.0795,35.3331: −84.0207,35.3880 | 10 | 678 | 1,440 | 593 | 635 | 37.66 |
| California | −122.9656,40.3960: −122.9069,40.4506 | 10 | 687 | 1,455 | 590 | 635 | 37.47 |
| Idaho | −115.4908,43.8068: −115.4298,43.8658 | 10 | 1,337 | 2,104 | 638 | 659 | 42.04 |

control points that the National Geodetic Survey (NGS) uses for gravity and geoid modeling (Smith and Roman 2001; National Geodetic Survey 2003) (Table 2).

The three locations (Table 3) chosen for validation are all source-basin areas of rivers (The reason has been given in Sect. 3.1) and they are square patches from Tennessee, California and Idaho respectively. The resolutions of DEM datasets of these three regions are all 10 m, i.e. 1/3 arc-s and they are all selected at the same area level with our experiments.

## *4.2 Analysis*

DEM aggregation and deviation of hydrological parameters are performed from the field data. The procedure is basically repeating the simulation experiment and all the results are listed in Table 4. The column *mean* from experiment is the average value of the four means with respect to different roughness parameters and the column of standard deviation is analogous. However, more accurate way for their calculation is for each of the field datasets, first trying to determine the corresponding fractal dimension using methods (Brivio and Marini 1993) like box counting, variance analysis, etc. And then construct the fractal terrain of the same scale to derive PDFs. Also, for a same dataset, these methods may return different fractal dimension values (Brivio and Marini 1993) which still need to be selected and thus they are not adopted here.

As is presented in the table, for the number of basins, although all values derived from field data are higher than the mean retrieved from simulations when the resolution is 10 m, still they fall into the one σ range and so do the aggregated DEMs, which implies the simulation can provide reliable number of basins.

As to the drainage density, the simulating result is much larger than values derived from field data, although in order to acquire low drainage density, we can

**Table 4** Values of hydrological parameters derived from field data and simulation

| Hydrological parameter | Resolution (m) | Tennessee | California | Idaho | Mean from experiments | Standard deviation from experiments |
|---|---|---|---|---|---|---|
| Number of basins | 10 | 16 | 15 | 14 | 13.760 | 2.903 |
| | 30 | 16 | 14 | 13 | 14.153 | 2.927 |
| | 60 | 16 | 14 | 13 | 14.405 | 2.867 |
| | 90 | 17 | 13 | 14 | 14.588 | 2.675 |
| Dainage density ($*10^{-3}$ m/m$^2$) | 10 | 1.505 | 1.310 | 1.332 | 1.956 | 0.166 |
| | 30 | 1.470 | 1.291 | 1.331 | 1.692 | 0.143 |
| | 60 | 1.441 | 1.315 | 1.294 | 1.590 | 0.148 |
| | 90 | 1.407 | 1.312 | 1.338 | 1.557 | 0.149 |
| Total stream length of the largest basin ($*10^4$ m) | 10 | 2.405 | 2.073 | 3.032 | 2.206 | 0.823 |
| | 30 | 2.343 | 2.039 | 3.017 | 1.906 | 0.708 |
| | 60 | 2.294 | 2.075 | 2.923 | 1.803 | 0.668 |
| | 90 | 2.270 | 2.080 | 3.032 | 1.791 | 0.672 |
| Average slope of the largest basin | 10 | 0.104 | 0.177 | 0.147 | 0.049 | 0.012 |
| | 30 | 0.103 | 0.174 | 0.159 | 0.040 | 0.012 |
| | 60 | 0.113 | 0.174 | 0.138 | 0.037 | 0.013 |
| | 90 | 0.103 | 0.168 | 0.139 | 0.035 | 0.012 |
| Average topographic index of largest basin | 10 | 5.010 | 5.573 | 5.119 | 4.807 | 0.247 |
| | 30 | 5.650 | 6.034 | 5.695 | 5.940 | 0.161 |
| | 60 | 6.354 | 6.577 | 6.325 | 6.830 | 0.204 |
| | 90 | 6.936 | 7.071 | 6.829 | 7.540 | 0.309 |

increase the threshold used to derive the stream network. But in a way, high drainage density is a characteristic implied in the fractal terrain constructed by diamond-square algorithm. Unless the approach for producing the fractal terrain is modified radically, the drainage density will not decrease in a natural sense. On the other hand, this parameter also differs notably in different regions and Tennessee basins present more dense stream network than the other two regions. So accurately simulating the drainage density needs further research.

Total stream length of the largest basin again presents satisfactory results even though the value derived from experiments seems lower. Actually, the areas covered by the field data are all slightly larger than area of the fractal terrain. And it also shows that the aggregation process does cause the decrease of the total stream length for both field data and virtual data.

When it comes to the average slope of the largest basin, the value of the fractal terrain is much lower than that of the real terrain. This is because as Table 3 shows, the range of elevation selected from different regions are all around 800 m, while the fractal terrain only covers a range of 200 m for elevation. By increasing the initial standard deviation in the first diamond step (Sect. 2), the mismatch issue can be addressed. In addition, for the field data, the aggregation does not always make

**Table 5** Tests against constraints on the fractal terrain

| | Tennessee | California | Idaho | Constraints |
|---|---|---|---|---|
| CV of drainage density | 0.37 | 0.81 | 0.38 | <0.5 |
| Bifurcation ratio | 3.06 | 5.00 | 3.29 | 2.5–5 |
| Stream length ratio | 2.14 | 3.32 | 2.22 | 1–3 |
| $S_1$–$S_{-1}$ | 0.08 | 0.19 | 0.17 | >0 |

the average stream slope of the largest basin decline as the data of Tennessee and Idaho indicates. This is possible since after averaging the original DEM, the stream length decreases, while the variation of elevation may not change too much to result in a decreasing slope.

For the average topographic index of the largest basin, the experiment fails to simulate extreme values presented by California with the highest resolution. Another unsatisfactory result is the decreasing rate is faster than that derived from the field data and this can be mostly attributed to the high decreasing rate of average slope. But, on the whole, the topographic index shows an increasing trend for both simulation and field data from aggregation.

Additionally, the rules for filtering the artificial stream network are also validated by the field data (Table 5).

Where $S_1$ refers to the average slope of streams in the first order while $S_{-1}$ represents the stream slope in the maximum order. In Table 5, stream networks derived from datasets of Tennessee and Idaho satisfy the standard of the artificial stream network while California fails. Its CV of drainage density is above 0.5, which means the drainage density fluctuates a lot within its geographic scope. Besides, its stream length ratio also exceeds the range. In fact, the stream length ratio should not be valued too much because the threshold used to delineate basins and the range of regions selected has significant effect on this value. For example, a lower threshold tends to reduce the stream length in the first order, and also if the geographic range of selected area is enlarged, other tributaries may join into the current stream system, thus disturbing the stream length ratio.

To sum up, the artificial stream network together with the fractal terrain shows some satisfactory results. However, improvements still need to be made. Also if more hydrological parameters were taken into account, situation would become more sophisticated. This research can be seen as an initiative to explore a standard prototype for modeling stream networks and it reveals positive aspects to introduce computer simulations based on fractal theory to discover hydrological laws.

## 5 Conclusions

In this research, an artificial stream network based on fractal terrain is developed and then several typical hydrological parameters concerned with stream flow are selected to analyse the effect of DEM resolution on hydrological responses roughly.

Actually, it is insufficient to analyse the DEM influence on hydrological responses without considering specific environment such as precipitation and evapotranspiration because a hydrologic system is composed of several hydrological processes. A more comprehensive simulation framework may be coupled with a precipitation model in the future.

The artificial stream network is delineated from a constrained fractal terrain developed by adopting the diamond-square algorithm. And the constraints come from empirical statistical understanding of natural channel networks. These recognitions were proposed around 1960s by Smarts (1968), Shreve (1966) with basic concepts originated from Horton (1945), which might not be advanced. They are only statistical properties like the average stream length ratio and the bifurcation ratio. Yet in reality, their range may not be appropriate (Table 5). But approaches based on the statistical knowledge to define the fractal terrain have the advantage of simplicity. Final simulation results keep consistent with previous studies, i.e. the low resolution of DEM leads to the reduction of the total stream length and the average stream slope (Li et al. 2004) and the increase of the topographic index (Wolock and Price 1994).

A specific characteristic of the artificial stream network described here is that it can only model the situation of stream networks in the source-basin areas. More meaningful work is to extract specific basins from the square fractal terrain and perform researches within a single basin. In order to achieve a large scale of basin, say, 100,000 $km^2$, much more random points should be generated for the fractal terrain given a high resolution. As current implementation of terrain generation for 1,000 times can cost half a day with a normal laptop, parallel implementation should be developed for the sake of efficiency. Nonetheless, the artificial stream network as a digital platform can serve for other experiments as well, for example, simulating the evolution of stream networks.

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