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Effects of raster resolution on landslide susceptibility mapping: A case study of Shenzhen

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Resolution has been playing a significant role in landslide susceptibility mapping and hazard assessment. Based on geographical information system (GIS) and information model, the effects of raster resolution on landslide susceptibility mapping are studied in a central area of Shenzhen, China. Eight factors are selected to calculate landslide susceptibility with eleven groups of different resolutions (5 to 190 m). It has been found that a finer resolution does not necessarily lead to a higher accuracy of landslide susceptibility mappings, while the result of 90 m-resolution has the best accuracy and the 150 m-resolution has the worst one. The accuracy curve is in a shape of "W" along with resolution decreasing: 1) The accuracy decreases from 5 to 70 m; 2) and then the best accuracy appears at 90 m, which is almost the same as the mean size of landslides in study area; 3) the accuracy decreases again from 110 to 150 m; 4) and finally the accuracy increases from 150 to 190 m. The sensitivity analysis indicates that the effects of raster resolution are mainly caused by the resolution impact on landform parameter derivation, while factors like geology and human activity are very insensitive to resolutions. A further study shows that in flat, ridge, and slope foot terrains, the susceptibility mapping result is sensitive to resolution, but in the sloping surface area the sensitivity is much less sensitive to resolution. At last, by choosing study areas with different sizes, it has also been found that the optimal resolutions are variable due to size of study area. But the study area is larger than a threshold, which is 135 km^2 in this study, and the optimal resolution is almost fixed.

resolution sensitivity, landslide, susceptibility mapping, digital elevation model (DEM), information model

Landslide susceptibility mapping is very important in landslide study and risk management engineering. In order to depict the spatial distribution of landslide susceptibility, many influential factors, as well as a properly selected mathematical or statistical model are needed. This kind of

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study becomes more and more efficient these years, especially after introducing geographical information system (GIS), from which a lot of experience has been gained[1−5]. However, before processing those influential factors in GIS, digitalization and discretization are necessary. If using grid-cells, the selection of cellsize brings forth uncertainties[6,7], and will eventually influence the susceptibility mapping. Nowadays, a variety of raster resolutions, significantly different[8,9], are used in landslide hazard assessment. Sometimes, it is selected merely considering the size of the slope and landslides[2,4]. Little work has been done on the effects of raster resolution on the landslide assessment and modeling. Guzzetti et al.[10] suggested that more than one unit could be tried and the most suitable one for the problems at hand should be used. Li and Zhou[11] focused on the representative diversity of terrain caused by different resolutions of digital elevation model (DEM) through hazard assessment. Lee et al.[12] compared landslide susceptibility indexes simulated with 5, 10, 30, 100 and 200 m resolution data and found 5, 10 and 30 m resolutions had a similar and more accurate result in Bour, Korea. Claessens et al.[13] paid extra attention to mass movement of shallow landslide hazard, and studied different landslides and their redistribution through different resolution DEMs.

Shenzhen has suffered much landslide damage following heavy rains in recent years. In this paper, a central part of Shenzhen was selected as study area to particularly study the effects of raster resolution on landslide susceptibility mapping. Eight factors related to landslide, representing terrain, geology, hydrology, land cover and human activity, were selected as influential factors. Based on information model, landslide susceptibility was calculated respectively for eleven groups of datasets, which were derived from eleven different spatial resolutions (5, 10, 30, 50, 70, 90, 110, 130, 150, 170 and 190 m). All results were compared and the optimal resolution for landslide susceptibility mapping in Shenzhen was found. Then, the spatial distribution of resolution sensitivity of susceptibility mapping was studied through information value analysis. At last, by applying this method to study areas of different sizes, relationship between optimal resolution and the area size was discussed.

1 Study area and data

The study area, 22°41′24″N to 22°32′31″N, and 113°54′29″E to 114°05′56″E, is located in the central part of Shenzhen, a city in south of China (Figure 1). The area is 342 km^2, 40% of which is mountain area. The bedrock is mainly composed of granite and diorite. Lying in East Asian monsoon

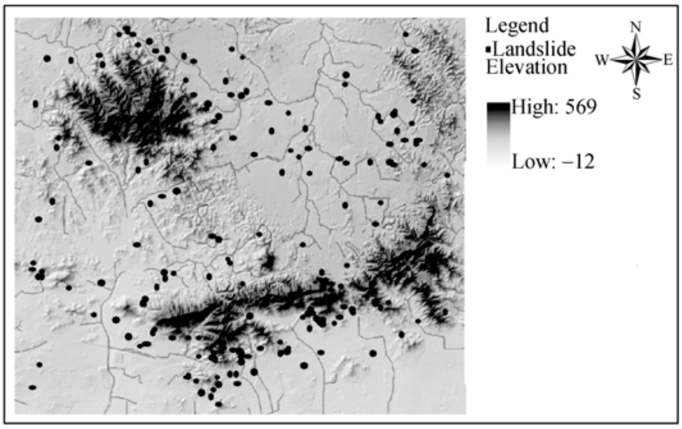


Figure 1 Study area.

region, the average annual temperature is 22.0℃ and the average annual rainfall is 1966 mm. Landslides have been a continual problem since 1980's in this area and they have caused great loss of life and property. Rainfall is one of the most significant inducing factors to landslide disaster. The 211 spots in Figure 1 stand for known landslide locations that were gathered from inspection reports made by the Bureau of Land and Resources of Shenzhen City.

In this study, 5-meter resolution DEM data (generated from 1∶10000 topographic map), 1∶10000 geologic maps, hydrological maps, road and building distribution maps as well as Satellite Pour l'Observation de la Terre (SPOT) were selected as major data sources. All of these were available as digital maps. All influential factors are based on or derived from these basic data. Elevation, slope and aspect are three kinds of important terrain factors effecting landslide occurrence. They were extracted from DEM data directly. Digitalized geological maps could be used for expressing information about fault and lithology. Proximity to river was used to measure the influence of hydrology. Most slopes in Shenzhen are artificial slopes and human activities play an important role in assessment of slope stability. Distance to road or building is used as index of human activity of engineering. Vegetation Index (VI), representing land cover, was derived from SPOT images.

The smallest cell size used in this study is 5 m, the resolution of the original DEM data. The biggest cell size used in this study is 190 m, being almost two times the average slope length in the study area. We do not apply larger cell sizes in this study because theoretically a larger cell will diminish the details in the cell area and practically it will be difficult to identify the real unstable slopes from a large cell predicted as highly prone to landslide, which will make the result almost inapplicable.

In order to get multi-resolution data, we resampled the original 5 m resolution DEM to get a series of data with ten other resolutions (10, 30, 50, 70, 90, 110, 130, 150, 170 and 190 m. Then those 1∶10000-scale influential factors were also resampled to the above resolutions. By deriving landform and slope parameters from DEMs with different resolution, eleven groups of multi-resolution data got available.

Moreover, to study the relationship between the optimal resolution and the size of study area, the study area was cut inward gradually and totally ten study sites (area *A* to *J*) were shaped, with area sizes being 342, 300, 261, 224, 190, 159, 135, 105, 82 and 62 km^2 respectively.

2 Information model

Information model is one of the statistic approaches for landslide modelling[10,14] in which many factors in relation with landslide occurrence[2,15,16,10] are considered. It was first defined by Yin to calculate the susceptibility for the occurrence of a slide[17], and developed by Westen[18]. Now it is widely used for landslide danger assessment[19−21]. We choose it to carry out the landslide susceptibility mapping.

In information model, landslide susceptibilities are represented as Landslide information values (LIV) on the corresponding locations. The most considered matter in an information model is the available information related to landslides in study area. For each influential factor, after proper classification, information value of this factor to landslide occurrence is calculated by

$$I(y, x_i) = \ln \frac{P(y, x_i)}{P(y)}, \tag{1}$$

where $P(y, x_i)$ is the probability for a landslide to occur in the presence of attribute x_i and $P(y)$ is the general probability for the landslide occurrence. For the sake of convenience in calculation, sample frequencies are usually taken to replace events probabilities, thus eq. (1) is converted to

$$I(y, x_i) = \ln \frac{S_i / S}{A_i / A}, \tag{2}$$

where S is the total area of the landslide occurrence, A is the total study area, S_i is the area of landslides which are known to have occurred in the presence of attribute x_i, and A_i is the area in the presence of attribute x_i, $I(y, x_i)$ is the LIV for factor x_i for landslide occurrence. When adding the LIV of all influential factors (eq. (3)), comprehensive LIV are acquired.

$$I = \sum_{i=1}^{n} I_i = \sum_{i=1}^{n} \ln \frac{S_i / S}{A_i / A}. \tag{3}$$

In information model, continuous information indexes have to be properly classified for the aim of presentation and comparisons. This work usually depends on the experience of experts[10,22−24]. Based on the study of Saha and Lee[25,26], considering the real character and distribution of the influential factors, each factor was classified (Table 1).

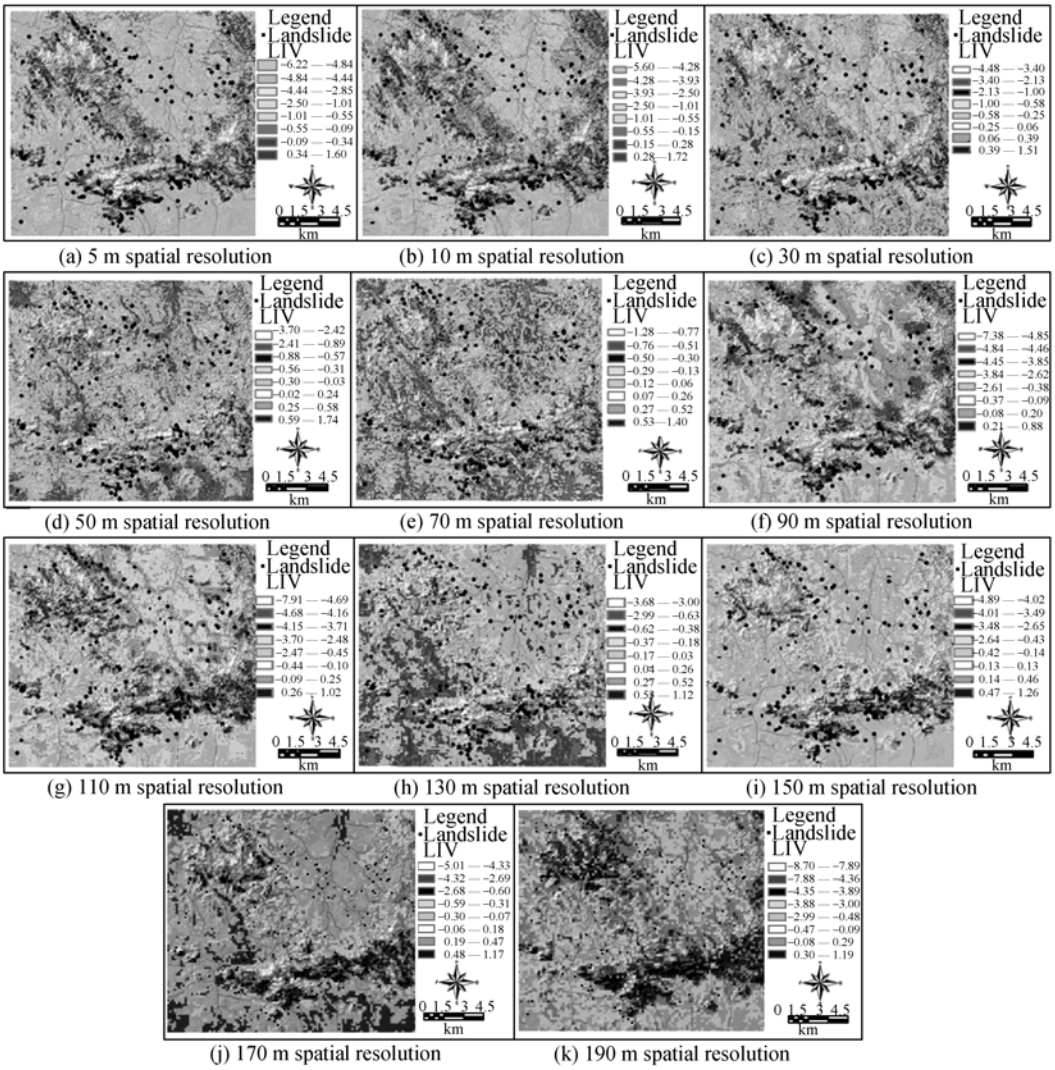
Table 1 Factors and classification

Factor	Classification								
Lithology	G1 (Chroismite and gneiss)	G2 (Extrusive rock)	G3 (Schist shale phyllite)	G4 (Redbeds)	G5 (Quaternary loose bed)	G6 (Clastic rock)	G7 (Intrusive rock)		
Fault (Distance to fault (m))	F_1 (0−200)	F_2 (200−400)	F_3 (400−600)	F_4 (600−800)	F_5 (>800)				
Elevation (m)	H_1 (<10)	H_2 (10−50)	H_3 (50−100)	H_4 (100−300)	H_5 (>300)				
Slope (°)	S_1 (0−5°)	S_2 (5°−35°)	S_3 (35°−50°)	S_4 (50°−60°)	S_5 (>60°)				
Aspect	D_1 (N)	D_2 (NE)	D_3 (E)	D_4 (SE)	D_5 (S)	D_6 (SW)	D_7 (W)	D_8 (NW)	D_9 (Flat)
Hydrology (Distance to river (m))	W_1 (0−200 m)	W_2 (200−400 m)	W_3 (400−600 m)	W_4 (600~1000 m)	W_5 (>1000 m)				
Human activity (Distance to road or building (m))	P_1 (<100)	P_2 (100−200)	P_3 (>200)						
Land cover	Z_1 (<10%)	Z_2 (10%−30%)	Z_3 (30%−60%)	Z_4 (>60%)					

3 Multi-resolution results and comparison

Using information model, the comprehensive LIV were calculated with different raster resolution. And then the susceptibility maps were made (Figure 2) and overlaid by the positions of historical landslides to represent the overall relationship between landslide occurrence and LIV. The index was classified into 8 classes using "natural breaks"[10].

For each spatial resolution, the verification of landslide susceptibility mapping result was done by studying the LIV of landslide occurrence positions using the accumulated frequency method (Table 2). The LIV of all landslide occurrence locations were picked, normalized and sorted into twenty classes in ascending order with the same intervals. Then the accumulative percentage of landslide occurrence under each LIV class was calculated. The above analysis procedure was applied to each susceptibility mapping result respectively to estimate its accuracy. For example, in



(a) 5 m spatial resolution (b) 10 m spatial resolution (c) 30 m spatial resolution
(d) 50 m spatial resolution (e) 70 m spatial resolution (f) 90 m spatial resolution
(g) 110 m spatial resolution (h) 130 m spatial resolution (i) 150 m spatial resolution
(j) 170 m spatial resolution (k) 190 m spatial resolution

Figure 2 Landslide susceptibility maps under different spatial resolutions.

the case of a spatial resolution of 5 m, the area with LIV less than 0.5 contains merely 0.48% of total landslide, in other words, 99.52% of the landslide happens in areas with the LIV greater than 0.5. The area with LIV less than 0.7 contains merely 11.9% of total landslide, i.e., 88.1% of the landslide happens in areas with the LIV greater than 0.7. Among all the mapping results, the greater LIV the landslide occurrence positions had, the higher accuracy mapping result had. It can be clearly seen from Table 2 that 90 m-resolution result is then the best, in which LIV of 0.7 were a turn point and 98.1% of landslide occurrence locations had LIV greater than 0.7.

In order to demonstrate the estimation result more clearly, two more figures are given below. Figure 3 shows the overall relationship between the accumulative landslide percentage and corresponding LIV, in which each curve stands for a specific resolution. For a given susceptibility mapping result, if all landslide occurrence locations are perfectly assigned to LIV of “1”, the result is evidently the best and the curve will become horizontal on the bottom with LIV range [0-1) and vertical to the right side with LIV of 1, i.e., the area percentage above that curve was 100%; on the

Table 2 Accumulative percentage of landslide occurrence under each LIV class

LIV	Accumulative percentage of landslide occurrence (%)										
	5 m	10 m	30 m	50 m	70 m	90 m	110 m	130 m	150 m	170 m	190 m
0	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.95
0.05	0.48	0.48	0.95	0.48	0.95	0.95	1.43	0.95	0.95	1.43	0.95
0.1	0.48	0.48	1.43	0.95	0.95	0.95	2.38	2.86	4.29	3.33	0.95
0.15	0.48	0.48	1.43	0.95	3.33	0.95	4.29	6.67	5.24	5.71	0.95
0.2	0.48	0.48	1.90	3.33	5.24	0.95	6.19	11.43	9.52	7.62	0.95
0.25	0.48	0.48	2.38	3.33	9.05	0.95	7.14	14.76	17.62	10.95	0.95
0.3	0.48	0.48	2.86	9.05	12.86	0.95	10.48	20.00	27.14	17.14	0.95
0.35	0.48	0.48	4.76	12.13	19.05	0.95	16.19	25.24	38.57	21.90	0.95
0.4	0.48	0.48	7.62	14.29	27.62	0.95	23.81	33.81	50.48	31.90	0.95
0.45	0.48	0.48	15.24	46.67	36.67	0.95	31.43	45.71	59.52	39.05	0.95
0.5	0.48	1.43	25.24	54.76	45.24	0.95	40.00	52.38	65.24	46.67	0.95
0.55	0.95	2.86	32.86	57.07	52.38	0.95	50.95	58.57	71.43	56.67	0.95
0.6	4.29	4.29	46.67	60.02	59.52	0.95	60.48	69.05	76.19	62.86	0.95
0.65	6.19	8.10	57.14	65.38	65.24	0.95	66.67	76.19	83.81	71.90	1.90
0.7	11.90	12.86	65.71	69.77	71.90	1.90	73.81	84.29	90.48	77.62	7.62
0.75	20.95	22.38	81.90	73.33	77.14	6.67	80.48	89.05	93.33	83.81	18.57
0.8	32.38	40.48	89.05	80.57	84.29	13.81	86.19	91.90	95.24	90.00	35.24
0.85	57.14	61.43	97.62	93.36	90.48	41.90	92.38	94.29	97.14	95.24	59.52
0.9	82.38	81.90	99.05	97.62	95.71	68.10	96.19	97.14	98.57	98.10	77.14
0.95	95.24	95.24	99.05	99.52	97.62	89.05	97.14	98.10	98.57	99.05	93.33
1	100	100	100	100	100	100	100	100	100	100	100

contrary, if LIV at every landslide location were “0”, the result is evidently the worst and the curve will be vertical to the left side with LIV value of 0 and horizontal on the top with LIV range (0-1], i.e. the area percentage above that curve was 0. The area percentage above each cure can be used as an index for the accuracy of corresponding result. The larger the percentage, the better the accuracy (Figure 4).

The curve in Figure 4 is basically in a shape of “W” along with resolution decreasing: 1) The accuracy decreases from 5 to 70 m; 2) the highest accuracy appears at 90 m; 3) the accuracy decreases again from 110 to 150 m; 4) finally accuracy increases from 150 to 190 m. The results with 90, 5, 10 and 190 m-resolutions are evidently better than the others while 90 m-resolution result is the best and 150 m-resolution one has the lowest accuracy among them all. The averge slope length of known landslide in the study area is 83.31 m, which is very close to the optimal resolution, 90 m.

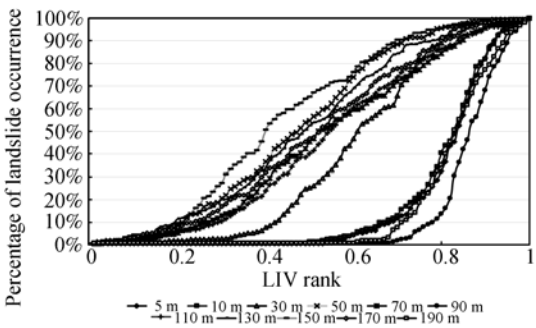


Figure 3 Relationship between landslide and corresponding LIV.

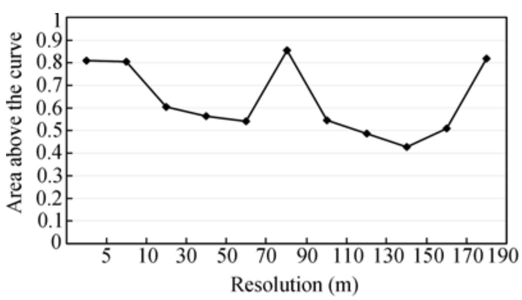


Figure 4 The results with different resolutions.

4 Analysis of resolution sensitivity

In information model, the susceptibility is represented by the comprehensive LIV, which is the sum of the information values of all influential factors. By studying the change of every factor's LIV along with different resolutions, the sensitivity to resolution of each factor can be analyzed. Figure 5 was made by subtracting the worst result (150 m) from the best resolution result (90 m). The smaller the difference, the more insensitive the factor to resolution. Negative values indicate that with the cell size enlarging, the information value increases, vice versa.

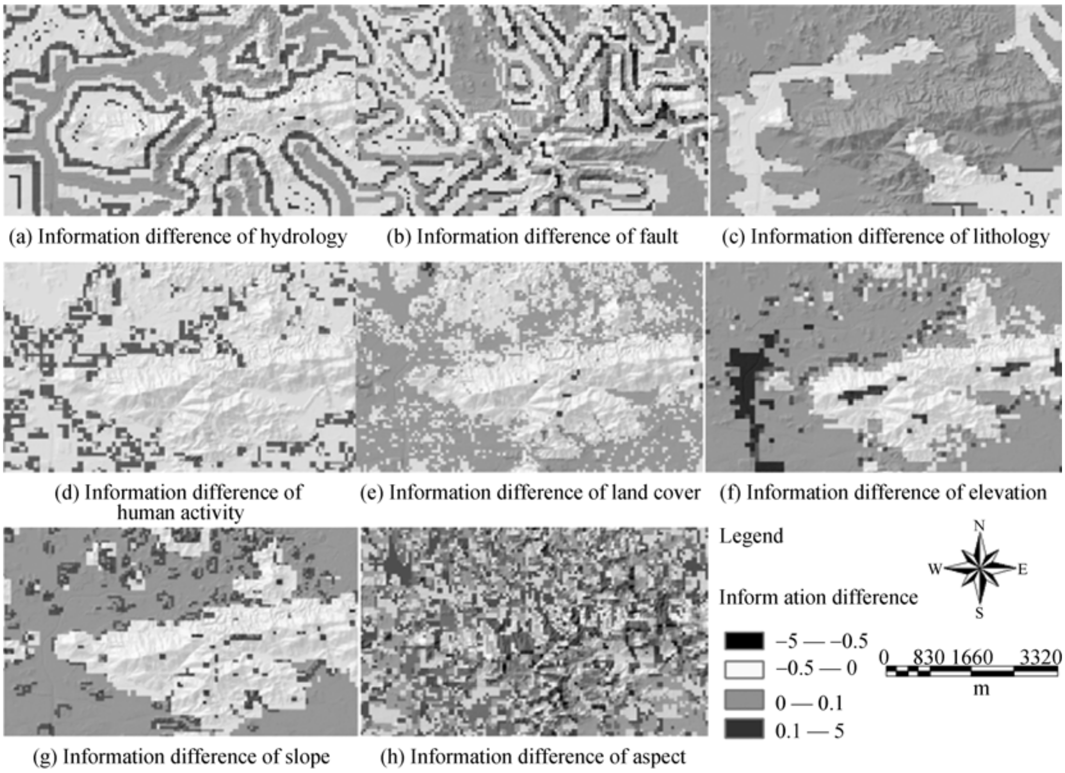


Figure 5 Difference of LIV of all influential factors.

It can be clearly concluded from Figure 5 that among all factors, hydrology, fault, lithology, and human activity have similar characters: When the resolution changes, there are little or small differences of LIV in most areas, except that in some areas one cell may change from one category to an adjacent one because of the resolution variation. The reason could be very simple, that is, these factors are planarly or continuously distributed. The values of these factors are not prone to the change of cell size.

As for elevation and vegetation index, there are significant LIV differences in areas where the elevation is lower than 10 m or vegetation index is higher than 60%. But in other areas the difference is very small. The reason for this is also simple. There are only 3 landslide occurrences in such areas with the resolution of 5 m. With smaller resolution, one or more landslides will be classified into cells that are higher than 10 m or the VI is less than 60%. For example, with the resolution of 150 m, there is no landslide occurrence in cells lower than 10 m or with VI higher than 60% . This will inevitably affect the LIV of the corresponding cells (eq. (3)).

The resolution sensitivity of slope and aspect factors is more complex. As for slope factor, the LIV difference is significant only in areas like ridge or slope foot where slope gradient changes drastically. The slope factor is derived from GIS by identifying the maximum rate of change in value from each cell to its neighbors[27]. Following this method, discrepancy appears when calculated from different resolution DEMs[28,29], shown in Figure 6 in detail. The slope of the central point in different resolution DEMs was calculated with the same algorithm. But the result varied a lot, from 0° to 53.2°. In this study, thus, the central cell will be classified into different categories. And this will inevitably influence the LIV a lot.

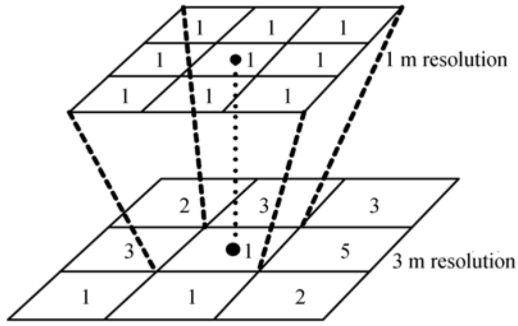


Figure 6 Slope variance with data resolution.

Figure 5(h) shows the spatial distribution of LIV difference of aspect factor. It is quite clear that the LIV difference of aspect factor is the largest in flat area, which is classified as category D9 in Table 1 where there is no aspect available due to very small slope value 0°—2°, with a value of –0.4475 (Table 3). The reason for this is the generalization effect of DEMs with different resolutions. With 90 m resolution and 150 m resolution, the areas in category D9 are 3.1 and 4.9 km^2 respectively, with a difference of 1.8 km^2, being 58% of 3.1 km^2. It means that some areas that are not flat with resolution of 90 m become flat with resolution of 150 m due to the generalization effect. This will cause the landslide occurrences in the D9 category with 150 m resolution may be changing to other categories with 90 m resolution, which inevitably affect the LIV of this category significantly.

Table 3 Statistics of information difference in different slope ranges (90 m resolution DEM)

Slope range	Area (km^2)	LIV difference mean	LIV difference STD	LIV difference sum
0°—2°	134.8	–0.4475	1.3550	–2683.9100
2°—6°	97.6	–0.0179	0.3926	–78.1513
6°—15°	68.6	–0.0184	0.1509	–55.2663
15°—45°	40.2	–0.0423	0.1387	–75.2527
45°—90°	1.3	–0.0610	0.1740	–3.53898

From the above analysis, we can now conclude that in landslide information model the landform factors, such as elevation, aspect, and slope, are more sensitive to resolution than other factors, such as hydrology, fault, lithology, and human activity, for landform parameters derivation are more prone to resolution and the change of parameters with different resolutions will inevitably change the categories of some landside occurrences. This conclusion can also be supported by a further STD analysis (Table 4). For each factor, we calculated the STD of the LIV of every cell with different resolutions. To be convenient, the analysis was based on the cells of the 5 m resolution grid.

Figure 7 is the distribution map of difference of comprehensive LIV between 90 and 150 m resolutions. It can be seen from the Figure 7 that large difference appears mainly in flat terrain, as well as ridge or foot of the slope in mountain area. On the sloping surface, where the slope gradient changes gently, the information difference is relatively small. Three large-scale landslides and their 3D view are also given in Figure 7.

Table 4 STD analysis of each factor

Factor	Mean	Min	Max
Elevation	0.2567	0.0391	1.4974
Aspect	0.2554	0.0382	1.8905
Slope	0.1682	0.0958	1.3953
Fault	0.0825	0.0193	0.2345
Hydrology	0.0785	0.0455	0.1625
Land cover	0.0732	0.0332	2.0497
Human activity	0.0542	0.0142	0.2308
Lithology	0.0335	0	0.3042

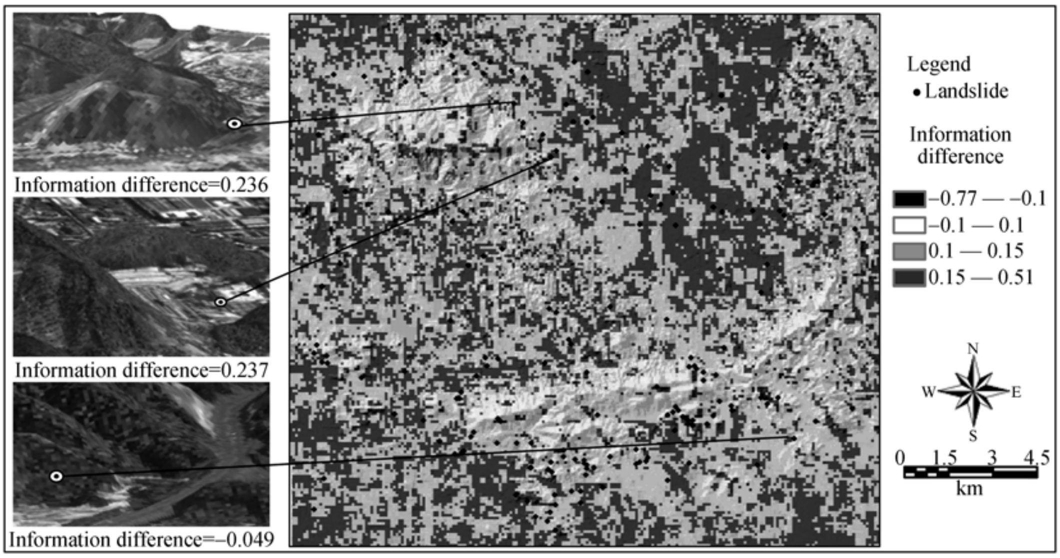


Figure 7 Difference of comprehensive LIV.

Applying the above analysis method to study areas of different sizes (as mentioned in part 1, areas *A* to *J*, with area sizes of 342, 300, 261, 224, 190, 159, 135, 105, 82 and 62 km^2 respectively), the relationship between the size of study area and its optimal resolution is studied. It has been found that the optimal resolution varies along with area sizes (Figure 8). A stable optimal resolution cannot be achieved in study areas with sizes less than 135 km^2, i.e., areas *G* to *J* (62 to 105 km^2). In these study areas we can see that differences between multi-resolution results are getting smaller and the average accuracy is rising with the study area enlarging. However, for the study areas with size of 135 km^2 or more, i.e. areas *A* to *F*, the optimal resolution stands steady at 90 m (Figure 8), which is very close to the average slope scale in the study area, 83.31 m (but we are not sure if this is coincident or there is an undiscovered rule). So, we can set 135 km^2 as a threshold of study area size in Shenzhen.

5 Discussion and conclusions

(1) It is pretty clear that spatial resolution affects the accuracy of landslide susceptibility mapping and the relationship between them is not singly linear. The tendency to use smaller and smaller grid-cells appears unjustified. The best resolution shall be determined considering the landslide susceptibility mapping accuracy, the amount of data, and the real landslide scale.

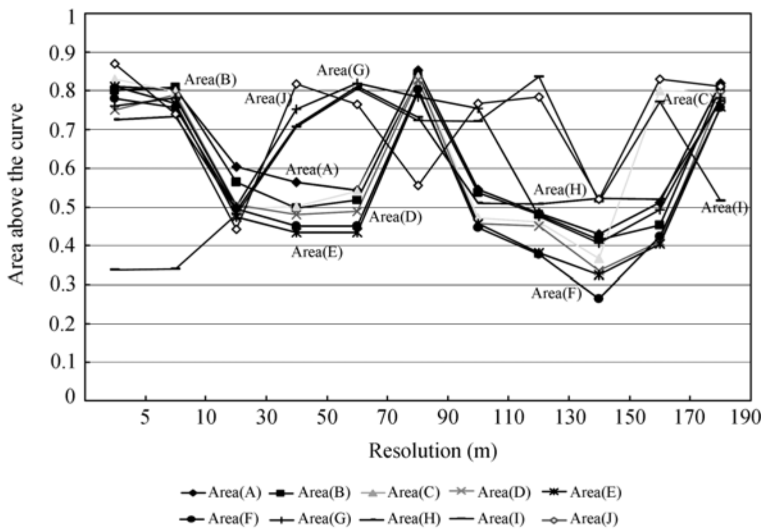


Figure 8 Multi-resolution results in different study areas.

(2) The resolution effects on LIV in information model are mainly caused by the resolution impact on landform parameters derivation, while the resolution effect on other factors like geology or human activity is much less significant. Large differences of comprehensive LIV appear in flat, ridge, and slope foot areas. On sloping surface the LIV difference is relatively smaller.

(3) The optimal resolution for landslide susceptibility mapping varies with the size of the study area. When the study area is below a threshold, which is 135 km^2 in this study, the optimal resolution is not stable and the best landslide susceptibility mapping accuracy increases with the area size enlarging. When the size of the study area is larger than the threshold, there will be a steady optimal resolution, 90 m, in this study.

In this study, it has also been found that the optimal resolution for the whole study area (also area A), 90 m, is very close to the average slope scale in the area, 83.31 m. We are still not sure if this is just coincident or if there is an undiscovered rule of it. Further studies are necessary to make this clear.

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