

Sensitivity analysis of relationships between hydrograph components and landscapes metrics extracted from digital elevation models with different spatial resolutions

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ABSTRACT

Evaluation of sensitivity of hydrograph components and landscape metrics extracted from various spatial resolutions reveals relationships between landscape metrics and outflow properties with the lowest error. In the present study, 14 Digital Elevation Models (DEMs) with different resolutions derived from a vector and raster-radar source were analyzed to evaluate sensitivity of relationships between simulated hydrograph components and landscape metrics using multiple regression methods in the Galazchai Watershed, West Azerbaijan Province, Iran. To this end, DEM, slope, flow length and direction and time of concentration were developed in the vector and raster scales of 1:25000 and Advanced Land Observing Satellite-1 (ALOS) with different resolutions using ArcGIS 10.5 and ArcHydro software. Accordingly, 588 Direct Runoff Hydrographs (DRHs) were produced and clustered using Clark's Instantaneous Unit Hydrograph (IUH) model. The results showed that the best regression fits for flood volume and peak discharge were determined with Number of Disjunct Core Areas (NDCA) and Patch Density (PD) landscape metrics. Furthermore, the best regression fitted for time to peak and base time were observed with Core Area (CA) and Normalized Landscape Shape Index (NLSI) landscape metrics. In addition, the sensitivity analysis shows that the most sensitive spatial resolutions in modeling relationship between flood volume and peak discharge were determined at 5, 10, 20, and 30 m. The results revealed that hydrograph components in association with landscape metrics had high sensitivity to spatial resolutions, while the relationships between hydrological components and landscape metrics without considering the optimal spatial resolutions resulted in unacceptable results.

1. Introduction

Water and soil processes play a fundamental role in landscape interactions (Turner, 1990; Wu and Loucks, 1995; Spetich et al., 1997). Quantitative assessment of water and soil processes largely depend on the spatial scale. Furthermore, landscapes are the result of nonlinear processes of water and soil redistribution (Schoorl et al., 2002) that are influenced by different topographic scales and watershed characteristics. In addition, topographic maps and Digital Elevation Models (DEMs) with different vector and raster scales represent different details of information (Wolock and Price, 1994; Orlandini et al., 2003; Wilbanks, 2006; Dar et al., 2010). Accordingly, different vector and raster map scales represent various results in modeling relationships between

landscape and watershed hydrological characteristics. Therefore, it is necessary to recognize optimal raster or vector scale and grid size, which in turn leads to determine the most precise hydrograph simulation components and landscape indices for the watershed. On the other hand, spatial pattern analysis of landscape models is influenced by scale directly, so that different scale and grain size lead to different outputs of the landscape metrics (Zhang and Montgomery, 1994; Qi and Wu, 1996; Lausch and Herzog, 2002; Corry and Laforteza, 2007; Zimmermann et al., 2010; Lustig et al., 2015; Feng et al., 2017; Inkoom et al., 2018; Tian et al., 2019).

In this regard, the Clark's Instantaneous Unit Hydrograph (IUH) model (Clark, 1945) is one of the event based hydrological models widely used for hydrological modeling (Usul and Yilmaz, 2002; Sadeghi

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et al., 2015, 2019; Moradi Dashtpagerdi et al., 2019). In this matter, one of the major input factors of Clark's IUH model is the Time Area Histogram (TAH), which is influenced by vector and raster scales and corresponding grain size. It itself leads to a distribution map of Time of Concentration (TC) with different levels of accuracy. The TC map accuracy directly depends on the physiographic features such as slope, flow length, flow direction, flow accumulation, watershed area, and other landscape indices. Changes in the map scale of the topography thus lead to changes in results of the Clark's IUH model simulation and landscape metrics as well.

The effects of scale on modeling processes and hydrological behavior of the watershed have been extensively investigated by former researchers. In this matter, Tarboton et al. (1991) studied DEMs obtained from 30 and 60 m resolutions for extracting channel networks in different basins of the United States. The results showed different spatial resolutions had an effective role on slope and channel network in different basins. They consequently recommended appropriate criterion to select the most accurate spatial resolution for extraction of the channel network. Schoorl et al. (2000) studied the effect of different spatial resolutions of artificial DEMs of 1, 3, 9, 18, 27 and 81 m in the process-based modelling of erosion and sediment based on landscape development. The results showed that effects of DEMs with different cell sizes led to overprediction of erosion and the underestimation of reseedimentation in a fine cell size using multiple flow routing. Similarly, Wu et al. (2002), Claessens et al. (2005), Wu et al. (2008) and Li and Wong (2010) studied the effect of different resolutions of DEMs on different landscape metrics. The results showed that changes in map resolutions represented more sensitivity than changes in map scale on different landscape metrics. Saldana et al. (2011) studied effects of map scales of 1:50000, 1:18000 and 1:100 for a watershed in Spain and proved that the changes in map scales lead to significantly different landscape index values. Charrier and Li (2012) evaluated effects of two types of DEMs obtained from the Light Detection and Ranging (LiDAR) with resolutions of 1, 3, 5, 10, 15 m and the United States Geological Survey (USGS) with resolutions of 5, 10 and 30 m on floodplain delineation in part of the Camp Creek Watershed, Missouri, USA. The results indicated that resolutions of 3 and 5 m of LiDAR DEMs created similar streams and floodplain boundaries within 10% difference of the source. Evaluation of scale effects on performance of landscape indices emphasized the importance of scale on watershed dynamics by former researcher (e.g., Minang et al., 2014; Plexida et al., 2014; Li et al., 2015; Woodrow et al., 2016). They wholly argued that metrics components were more correlated to the watershed dynamics at the small scale. They also concluded that each DEM gave a particular result and therefore the decision to use appropriate DEMs could play important role to select the Best Management Practices (BMPs). Huang et al. (2017) analyzed the landscape index of soil erosion intensities types at map scales of 30–240 m in the Danjiangkou Watershed, China. The results showed that the landscape indices represented different results in different scales and 60 m map scale was defined as optimal scale based on information entropy theory. Amatulli et al. (2018) used DEMs resulted from products of near-global 90 m SRTM 4.1dev and global 250 m GMTED 2010 to extract topographic variables viz., elevation, curvature, slope, aspect, roughness, Topographic Position Index (TPI) and Terrain Ruggedness Index (TRI). The results showed TPI and TRI derived from the 250 m GMTED compared to those derived from the 90 m SRTM represented a higher variance. In this matter, performance of various spatial resolutions resulting from different topographic maps on estimation accuracy of runoff simulation and water quality using regression models was already approved by Zhang et al. (2018) and Nagaveni et al. (2019).

Although effects of scales and spatial resolutions were evaluated on the hydrological parameters separately in previous studies but the evaluation of impacts of vector scale through land surveying and raster scale with the help of satellite images on hydrological models are just as necessary. One of the few examples is Pan et al. (2019), who evaluated quantitative relationships between soil landscape indices and different

spatial resolutions. They used 28 landscape indices by linear, logarithmic, quadratic, and power functions and reported various sensitivities. The results showed that 13 landscape indices with high Pearson correlation coefficients ($r > 0.90$) could be used in a new approach to quantitatively predict the spatial patterns of soil distribution within a landscape.

Literature shows that there have been many studies verifying that DEMs with different spatial resolutions are important in the modeling of relationships between landscape metrics and hydrograph components. However, the sensitivity analysis of separate hydrograph components to the metrics and properties resulting from various DEMs obtained from different sources, has not been concisely considered. Therefore, the current study aimed to evaluate the effects of different spatial Vector Based DEM resolutions (VBD) with original resolution of 5 m and resized resolutions of 10, 20, 30, 50, 100 and 200 m, and Raster or Radar Based DEM resolutions (RBD) resulting from satellite images with original resolution of 12.5 m and resized resolutions of 5, 10, 20, 30, 50, 100 and 200 m different hydrological components based on event based Clark's IUH hydrological model as well as spatial pattern analysis of landscape metrics, all in the Galazchai Watershed, Iran.

2. Materials and methodology

2.1. Study watershed

The study area is the Galazchai Watershed located in West-Azarbaijan Province, NW Iran. The watershed has an area of some 103 km² and between 44°56' and 45°35' E, 37°01' and 37°09' N, datum WGS84. The mean annual precipitation and temperature of the area is 482 mm and 11.8 °C, respectively, characterizing a dry arid and dry semi-arid climatic classes based on the De-Martonne and Emberger classifications. The average watershed slope is 32%. The altitude of the study watershed varies from 1503 to 3299 m above mean sea level. The study area is mountainous with steep slopes (Mostafazadeh et al., 2015; Sadeghi et al., 2019). The study watershed has the Oshnavieh recording rain gauge and the Galazchai hydrometric station at the main outlet. The study area represents most parts of the small agricultural dominant watersheds in the region. The study watershed and existing comprehensive studies (Mostafazadeh et al., 2015; Adhami et al., 2018, 2019, 2020; Sadeghi et al., 2019) were also accessible to the authors. The general location, land use and some other characteristics are shown in Fig. 1.

2.2. Data acquisition

The Raster or Radar Based DEM resolutions (RBD) were obtained from a dataset of the Phased Array type L-band Synthetic Aperture Radar (PALSAR), with 12.5 m original spatial resolution (one of the instruments on the Advanced Land Observing Satellite-1 (ALOS)) (<http://vertex.daac.asf.alaska.edu/>). The Vector Based DEM resolutions (VBD) were processed from topographic maps of 1:25000 obtained from the National Geography Organization of Iran (NGO; <http://www.ngo-iran.ir/>). From both RBD and VBD sources, in total 14 DEMs with resolutions of 5, 10, 20, 30, 50, 100, and 200 m were extracted. VBDs were produced based on contour tracing technique using interpolation method developed in Topo to Raster tool in ArcGIS 10.5 and designed for the production of DEMs based on the ANUDEM program (Hutchinson and Dowling, 1991; Mishra, 2012) to DEM in ArcGIS10.5 software. RBDs were also produced based on resize of original DEM to RBDs with different spatial resolutions. The slope, flow direction, flow accumulation, flow length, and TC maps were produced for all 14 DEMs with different resolutions of 5, 10, 20, 30, 50, 100, and 200 m for raster and vector scales using ArcGIS 10.5 and ArcHydro software. Furthermore, the 7 RBD and 7 VBD different DEMs resolution were evaluated based on 42 storms, recorded over the years 2003 to 2013 and reported in previous researches (i.e., Mostafazadeh et al., 2015; Saeidi et al., 2016). The

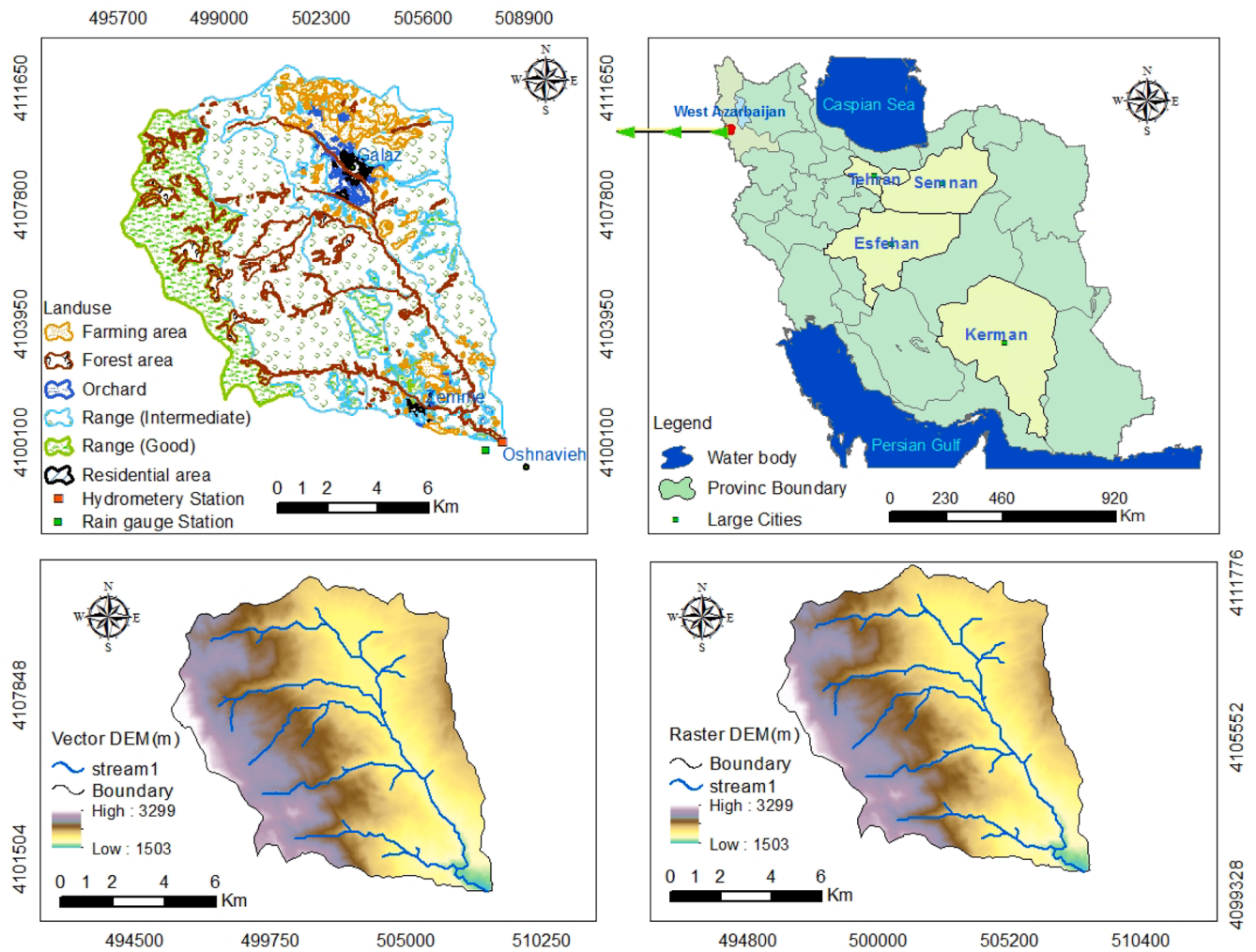


Fig. 1. General location (top right), land use (top left) and DEMs with 10 m cell sizes derived from Raster and Vector (bottom right and left) of the Galazchay Watershed, Iran.

hydrological modeling was performed using the event based Clark's IUH model. The detailed characteristics of the studied storms are shown in Table 1. The direct runoff hydrograph (DRH) was obtained through subtracting the base flow using the fixed-value method. In this method the separation of the base flow is obtained by joining with a straight line at the beginning of the surface runoff to a point on the recession limb representing the end of DRH (Agirre et al., 2005). The storage coefficient (K) was also determined from the recession part of the observed flood hydrograph of the total watershed to represent the storage characteristic of the watershed stream (Sadeghi et al., 2019). In this matter, the phi-index was dissected so that the volume of direct runoff equaled the whole excess rainfall distributed during the storms (Sadeghi et al., 2015).

2.3. Model description

2.3.1. Event based Clark's IUH hydrological model

Clark model is one of the most popular event based methods to derive a simultaneous unit hydrograph (Clark, 1945). This model is based on lag and route technique and Muskingum method. In preparing the simultaneous unit hydrograph, it is assumed that there is a virtual repository at the end of the river and water is stored with one input discharge. Then, based on input discharge components (Eq. (1)), time of concentration, and watershed storage coefficient, values of simultaneous unit hydrograph were obtained from Eq. (2) (Sadeghi et al.,

2015).

$$I_i = 2.78 \frac{A_i}{\Delta t_c} \quad (1)$$

where, I_i is the input discharge at any time period ($\text{m}^3 \text{s}^{-1}$), A_i is the area engaged in the runoff at the end of the period (km^2) and Δt_c is the time period of simulated unit hydrograph (h).

$$Q_2 = \left(\frac{\Delta t_c}{K + 0.5 \Delta t_c} \right) I_1 + \left(\frac{K - 0.5 \Delta t_c}{K + 0.5 \Delta t_c} \right) Q_1 \quad (2)$$

where, I_i and Q_1 respectively for the initial input and output flows, and Q_2 is the output flow ($\text{m}^3 \text{s}^{-1}$) after t_1 .

The variable K is water storage coefficient (h) obtained from the graphical method due to better performance, compared to other methods using Eq. (3) (Chow et al., 1988; Sadeghi and Dehghani, 2006).

$$k = \frac{\Delta t}{\ln \left(\frac{Q_0}{Q_t} \right)} \quad (3)$$

Q_0 is the discharge at the start of time interval ($\text{m}^3 \text{s}^{-1}$). Q_t is the discharge after a logarithmic time base Δt ($\text{m}^3 \text{s}^{-1}$), and t is the time interval (h).

The variable Δt_c is the time of concentration for each segment of isochrones (h) resulted from TAHs (time intervals of isochrones) based

Table 1

Characteristics of rainfall- runoff storm events for the Galazchai Watershed, Iran (adapted from Mostafazadeh et al., 2015; Saeidi et al., 2016).

No.	Rainfall storm event date	Total rainfall (mm)	Rainfall duration (h)	Average intensity (mm h ⁻¹)	Phi-index (mm h ⁻¹)	Base time (h)	Time to peak (h)	Discharge peak (m ³ s ⁻¹)	Flood volume (m ³)	Storage coefficient (h)
1	Apr. 6, 2003	6.3	5	1.1	0.8	14	6.5	15.26	260366.04	6.85
2	Dec. 9, 2003	9.2	6.5	1.2	1.1	10.5	5.5	7.9	89985.49	6.93
3	Apr. 23 2004	5.1	5	0.8	0.2	10	7.5	11.48	201934.44	7.49
4	May. 29 2004	18.8	7	2.5	0.4	19.5	15	15.77	773198.1	5.06
5	Apr.14, 2005	4.6	3	1.3	0.2	14.5	7	6.42	166319.28	6.33
6	Dec. 17, 2007	8.6	7.5	1	0.9	16	11	1.59	43170.84	3
7	Apr.14, 2008	9.1	6	1.4	0.9	13.5	7	7.54	205475.4	6.36
8	Apr. 23, 2008	11.3	6	1.7	0.6	19.5	6.5	20.11	574996.32	5.83
9	May. 29, 2008	13.6	5	2.5	0.1	11	8	2.02	29893.68	5.03
10	Oct. 1, 2008	12.4	6	1.9	2	19	11	1.77	53105.04	5.62
11	Oct. 25, 2008	33.1	14	2.3	4	11	7.5	3.5	69639.48	5.33
12	Mar. 10, 2009	12.9	6.5	1.8	4.1	10.5	8.5	6.35	115664.76	5.71
13	Mar. 14, 2009	3.9	4.5	0.8	0.5	19.5	8	1.99	99789.84	7.96
14	May. 17, 2009	5.1	4	0.9	0.9	22	8	8.06	390881.52	7.75
15	Sep. 22, 2009	3.2	3	0.9	0.2	17	12	1.37	60170.4	7.31
16	Apr. 21, 2011	6.3	8	0.7	0.6	14.5	11	6.08	137811.24	8.28
17	Apr. 23, 2011	8	10	0.8	0.4	8	5.5	1.26	13485.78	8.21
18	Oct. 29, 2011	2.4	3	1.7	2.9	12	4	1.32	27177.12	5.86
19	Oct. 30, 2011	13.2	8	1.65	3.1	10.5	6	1.07	25234.02	7.7
20	Nov. 4, 2011	13.6	4.5	0.5	2	13	6	0.98	18369.9	8.19
21	Nov. 5, 2011	4.6	3	1.53	1.1	12.5	5.5	2.28	48077.28	6.15
22	Apr. 11, 2012	14.3	2	1.9	5.3	10.5	2.5	4.21	72778.14	4.83
23	Apr. 20, 2012	4.6	3	1.3	1.1	11	5	4.81	110098.44	6.33
24	Nov. 3, 2012	8.3	2	4.1	3.3	10	3	9.6	132402.4	3.42
25	Nov. 11, 2012	13.5	2.5	5.4	3.9	10	2	7.1	261921.78	4.27
26	Nov. 12, 2012	8.7	2	4.4	2.4	9	2	4	102260.52	2.5
27	Nov. 13, 2012	14.7	4	3.7	2	15	3	3.62	83347.38	4.18
28	Nov. 14, 2012	2.4	4	1.7	1.4	10.5	3.5	3.26	71,523	4.47
29	Nov. 19, 2012	5.2	3	4.1	2.3	7.5	2.5	2.81	41289.84	6.04
30	Nov. 20, 2012	10.3	2.5	1.1	0.5	6	3	2.29	22246.57	4.27
31	Nov. 25, 2012	3.4	3	1.13	2.2	6	4	2.95	28795.76	7.14
32	Mar. 10, 2013	6.4	2.5	2.56	1.2	7	3	3.82	62388.9	5.16
33	Mar. 17, 2013	4.6	5	0.92	0.5	4	3	1.1	10563.08	4.3
34	Mar. 30, 2013	5.5	6.5	0.85	0.5	4.5	3	1.87	15838.89	6.2
35	Apr. 13, 2013	15	6	2.5	1	16	10.5	14.88	587803.66	5.5
36	Apr. 18, 2013	7	8	0.88	1.1	6	2.5	6.91	139034.49	3.6
37	Oct. 19, 2013	5	5.5	0.91	1.1	7	3	7.09	96159.52	3.3
38	Oct. 20, 2013	5.5	6	0.92	1.5	5.5	2	6.92	121063.92	5.2
39	Nov. 2, 2013	3.5	4	0.88	0.8	7.5	3.5	2.8	38158.31	7.2
40	Nov. 16, 2013	4	4.5	0.89	0.7	11	5.5	4.05	89051.13	4
41	Nov. 22, 2013	6.3	4.5	1.33	0.6	9	5.5	4.95	66017.34	3.7
42	Dec. 13, 2013	8	3	2.67	0.2	14	8	6.18	154178.1	3
Maximum		33.10	14.00	5.40	5.30	22.00	15.00	20.11	773198.10	8.28
Minimum		2.40	2.00	0.50	0.10	4.00	2.00	0.98	10563.08	2.50
Mean		6.70	4.50	1.32	1.05	10.75	5.50	4.03	86199.26	5.67
Coefficient of variations (%)		65.74	48.41	65.65	87.23	38.76	53.86	82.16	121.06	28.70

on Kirpich method (Eq. (4)). The Kirpich method which was obtained from watershed characteristics was applied to develop TAHs (Kirpich, 1940; Sahoo et al., 2006).

$$T_C = 0.06628 * L_i^{0.77} * S^{-0.385} \quad (4)$$

where T_C , is time of concentration (h), L_i is length of the channel network (km) S is average slope of the stream (dimensionless). The TCs were dissected from vector scale (1:25000 topographic map and the resolutions of 5, 10, 20, 30, 50, 100, and 200 m) and raster scale (ALOS PALSAR and the resolutions of 5, 10, 20, 30, 50, 100, and 200 m) and consequently used to create TAHs. Note that consequently the TAHs are influenced by both spatial resolution as temporal changes in runoff (Sadeghi et al., 2009; Matei, 2012). Finally, a total of 588 cases were provided for all RBD and VBD resolutions combined with the 42 storm events through applying VBA (Visual Basic for Applications) programming in Excel 2013. The instantaneous unit hydrographs were converted to unit hydrograph (UH) with a time lag. Ultimately, direct hydrograph (DH) was produced for each individual storm event considering effective rainfall and rain pulse through lag technique.

2.3.2. Evaluation of the Clark's IUH model performance

The main Clark's IUH Model simulated components, namely flood volume, peak discharge, time to peak and base time were compared with those of observed components of 42 storm events using evaluation criteria viz., root mean square error (RMSE; Eq. (5)), relative errors (REs; Eq. (6)) and coefficient of efficiency (CE; Eq. (7)) based on Nonlinear Generalized Gradient Algorithm (NGGA) (Sadeghi et al., 2009, 2019; Sadeghi and Asadi, 2010; Thirel et al., 2015; Moradi Dashtpajardi et al., 2019).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_{Sim(i)} - Q_{Obs(i)})^2} \quad (5)$$

$$RE(\%) = \left| \frac{(V_{Obs(i)} - V_{Sim(i)})}{V_{Obs(i)}} \right| \times 100 \quad (6)$$

$$CE = 1 - \frac{\sum_{i=1}^n (Q_{Obs(i)} - Q_{Sim(i)})^2}{\sum_{i=1}^n (Q_{Obs(i)} - \bar{Q}_{Obs})^2} \quad (7)$$

where $V_{Obs(i)}$ and $V_{Sim(i)}$, respectively were the observed and simulated

components of the hydrograph including peak discharge (m^3s^{-1}), flood volume (m^3), time to peak (h) and base time (h). $Q_{\text{Obs}(i)}$, $Q_{\text{Sim}(i)}$ and $\bar{Q}_{\text{Obs}}$ were observed, simulated and average of discharges (m^3s^{-1}) at time i and n is the time horizon in the hydrographs, respectively. The model performance was then evaluated for all RBD and VBD resolutions. Finally, 588 evaluation criteria of relative errors (for flood volume, peak discharge, time to peak and base time), CE and RMSE were produced for all different spatial resolutions and storm events. Acceptable performance of the model was approved by the highest CE and the smaller values of RMSE and REs criteria (Krause et al., 2005; Jain and Sudheer, 2008; Gupta and Kling, 2011).

2.3.3. Two-step cluster analysis algorithm

One of the more suitable methods for clustering large data is the Two-step Cluster Analysis Algorithm (TCAA) proposed by Garson (2009). TCAA represents two major steps, in the first step, observation data were classified into subclusters, and then in the second step, number of the clusters were selected by combining these subclusters based on statistical characteristics. The Euclidean distance was selected to determine the number of clusters. Euclidean distance between cluster centroids represent the number of clusters by the means of all variables in every cluster (Kovács et al., 2009; Sarstedt and Mooi, 2014). Therefore, the 588 simulated hydrograph evaluation criteria derived from the 14 RBD and VBD resolutions were clustered and then optimal clusters were selected based on the highest accuracy of the evaluation criterion. Finally, the optimal spatial resolution and data source for each hydrograph component was defined based on analysis of optimal clusters using IBM SPSS Statistic 22 software package.

2.3.4. Spatial pattern analysis of landscape metrics

The landscape metrics were computed in FRAGSTATS 4.2 in four categories of area and edge, shape, aggregation and core area using a moving window method (Mcgarigal and Marks, 1995; Weng et al., 2007; Schindler et al., 2008; Plexida et al., 2014; Feng and Liu, 2015; Feng et al., 2018). Landscape metrics were produced based on the 7 VBD resolutions (5, 10, 20, 30, 50, 100 and 200 m) due to higher accuracy of CE evaluation criterion of vector scale in comparison to raster scale. The produced VBDs with different spatial resolutions were intersected with land use map derived from 1:25000 original resolution updated from previous study (i.e., Mostafazadeh et al., 2015) using ArcGIS 10.5. In this study, 80 landscape metrics at class level were produced based on 7 different resolutions of 1:25000 vector scale. On the other hands, principal component analysis (PCA) and varimax algorithm were used as one of the data reduction methods for analyzing relationships between calculated landscape metrics. In factor analysis, landscape metrics were abridged to a smaller number of parameters. Then, based on the correlation coefficients and rotated component matrix of components of specific landscape metrics, the role of the metrics as principal factor and their impact were determined (Moradi Dashtpajardi et al., 2013; Bro and Smilde, 2014; Suganyadevi and Savitha, 2016).

2.3.5. Relationship between landscape metrics and simulated hydrograph components

Regression relationships between landscape metrics resulting from the 7 different resolutions (for both RBD and VBD sources) and simulated hydrograph components viz., flood volume, peak discharge, time to peak and base time were developed using IBM SPSS Statistics 23. These regression relationships of landscape metrics in two parts with hydrograph components of the best cluster (namely the best resolutions and the most precise simulation) and hydrograph components of the worst cluster (the worst resolutions and the least precise simulation) were separately tested using different important evaluation criteria viz., relative errors of flood volume, peak discharge, time to peak, base time and also CE and RMSE. Different types of multiple regressions of linear (Eq. (8)), logarithmic (Eq. 9), power (Eq. 10), exponential (Eq. 11), and

logistic (Eq. 12) were developed between each hydrograph component for different cell sizes and storm events and landscape metrics, separately. The best regressions were then selected based on criteria of adjusted R^2 , beta and significant level. They were applied to determine relationships between independent and dependent variables based on the best fitting equation to predict the dependent variable (i.e., flood volume, peak discharge and time to peak) (Wu et al., 2012).

$$HC = a_0 + a_1L_1 + a_2L_2 + \dots + a_nL_n \quad (8)$$

$$HC = a + b \cdot \ln L \quad (9)$$

$$\ln HC = \ln a + b_1 \cdot \ln L \quad (10)$$

$$HC = aeb^{b_1 \cdot L} \quad (11)$$

$$HC = \frac{1}{\frac{1}{U} + ab_1L} \quad (12)$$

where HC (hydrograph component under consideration) is the dependent variables, $L_1 \dots L_n$ (landscape metrics) are the independent variables, a, b and b_1 are the coefficients, n is the number of variables, and U is upper confidence limit.

3. Results

3.1. VBD and RBD based hydrograph components

An example set of detailed information of simulated hydrograph components based on VBD and RBD resolutions for an arbitrary storm event (Nov. 20, 2012) is shown in Table 2.

Measurements of relative errors of flood volume, peak discharge, time to peak, base time and also CE and RMSE were defined in four clusters for vector and raster scales, separately. The distribution characteristics belonging to each cluster and also cluster characteristics for each hydrograph component are shown in Tables 3 and 4.

As Table 4 shows, the significance levels (sig.) of hydrograph component evaluation criteria were quite low and then classifying clusters were approved for both VBD and RBD resolutions. Indeed,

Table 2

Characteristics of hydrographs components resulted from applying DEMs based on vector and raster scales in different cell sizes for Nov. 20, 2012 storm event in the Galazchai Watershed, Iran.

No	Cell size (m)	Scale	Flood volume (m^3)	Peak discharge (m^3s^{-1})	Time to peak (h)	Base time (h)
1	5	Vector	23155.11	2.46	1.75	7.50
		Raster	23238.14	2.41	1.75	7.50
2	10	Vector	23264.44	2.32	1.75	7.50
		Raster	23168.44	2.39	1.75	7.50
3	20	Vector	23211.67	2.34	1.75	8.00
		Raster	23293.97	2.32	1.75	7.50
4	30	Vector	23199.00	2.24	1.75	8.00
		Raster	23221.17	2.34	1.75	8.00
5	50	Vector	23242.58	2.46	1.75	7.50
		Raster	23208.20	2.24	1.75	8.00
6	100	Vector	23242.58	2.49	1.50	7.50
		Raster	23282.58	2.51	1.75	7.50
7	200	Vector	23597.23	2.67	1.25	8.00
		Raster	23659.02	2.75	1.50	7.50
Maximum		Vector	23597.23	2.67	1.75	8.00
		Raster	23659.02	2.75	1.75	8.00
Minimum		Vector	23155.11	2.24	1.25	7.50
		Raster	23168.44	2.24	1.50	7.50
Mean		Vector	23242.58	2.46	1.75	7.50
		Raster	23238.14	2.39	1.75	7.50
Coefficient of variation (%)		Vector	0.63	5.74	11.97	3.46
		Raster	0.71	6.83	5.51	3.19

Table 3
Clusters distribution characteristics of vector and raster scales

Cluster No.	Scale	N	% of Total
1	Vector	71	24.14
	Raster	63	21.4
2	Vector	61	20.74
	Raster	94	32.0
3	Vector	73	24.83
	Raster	42	14.3
4	Vector	89	30.27
	Raster	95	32.3
Total	Vector	294	100.0%
	Raster	294	100.0%

clusters 3, 1, 3, 4, 2 and 4 were selected as an optimal cluster (based on the lowest errors) for flood volume, peak discharge, time to peak, base time, CE and RMSE, respectively, for the VBD resolutions. While in fact, clusters 1, 1, 4, 2, 3 and 2 were selected as optimal clusters with the lowest errors for flood volume, peak discharge, time to peak, base time, CE and RMSE, respectively, for RBD resolutions. RMSE and CE criteria as two major evaluation criteria of hydrological models performance were classified in different clusters (i.e., clusters 4 and 2 for VBD and clusters 2 and 3 clusters for RBD). In fact, the highest precision of simulated hydrographs based on the best CE and RMSE evaluation criteria were dissimilar and then precision of hydrological models performance depended to type of evaluation criteria of RMSE and CE. On the other hand, cluster 1 for both VBD and RBD resolutions behaved similarly in estimation of peak discharge. However, other criteria were significantly different. Table 5 shows optimal resolutions related to VBD and RBD sources based on the best simulated direct hydrographs with the lowest errors resulted from optimal clusters.

As shown in Table 5, for the VBD, resolutions of 5 and 10 m (for flood volume hydrograph component), resolution of 5 m (for peak discharge hydrograph component), resolutions of 5 and 20 m (for time to peak hydrograph component) and resolutions of 30 and 20 m (for base time hydrograph component) were determined as optimal resolutions association with optimal clusters. Whereas, for the RBD, resolutions of 20 and 30 m (for flood volume hydrograph component), resolutions of 5 and 10 m (for peak discharge hydrograph component), resolution of 10 m (for time to peak hydrograph component) and resolutions of 10 and 50 m (for base time hydrograph component) were selected as optimal resolution association with optimal clusters. According to Table 5, the maximum frequency of VBD and RBD resolutions were 5 and 10 m, respectively. On the other hand, in Table 5, the number and contribution of variables of selected optimal clusters are represented and these range between 20.74 and 30.27 (for VBD) and 14.3 and 32 percent (for RBD). In addition, errors were calculated through average REs for flood volume, peak discharge, time to peak and base time in each selected optimal cluster for VBD and RBD resolutions, separately. Accordingly, REs derived from flood volume, peak discharge, time to peak and base

time components of simulated hydrographs resolutions were estimated 3.46, 4.61, 3.98 and 5.94 percent for VBD and 3.17, 4.16, 4.23 and 4.74 percent for RBD, respectively. Furthermore, average values of CE and RMSE evaluation criteria of simulated hydrographs based on selected optimal clusters were estimated 82 and 0.87% for VBD and 74 and 0.78% for RBD, respectively. According to Table 5, CE evaluation criterion based on VBD was suitable to evaluate base time while RMSE based on VBD was the most suitable criterion to evaluate base time and time to peak. CE evaluation criterion based on RBD resolutions was also suitable for evaluating base time and flood volume while RMSE based on RBD was the most suitable criterion to evaluate hydrograph base time only.

3.2. VBD and RBD based time of concentrations

TCs based on VBD and RBD resolutions are shown in Fig. 2. The lowest TC values are allocated to finer resolutions viz., 5, 10, 20, and 30 m, while the TC values of 50, 100, and 200 m resolutions were the highest. In addition, Fig. 3 shows optimal resolutions related to hydrograph components based on VBD and RBD resolutions.

According to Fig. 3, resolutions of 5, 10, 20, and 30 m (finer resolutions) were recognized as optimal resolution for VBDs and RBDs in all components of the hydrograph. It can be further said that there were significant relationships between optimal resolutions viz., 5, 10, 20 and 30 m and the lowest TC.

3.3. Landscape metrics

To analyze the landscape metrics, 80 landscape class-levels metrics were tested and have been shown in Table 6. A selection was then made of 20 landscape metrics based on PCA in four categories including area and edge, shape, aggregation and core area as shown in Table 7.

3.4. Landscape metrics and hydrograph components relationships

In the best cluster, the highest accuracy of hydrograph components viz., flood volume, peak discharge, and time to peak and base time based on 5, 10, 20 and 30 resolutions was achieved. On the other hand, in the worst cluster, hydrograph components viz., flood volume, peak discharge, time to peak and base time with the highest error based on the most contribution of resolutions of 50, 100, and 200 m were defined. Then, regression between landscape metrics with the best and the worst hydrograph components in association with the different spatial resolutions were analyzed and finally, level of significance of regression between landscapes with the best and the worst hydrograph components were tested. Characteristics of selected landscape metrics and corresponding adjusted R^2 and also regression functions between dependent variables (hydrograph components) and independent variables (landscape metrics) have been shown in Table 8.

Table 4
Statistical characteristics of the hydrograph components for vector and raster scales

Variables	Scale	Cluster		Error		F-Value	Significant level	Best cluster
		Mean Square	df	Mean Square	df			
Flood volume	Vector	235.59	3	7.15	290	56.78	0.015	3
	Raster	238.55	3	4.00	290	59.61	0.000	1
Peak discharge	Vector	19.65	3	5.82	290	3.37	0.019	1
	Raster	18.42	3	5.85	290	3.14	0.026	1
Time to peak	Vector	185.79	3	10.60	290	17.52	0.000	3
	Raster	171.54	3	10.60	290	16.17	0.000	4
Base time	Vector	10060.15	3	7.73	290	1301.32	0.000	4
	Raster	10363.99	3	5.76	290	1796.54	0.000	2
CE	Vector	6.90	3	0.04	290	147.18	0.000	2
	Raster	6.80	3	0.04	290	147.46	0.000	3
RMSE	Vector	84.07	3	1.81	290	46.43	0.000	4
	Raster	84.82	3	1.77	290	47.90	0.000	2

Table 5
Characteristics of vector and raster scales with different cell sizes for the simulated direct hydrographs derived from optimal clusters in the Galazchai Watershed, Iran

Variables	Scale	Optimal cell size resulted from simulated hydrographs of optimal cluster (m)	Number of variables in optimal cluster	Contribution of optimal cluster variables (%)	Contribution of optimal cluster optimal cluster (%)	Errors related to variables in optimal cluster (%)
Flood volume	Vector	5 and 10	73	24.83	32.65	3.46
Peak discharge	Raster	20 and 30	63	21.4	30.41	3.17
Time to peak	Vector	5	71	24.14	24.12	4.61
Base time	Raster	5 and 10	63	21.4	36.35	4.16
CE	Vector	5 and 20	73	24.83	38.15	3.98
RMSE	Raster	10	95	32.3	26.80	4.23
	Vector	30 and 20	89	30.27	30.50	5.94
	Raster	10 and 50	94	32.0	34.25	4.74
	Vector	30	61	20.74	25.60	0.82
	Raster	30 and 50	42	14.3	35.45	0.74
	Vector	20 and 30	89	30.27	38.50	0.87
	Raster	50	94	32.0	27.34	0.78

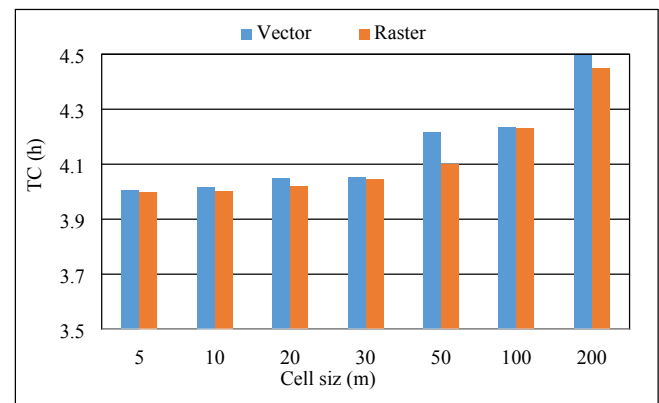


Fig. 2. Simulated TCs based on vector and raster scales and different cell size in the Galazchai Watershed, Iran.

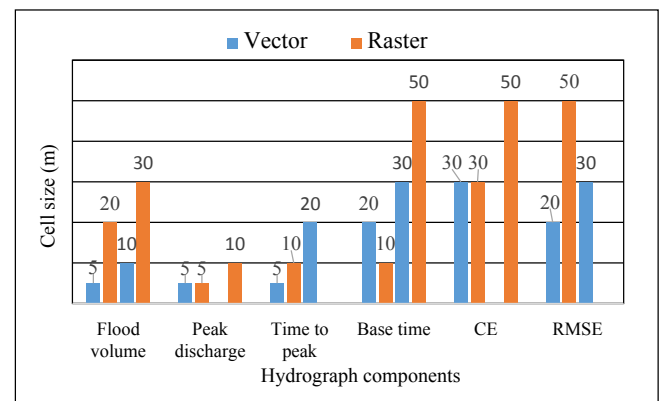


Fig. 3. Optimal cell sizes based on vector and raster scales in the Galazchai Watershed, Iran.

According to Table 8, there was acceptable adjusted R^2 to fit produced line in position of the best cluster between flood volume with NDCA (0.82), peak discharge with PD (0.60), time to peak with CA (0.53) and also base time with NLSI (0.51). In the worst cluster, namely simulated hydrograph components with the highest errors based on resolutions with the most contribution of 50, 100, and 200 m, no acceptable adjusted R^2 could be found for flood volume and peak discharge but there was acceptable adjusted R^2 for time to peak (0.57) and base time (0.50). As Table 8 shows, landscape class level metrics of NDCA, PD, CA, and NLSI were associated with hydrograph components of flood volume, peak discharge, time to peak, and base time, respectively. In addition, Beta index represented change rates in dependent variables (i.e., hydrograph components) affected by changes in landscape metrics. The highest variability of dependent variables was related to flood volume and NDCA (0.92). Beta value for peak discharge and PD also was high (0.81). On the other hand, variability of time to peak related to CA landscape metrics for the best and worst clusters were found 0.76 and 0.80, respectively. Variability of base time related to NLSI landscape metric for the best and worst clusters, was also defined 0.75 and 0.76, respectively. The highest correlation levels with the lowest significant levels (i.e., 0.003 and 0.023) were belonged to flood volume and peak discharge components related to the best spatial resolutions. Indeed, significant levels for temporal components related to the worst spatial resolutions were defined 0.03 and 0.046. In this regard, Eqs. (13) and (14) in Table 8 showed the acceptable regression function for modeling flood volume and peak discharge with NDCA and PD landscape metrics. The regressions were determined based on the highest accuracy of simulated flood volume and peak discharge. On the other hands, the highest accuracy of simulated flood volume and peak

Table 6

Rotated matrix of PCA components of the study landscape metrics for the study watershed

NO.	Acronym	Component				NO.	Acronym	Component			
		1	2	3	4			1	2	3	4
1	NP	0.497	0.857	0.054	0.121	41	CONTIG_AM	0.758	0.511	0.405	0.003
2	PD	0.497	0.857	0.053	0.121	42	CONTIG_MD	0.96	−0.055	0.092	0.146
3	LPI	−0.154	−0.849	−0.467	0.13	43	CONTIG_RA	0.757	0.51	0.409	−0.007
4	NLSI	0.759	0.511	0.402	0.033	44	CONTIG_SD	0.479	0.467	0.739	−0.067
5	TA	0.775	0.617	0.065	0.114	45	CONTIG_CV	−0.923	0.225	0.145	−0.211
6	AREA_MN	−0.873	−0.417	−0.217	0.12	46	PAFRAC	−0.362	−0.88	−0.3	−0.02
7	AREA_AM	0.111	−0.897	−0.42	0.063	47	CA	0.718	0.557	0.416	0.016
8	AREA_MD	−0.893	−0.29	−0.336	0.015	48	NDCA	0.595	0.495	0.62	0.061
9	AREA_RA	−0.145	−0.851	−0.465	0.131	49	DCAD	0.595	0.495	0.62	0.061
10	AREA_SD	−0.723	−0.626	−0.287	0.053	50	CORE_MN	−0.74	−0.665	−0.079	0.039
11	GYRATE_MN	−0.85	−0.47	−0.222	0.08	51	CORE_AM	0.946	−0.281	0.103	0.106
12	GYRATE_AM	0.41	−0.844	−0.323	0.002	52	CORE_RA	0.96	0.038	0.231	0.106
13	GYRATE_MD	−0.863	−0.379	−0.321	0.076	53	CORE_SD	−0.346	−0.929	−0.122	0.02
14	GYRATE_RA	0.148	−0.91	−0.324	0.171	54	CORE_CV	0.807	0.56	−0.119	0.136
15	GYRATE_SD	−0.812	−0.547	−0.196	0.016	55	DCORE_MN	−0.883	−0.27	−0.38	0.009
16	GYRATE_CV	0.561	0.814	0.101	0.094	56	DCORE_AM	0.949	0.035	0.286	0.097
17	SHAPE_MN	0.623	0.153	0.766	0.021	57	DCORE_MD	−0.934	−0.2	−0.2	0.202
18	SHAPE_AM	0.939	0.147	0.287	0.099	58	DCORE_RA	0.923	0.234	0.303	−0.033
19	SHAPE_RA	0.495	0.84	−0.103	0.19	59	DCORE_SD	−0.27	−0.532	−0.739	−0.288
20	SHAPE_SD	0.602	0.471	0.644	−0.012	60	CPLAND	0.805	0.251	0.518	0.113
21	SHAPE_CV	0.612	0.584	0.532	−0.005	61	CAI_MN	0.433	0.553	0.706	−0.064
22	FRAC_MN	0.712	0.405	0.56	0.092	62	CAI_AM	0.718	0.557	0.416	0.015
23	FRAC_AM	0.898	0.283	0.336	0.032	63	CAI_RA	0.754	0.51	0.414	0.001
24	FRAC_MD	0.693	0.557	0.299	−0.015	64	CAI_SD	0.466	0.719	0.514	0.01
25	FRAC_RA	0.423	0.862	0.278	−0.002	65	CAI_CV	−0.793	−0.229	−0.564	−0.015
26	FRAC_SD	0.597	0.551	0.581	0.031	66	CLUMPY	0.688	0.593	0.417	0.023
27	FRAC_CV	0.598	0.553	0.579	0.031	67	PLADJ	0.769	0.498	0.401	0
28	PARA_MN	0.268	0.958	0.029	0.096	68	IJI	0.893	0.288	0.127	−0.294
29	PARA_AM	0.761	0.51	0.4	0.032	69	COHESION	0.877	0.357	0.31	−0.085
30	PARA_MD	0.259	0.959	0.06	0.088	70	DIVISION	−0.106	0.897	0.422	−0.061
31	PARA_RA	0.273	0.955	0.07	0.086	71	MESH	0.111	−0.897	−0.42	0.063
32	PARA_SD	0.257	0.955	0.137	0.051	72	SPLIT	−0.07	0.906	0.404	−0.085
33	PARA_CV	0.575	0.388	0.718	−0.023	73	SHDI	0.711	0.195	0.432	0.448
34	CIRCLE_MN	0.942	0.089	0.248	0.15	74	SIDI	0.923	0.206	0.263	0.048
35	CIRCLE_AM	0.861	0.33	0.353	−0.123	75	MSIDI	0.917	0.201	0.295	0.066
36	CIRCLE_MD	0.984	0.121	0.022	−0.117	77	SIEI	0.924	0.189	0.286	0.073
37	CIRCLE_RA	0.741	0.514	0.422	0.075	78	MSIEI	0.914	0.2	0.293	0.078
38	CIRCLE_SD	0.596	0.366	0.698	−0.086	79	ED	0.581	0.682	0.385	0.014
39	CIRCLE_CV	−0.984	−0.014	−0.023	−0.094	80	TE	0.791	0.201	0.195	0.046
40	CONTIG_MN	0.747	0.29	0.581	0.087	81	AI	0.761	0.506	0.406	0.005

discharge occurred in resolutions of 5, 10, 20, and 30 m. Indeed, role of adaption and consistency of the best simulated time to peak and CA landscape metric was also approved in Eq. (15). On the other hand, correlation between the worst simulated time to peak and CA landscape metric based on Eq. (16) was also acceptable. In fact, it can be claimed that although 5, 10, 20, and 30 m resolutions were selected as optimal spatial resolutions for simulating the best time to peak but they did not play main role for CA landscape metric compared other resolutions.

4. Discussion

4.1. Evaluation of time of concentration derived from VBDs and RBDs

In this study, resolutions with minimum TCs play a very important role in determination of optimal resolution. Therefore, in interpretation of selecting optimal resolutions related to hydrograph components, we must consider the watershed physiographic characteristics, and particularly slope, stream and TC. To support this, [Das et al. \(2016\)](#) also showed changes in resolutions had different effects on physiographic and morphometric parameters of their case study. The Galazchai Watershed thanks to high elevations, steep slopes, and mountainous topography has a short TC leading to rapid hydrological response. In addition, [Salimi et al. \(2017\)](#) in their researches proved that changes in watershed parameters led to changes in TC. This is consistent with findings of [Green and Nelson \(2002\)](#) and [Moradi Dashtpajardi et al. \(2019\)](#) that showed interaction of parameters of impact on watershed

and TC led to changes of rainfall-runoff modelling results. In fact, fine resolutions lead to production of TC with lower values and finally, can represent what occur really in Galazchai Watershed as well.

4.2. Analysis of optimal resolutions

In this research, 5 m resolution for VBD was selected as optimal for flood volume, peak discharge, and time to peak. For RBD, 10 m resolution was also determined as optimal for flood volume, peak discharge, and time to peak. In this matter, [Zhang and Montgomery \(1994\)](#) also showed that 10 m DEM resolution was sufficient for proper estimating physiographic and hydrologic parameters. In addition, [Usery et al. \(2004\)](#) represented that DEMs between 3 and 30 m resolution had higher accuracy and correlation ($r = 0.9$) compared to coarser resolution. [Sørensen and Seibert \(2007\)](#) argued higher resolution DEMs had better performance. On the other hands, the simulation results of hydrograph components using Clark's IUH hydrological model and applying all DEMs derived from RBD did not show distinct differences. This finding certainly helps managers and experts optimize time and cost effectiveness for getting reliable outcomes. This is consistent with findings of [Sørensen and Seibert \(2007\)](#) who proved sufficient accuracy of DEMs with resolutions of 5 to 10 m to compute topographic indices. [Charrier and Li \(2012\)](#) also proved the appropriateness of RBD source with coarser resolutions beyond 10 m for studying some physiographic components of the watershed. Indeed, [Cai and Wang \(2006\)](#) showed that DEMs with 90 m resolution represented better performance to assess

Table 7

Analyzed Landscape metrics based on vector scale and cell sizes of 5, 10, 20, 30, 50, 100, and 200 m in the Galazchai Watershed, Iran.

NO.	Acronym	Name	Type	Units
1	TA	Total area	Area and edge metrics	Ha
2	TE	Total edge		%
3	ED	Edge density		m/ha
4	LPI	Largest patch	Shape metrics	index %
5	PAFRAC	Perimeter-Area fractal dimension		dimensionless
6	AI	Aggregation index	Aggregation metrics	%
7	NLSI	Normalized Landscape Shape Index		dimensionless
8	CLUMPY	Clumpiness	Core area	%
9	IJI	Interspersion juxtaposition index		%
10	COHESION	Patch cohesion index		dimensionless
11	LSI	Landscape shape index		dimensionless
12	MESH	Effective mesh size		Ha
13	PD	Patch density	Core area	number/100 ha
14	NP	Number of patches		dimensionless
15	PLADJ	Proportion of like adjacencies		%
16	SPLIT	Splitting Index		dimensionless
17	CA	Core area		Ha
18	CPLAND	Core area percent of landscape	Core area	%
19	NDCA	Number of disjunct core areas		dimensionless
20	DCAD	Disjunct core area density		number/100 ha

topographic characteristics than a 30 m DEM. Beside these, CE and RMSE based on VBD, showed higher accuracy in map than CE and RMSE based on RBD. Although no discrepancy of significance was found but CE and RMSE for VBD were higher and it was therefore recognized as the more optimal mapping source. Zhang et al. (2008), Hladik and Alber (2012) and Holisaz et al. (2016) proved that simulated evaluation criteria of topographic and hydrological parameters represent different accuracies in association with different scales and resolutions. In fact, it can be said that different scales and spatial resolutions represent different details and finally they lead to different outputs for the models. In this matter, Du et al. (2017), Mondal et al. (2017) and Siles et al. (2020) also argued that raster open source DEMs (i.e., SAR, SRTM, ASTER and CARTOSAT) showed acceptable performance to extract case study physiographic parameters. Recently, Moradi Dashtpajardi et al. (2019) and Sadeghi et al. (2019) also verified that performance of various spatial resolutions from different sources represented different results in simulation of sedimentgraph and hydrograph components.

4.3. Sensitivity analysis of landscape metrics and hydrograph components

In resolutions of 5, 10, 20, and 30 m, there were high correlations between hydrograph components and landscape metrics. However,

simulated time to peak and base time with the highest error also represented higher correlation than the highest accuracy of simulated time to peak and base time. In fact, sensitivity of relationship between landscape metrics and flood volume and peak discharge influenced by 5, 10, 20 and 30 m resolutions and consequently the best simulation. It can be said that relationship between landscape metrics and flood volume and peak discharge components depends on cluster with the highest accuracy of resolutions viz., 5, 10, 20, and 30 m. This is consistent with findings of Wu (2004) who showed that impacts of scaling relations on the landscape class level metrics were tangible. Plexida et al. (2014) also showed that the correlations between shape metrics and other metrics were not strong at any scale. Zhang et al. (2018) approved effectability of water quality indices from landscape metrics in different scales using regression models. In this matter, representation of more details in resolutions of 5, 10, 20, and 30 m (finer spatial resolutions) led to higher accuracy of hydrograph components and landscape metrics. This is comparable with findings of Claessens et al. (2005) who verified DEMs with finer resolutions represent more detail and consequently the more accuracy. In fact, the resolutions of 5, 10, 20, and 30 m had the best results to analyze spatial pattern (using NDCA and PD metrics) and also these spatial resolutions had the best results to simulate hydrograph components. Therefore, these resolutions played major role in NDCA and PD landscape metrics. It can be said also that adaption and consistency of the best simulated flood volume and peak discharge, and NDCA and PD landscape metrics due to same spatial resolutions led to a regression with high correlation. In this regard, Wu et al. (2002) showed there was acceptable correlation between different spatial resolutions and landscape metrics so that change in spatial resolution led to change in type of landscape metrics. Therefore, CA landscape metric had no sensitivity to spatial resolutions which were the best spatial resolution in simulation of hydrograph components. In this matter, sensitivity of NLSI landscape metric to spatial resolution for base time was similar to sensitivity of CA landscape metrics for time to peak so that NLSI also was not sensitive to resolutions. Beside these, sensitivity of flood volume and peak discharge related to landscape metrics was higher than those for time to peak and base time. Plexida et al. (2014) found also that Patch Cohesion Index (PCI) and Area-Weighted Mean Fractal Dimension Index (AWMFD) were suitable to analyze landscape metrics without effectability from the scale. Generally, various studies showed that change in landscape patterns due to change in spatial structure and configuration was significantly influenced by natural factors (Turner, 1990; Gustafson, 1998; Déjeant-Pons, 2006).

5. Conclusions remarks

In this research, we evaluated impacts of DEMs with different sources and spatial resolutions to simulate hydrograph components based on storm event Clark's IUH model. Also, the most accuracy of scale and spatial resolutions based on evaluation criteria were selected and then, relationships between landscape metrics and hydrograph components were modeled. The results showed that the optimal spatial resolutions to simulate hydrograph components related to 1:25000 contour line (vector scale) were selected 5, 10, 20 and 30 m and also the optimal

Table 8

Characteristics of regression functions between landscape metrics variables and the highest and lowest accuracy of hydrograph components in the Galazchai Watershed, Iran

Dependent variable	Error	Maximum No. of contribution of cell sizes	Adjusted R ²	Regression	Beta	Significant level
Volume flood (m ³)	Low (the best cluster)	5, 10, 20 and 30	0.82	5263.27 + 0.876 NDCA Eq. (13)	0.92	0.003
	High (the worst cluster)	50, 100 and 200	–	Not found	–	–
Peak discharge (m ³ s ⁻¹)	Low (the best cluster)	5, 10, 20 and 30	0.60	0.345 + 0.029 PD Eq. (14)	0.81	0.023
	High (the worst cluster)	50, 100 and 200	–	Not found	–	–
Time to peak (h)	Low (the best cluster)	5, 10, 20 and 30	0.53	141.24-0.109 CA Eq. (15)	-0.76	0.04
	High (the worst cluster)	50, 100 and 200	0.57	234.752-0.182 CA Eq. (16)	-0.80	0.03
Base time (h)	Low (the best cluster)	5, 10, 20 and 30	0.51	15.028 + 0.393 NLSI Eq. (17)	0.75	0.045
	High (the worst cluster)	50, 100 and 200	0.50	26.501-5.157 NLSI Eq. (18)	-0.76	0.046

resolutions to simulate hydrograph components related to DEM derived from ALOS (raster scale) were selected 5, 10, 20, 30 and 50 m. In this regard, although CE of vector scale were defined higher than CE of raster scale but significant difference between hydrograph components based on vector and raster was not observed. Therefore, it is crucial importance that DEM derived from ALOS satellite is available and free and can be suitable alternative to 1:25000 contour lines for simulating hydrological model. On the other hand, we established relationships between hydrograph components and landscape metrics based on different spatial resolutions. Creating modelling relationships between landscape metrics and hydrograph simulated components considering the ambiguities and complexity of effects of spatial resolution on this modelling was our other goal. So that finally, we can overcome on complexity of simulation of hydrological components through landscape metrics that were estimated based on only watershed landuse without need to other factors. In this matter, 5, 10, 20 and 30 m resolutions were defined optimal spatial resolutions for both the most compatible NDCA and PD landscape metrics and the most accuracy of simulated flood volume and peak discharge. According to this, strong relationship between flood volume and peak discharge with NDCA and PD based on 5, 10, 20 and 30 m was established. Indeed, relationship between flood volume and peak discharge with landscape metrics based on 50, 100, and 200 m was not established so that showed there was not any regression equation between landscape metrics and the lowest accuracy of simulated flood volume and peak discharge. On the other hand, sensitivity of modeling between landscape metrics and times (time to peak and base time) was complex and the regression relationships were established for both the highest and lowest accuracy of times with CA and NLSI landscape metrics. In this regard, the findings showed times regression relationships (time to peak and base time) had same sensitivity to different spatial resolutions and relationship between times and landscape metrics could not be influenced by spatial resolution. Modeling times with landscape metrics showed these components had acceptable correlation with both finer and coarser resolutions viz., 5, 10, 20, 30, 50, 100, and 200 m. Although landscape metrics for modeling time to peak and base time based on the best and worst spatial resolutions were same but regression coefficients were different. In fact, we approved that verification of modeling relationship between hydrograph components and landscape metrics based on optimal spatial resolutions for flood volume and peak discharge is acceptable so that represented regression can predict the most accuracy of flood volume and peak discharge. On the other hand, represented regression relationship between times with landscape metrics could not represent the best simulated time to peak and base time because of there were acceptable regression for both the best and worst simulated times. Therefore, it is necessary that researchers must represent regression equation which in turn lead to predict the most accuracy of hydrograph components based on the optimal spatial resolutions. In the long run, we suggest that modeling relationship between landscape metrics and hydrograph components without considering to accuracy of spatial resolutions on input maps can fake analysis of results out. It is vital for the managers and policy makers who are supposed to invest time and money for getting the most reliable, precise, and detailed information and data while bearing the least cost. It is obvious that some of the results of such studies are local and even time specific but the general findings of the results may certainly narrow the field of endeavors and remove divergences in hydrologic studies as far as spatial resolutions and scale are concerned.

CRedit authorship contribution statement

Seyed Hamidreza Sadeghi: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Mostafa Moradi Dashtpagerdi:** Conceptualization, Methodology, Validation, Investigation, Data curation, Resources, Formal analysis, Validation, Writing - original draft, Software. **Hamidreza Moradi Rekabdarkoolai:**

Conceptualization, Methodology, Supervision. **Jeroen M. Schoorl:** Conceptualization, Methodology, Writing - original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- Adhami, M., Sadeghi, S.H.R., Sheikhmohammady, M., 2018. Making competent land use policy using a co-management framework. *Land Use Policy* 72, 171–180.
- Adhami, M., Sadeghi, S.H.R., Duttman, R., Sheikhmohammadi, M., 2019. Changes in watershed hydrological behavior due to land use comanagement scenarios. *J. Hydrol.* 577, 124001 <https://doi.org/10.1016/j.jhydrol.2019.124001>.
- Adhami, M., Sadeghi, S.H.R., Duttman, R., Sheikhmohammady, M., 2020. Best soil comanagement practices for two watersheds in Germany and Iran using game theory-based approaches. *Sci. Total Environ.* 698, 134265 <https://doi.org/10.1016/j.scitotenv.2019.134265>.
- Agirre, U., Goñi, M., López, J.J., Gimena, F.N., 2005. Application of a unit hydrograph based on subwatershed division and comparison with Nash's instantaneous unit hydrograph. *Catena* 64 (2–3), 321–332.
- Amatulli, G., Domisch, S., Tuanmu, M.N., Parmentier, B., Ranipeta, A., Malczyk, J., Jetz, W., 2018. A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. *Sci. Data* 5, 180040.
- Bro, R., Smilde, A.K., 2014. Principal component analysis. *Anal. Methods* 6 (9), 2812–2831.
- Cai, X., Wang, D., 2006. Spatial autocorrelation of topographic index in catchments. *J. Hydrol.* 328 (3–4), 581–591.
- Charrier, R., Li, Y., 2012. Assessing resolution and source effects of digital elevation models on automated floodplain delineation: a case study from the Camp Creek Watershed, Missouri. *Appl. Geogr.* 34, 38–46.
- Chow, V.T., Maidment, D.R., Mays, L.W., 1988. *Applied Hydrology*. Editions McGraw-Hill, New York, p. 572.
- Claessens, L., Heuvelink, G.B.M., Schoorl, J.M., Veldkamp, A., 2005. DEM resolution effects on shallow landslide hazard and soil redistribution modelling. *Earth Surf. Proc. Land.* 30 (4), 461–477.
- Clark, C.O., 1945. Storage and the unit hydrograph. *Proc. Am. Soc. Civ. Eng.* 69 (9), 1333–1360.
- Corry, R.C., Lafortezza, R., 2007. Sensitivity of landscape measurements to changing grain size for fine-scale design and management. *Landscape Ecol.* 3 (1), 47–53.
- Dar, I.A., Sankar, K., Dar, M.A., 2010. Remote sensing technology and geographic information system modeling: an integrated approach towards the mapping of groundwater potential zones in Hardrock terrain, Mamundiyyar basin. *J. Hydrol.* 394 (3–4), 285–295.
- Das, S., Patel, P.P., Sengupta, S., 2016. Evaluation of different digital elevation models for analyzing drainage morphometric parameters in a mountainous terrain: a case study of the Supin-upper tons basin, Indian Himalayas. *Springer Plus* 5 (1), 1544.
- Déjeant-Pons, M., 2006. The European landscape convention. *Landscape Res.* 31 (4), 363–384.
- Du, C., Ye, A., Gan, Y., You, J., Duan, Q., Ma, F., Hou, J., 2017. Drainage network extraction from a high-resolution DEM using parallel programming in the. *NET Framework. J. Hydrol.* 555 (1), 506–517.
- Feng, Y., Liu, Y., 2015. Fractal dimension as an indicator for quantifying the effects of changing spatial scales on landscape metrics. *J. Ecol. Indic.* 53 (1), 18–27.
- Feng, Y., Liu, Y., Tong, X., 2018. Spatiotemporal variation of landscape patterns and their spatial determinants in Shanghai, China. *J. Ecol. Indic.* 87 (1), 22–32.
- Feng, H., Zou, B., Tang, Y., 2017. Scale-and region-dependence in landscape-PM2. 5 correlation: implications for urban planning. *Remote Sens.* 9 (9), 918.
- Garson, D. 2009: Cluster analysis from Statnotes: Topics in Multivariate analysis retrieved from <http://faculty.chass.ncsu.edu/garson/pa765/statnote.htm>.
- Green, J.L., Nelson, E.J., 2002. Calculation of time of concentration for hydrologic design and analysis using geographic information system vector objects. *J. Hydroinf.* 4 (2), 75–81.
- Gupta, H.V., Kling, H., 2011. On typical range, sensitivity, and normalization of Mean Squared Error and Nash-Sutcliffe Efficiency type metrics. *Water Resour. Res.* 47 (10), 10601–10603.
- Gustafson, E.J., 1998. Quantifying landscape spatial pattern: what is the state of the art? *J. Ecosyst.* 1 (2), 143–156.

- Hladik, C., Alber, M., 2012. Accuracy assessment and correction of a LIDAR-derived salt marsh digital elevation model. *J. Remote Sens. Environ.* 121, 224–235.
- Holisaz, A., Ahadios, B., Kamangar, M., Ameli, A., 2016. Assessing the effect of spatial scale change in flood estimation, Jamash Watershed, Hormozgan Province. *J. Water Soil Sci.* 20 (76), 45–57 (In Persian).
- Huang, Q., Huang, J., Yang, X., Ren, L., Tang, C., Zhao, L., 2017. Evaluating the scale effect of soil erosion using landscape pattern metrics and information entropy: a case study in the Danjiangkou reservoir area, China. *J. Sustain.* 9 (7), 1243.
- Hutchinson, M.F., Dowling, T.I., 1991. A continental hydrological assessment of a new grid-based digital elevation model of Australia. *Hydrol. Process.* 5, 45–58.
- Inkoom, J.N., Frank, S., Greve, K., Walz, U., Fürst, C., 2018. Suitability of different landscape metrics for the assessments of patchy landscapes in West Africa. *J. Ecol. Indic.* 85 (1), 117–127.
- Jain, S.K., Sudheer, K.P., 2008. Fitting of hydrologic models: a close look at the Nash-Sutcliffe index. *J. Hydrol. Eng.* 13 (10), 981–986.
- Kirpich, Z.P., 1940. Time of concentration of small agricultural watersheds. *Civ. Eng.* 10 (6), 362.
- Kovács, P., Szép, K., Katona, T., 2009. Challenges for analysis of the economy, the businesses, and social progress. *Faculty Econ. Bus. Admin.* 302–318.
- Krause, P., Boyle, D.P., Båse, F., 2005. Comparison of different efficiency criteria for hydrological model assessment. *J. Adv. Geosci.* 5 (1), 89–97.
- Lausch, A., Herzog, F., 2002. Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution, and interpretability. *J. Ecol. Indic.* 2 (1–2), 3–15.
- Li, H., Liu, L., Ji, X., 2015. Modeling the relationship between landscape characteristics and water quality in a typical highly intensive agricultural small watershed, Dongting Lake basin, south central China. *Environ. Monit. Assess.* 187 (3), 129.
- Li, J., Wong, D.W., 2010. Effects of DEM sources on hydrologic applications. *Comput. Environ. Urban Syst.* 34 (3), 251–261.
- Lustig, A., Stouffer, D.B., Roigé, M., Worner, S.P., 2015. Towards more predictable and consistent landscape metrics across spatial scales. *J. Ecol. Indic.* 57, 11–21.
- Matei, D., 2012. Runoff modeling using GIS. Application in torrential basins in the Apuseni Mountains (Doctoral dissertation, PhD Thesis, Physical and Technical Geography, University Cluj-Napoca, Romania). p. 2712.
- Mcgarigal, K., Marks, B.J., 1995. Spatial pattern analysis program for quantifying landscape structure. *Gen. Tech. Rep. PNW-GTR-351*. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, p. 122.
- Minang, P. A., Duguma, L. A., Alemagi, D., Noordwijk, M., 2014. Scale considerations in landscape approaches. *Climate-Smart Landscapes: Multifunctionality in Practice*, 121–133.
- Mishra, P., 2012. Contour tracing technique using interpolation method. *Int. J. Inf. Operations Manage.* 3, 111–113.
- Mondal, A., Khare, D., Kundu, S., Mukherjee, S., Mukhopadhyay, A., Mondal, S., 2017. Uncertainty of soil erosion modelling using open source high resolution and aggregated DEMs. *J. Geosci. Front.* 8 (3), 425–436.
- Moradi Dashtpagerdi, M., Nohegar, A., Vaghafard, H., Honarbakhsh, A., Mahmoodinejad, V., Noroozi, A., Ghonchehpour, D., 2013. Application of spatial analysis techniques to select the most suitable areas for flood spreading. *Water Resour. Manage.* 27 (8), 3071–3084.
- Moradi Dashtpagerdi, M., Sadeghi, S.H.R., Rekabdarkoolai, H.M., 2019. Changeability of simulated watershed hydrographs from different vector scales and resolutions. *Catena* 182, 104097.
- Mostafazadeh, R., Sadeghi, S.H.R., Sadoddin, A., 2015. Analysis of storm-wise sedimentgraphs and rating loops in Galazchai watershed, West-Azerbaijan. *J. Water Soil Conserv.* 21 (5), 175–191.
- Nagaveni, C., Kumar, K.P., Ravibabu, M.V., 2019. Evaluation of TanDEMx and SRTM DEM on watershed simulated runoff estimation. *J. Earth Syst. Sci.* 128 (1), 1–11.
- Orlandini, S., Moretti, G., Franchini, M., Aldighieri, B., Testa, B., 2003. Path-based methods for the determination of nondispersive drainage directions in grid-based digital elevation models. *Water Resour. Res.* 39 (6), 1–8.
- Pan, Y., Lu, X., Yu, D., Huang, J., Sun, X., Xu, Z., 2019. Quantitative relationships between soil landscape index and classification grain. *J. Soils Sediments* 19 (2), 903–916.
- Plexida, S.G., Sfougaris, A.I., Ispikoudis, I.P., Papanastasis, V.P., 2014. Selecting landscape metrics as indicators of spatial heterogeneity—a comparison among Greek landscapes. *Int. J. Appl. Earth Obs. Geoinf.* 26 (1), 26–35.
- Qi, Y., Wu, J., 1996. Effects of changing spatial resolution on the results of landscape pattern analysis using spatial autocorrelation indices. *Landscape Ecol.* 11 (1), 39–49.
- Sadeghi, S.H.R., Asadi, H., 2010. Importance of travel time duration between isochrones in estimation of flood resulting from Clark instantaneous unit hydrograph. *J. Water Soil* 24 (4), 625–635 (In Persian).
- Sadeghi, S.H.R., Dehghani, M., 2006. Efficacy of estimation methods for storage coefficient of instantaneous unit hydrograph in flood unit hydrograph regeneration. *J. Agric. Sci. Natural Resour.* 13 (3), 152–160 (In Persian).
- Sadeghi, S.H.R., Mizuyama, T., Singh, J.K., Tofighi, B., 2009. Applicability of instantaneous unit sediment graph model in an Iranian large watershed. *Int. J. Ecol. Econ. Statistics* 13 (W09), 30–45.
- Sadeghi, S.H., Moradi Dashtpagerdi, M., Rekabdarkoolai, H.M., Schoorl, J.M., 2019. Accuracy of sedimentgraph modeling from topography map scale and DEM mesh size. *Int. Soil Water Conserv. Res.* 7 (2), 138–149.
- Sadeghi, S.H.R., Mostafazadeh, R., Sadoddin, A., 2015. Changeability of simulated hydrograph from a steep watershed resulted from applying Clark's IUH and different time-area histograms. *Environ. Earth Sci.* 74 (4), 3629–3643.
- Saeidi, P., Sadeghi, S.H.R., Telvari, A., 2016. Simulation of sediment graph using hydrograph. *Watershed Eng. Manage.* 8 (1), 28–41 (In Persian).
- Sahoo, B., Chatterjee, C., Raghuwanshi, N.S., Singh, R., Kumar, R., 2006. Flood estimation by GIUH-based Clark and Nash models. *J. Hydrol. Eng.* 11 (6), 515–525.
- Saldana, A., Ibáñez, J.J., Zinck, J.A., 2011. Soil scape analysis at different scales using pattern indices in the Jarama-Henares interfluvium and Henares River valley, Central Spain. *Geomorphology* 135 (3–4), 284–294.
- Salimi, E.T., Nohegar, A., Malekian, A., Hoseini, M., Holisaz, A., 2017. Estimating time of concentration in large watersheds. *Paddy Water Environ.* 15 (1), 123–132.
- Sarstedt, M., Mooi, E., 2014. Berlin, Heidelberg. In: *Cluster Analysis*. In a Concise Guide to Market Research, pp. 273–324.
- Schindler, S., Poirazidis, K., Wrba, T., 2008. Towards a core set of landscape metrics for biodiversity assessments: a case study from Dadia National Park, Greece. *J. Ecol. Indic.* 8 (5), 502–514.
- Schoorl, J.M., Sonneveld, M.P.W., Veldkamp, A., 2000. Three-dimensional landscape process modelling: the effect of DEM resolution. *Earth Surf. Processes Landforms* 25 (9), 1025–1034.
- Schoorl, J.M., Veldkamp, A., Bouma, J., 2002. Modeling water and soil redistribution in a dynamic landscape context. *Soil Sci. Soc. Am. J.* 66 (5), 1610–1619.
- Siles, G., Trudel, M., Peters, D.L., Leconte, R., 2020. Hydrological monitoring of high-latitude shallow water bodies from high-resolution space-borne D-InSAR. *J. Remote Sens. Environ.* 236, 111444.
- Sørensen, R., Seibert, J., 2007. Effects of DEM resolution on the calculation of topographical indices: TWI and its components. *J. Hydrol.* 347 (1–2), 79–89.
- Spetch, M.A., Parker, G.R., Gustafson, R.J., 1997. Spatial and temporal relationships of old-growth and secondary forests in Indiana. *Natural Areas J.* 17 (1), 118–130.
- Suganyadevi, P., Savitha, J., 2016. Application of enhanced clustering for different data mining techniques. *Int. J. Emerging Technol. Eng. Res.* 4 (1), 81–87.
- Tarboton, D.G., Bras, R.L., Rodriguez, B.I., 1991. On the extraction of channel networks from digital elevation data. *Hydrol. Process* 5 (1), 81–100.
- Thirel, G., Andréassian, V., Perrin, C., Audouy, J.N., Berthet, L., Edwards, P., Folton, N., Furusho, C., Kuentz, A., Lerat, J., Lindström, G., 2015. Hydrology under change: an evaluation protocol to investigate how hydrological models deal with changing catchments. *Hydrol. Sci. J.* 60 (7–8), 1184–1199.
- Tian, P., Cao, L., Li, J., Pu, R., Shi, X., Wang, L., Liu, R., Xu, H., Tong, C., Zhou, Z., Shao, S., 2019. Landscape Grain effect in Yancheng coastal wetland and its response to landscape changes. *Int. J. Environ. Res. Public Health* 16 (12), 2225.
- Turner, M.G., 1990. Spatial and temporal analysis of landscape patterns. *Landscape Ecol.* 4 (1), 21–30.
- Usery, E.L., Finn, M.P., Scheidt, D.J., Ruhl, S., Beard, T., Bearden, M., 2004. Geospatial data resampling and resolution effects on watershed modeling: a case study using the agricultural non-point source pollution model. *J. Geogr. Syst.* 6 (3), 289–306.
- Uslu, N., Yilmaz, M., 2002. Estimation of instantaneous unit hydrograph with Clark's Technique in GIS. In: *Proceedings of 2002 ESRI International User Conference, USA*, p. 21.
- Weng, Q., Liu, H., Lu, D., 2007. Assessing the effects of land use and land cover patterns on thermal conditions using landscape metrics in city of Indianapolis, United States. *Urban Ecosyst.* 10 (2), 203–219.
- Wilbanks, T.J., 2006. *How Scale Matters: Some Concepts and Findings Millennium Ecosystem Assessment*. Island Press, pp. 21–35.
- Wolock, D.M., Price, C.V., 1994. Effects of digital elevation model map scale and data resolution on a topography-based watershed model. *Water Resour. Res.* 30 (11), 3041–3052.
- Woodrow, K., Lindsay, J.B., Berg, A.A., 2016. Evaluating DEM conditioning techniques, elevation source data, and grid resolution for field-scale hydrological parameter extraction. *J. Hydrol.* 540 (1), 1022–1029.
- Wu, J., 2004. Effects of changing scale on landscape pattern analysis: scaling relations. *Landscape Ecol.* 19 (2), 25–138.
- Wu, S., Li, J., Huang, G.H., 2008. A study on DEM-derived primary topographic attributes for hydrologic applications: sensitivity to elevation data resolution. *Appl. Geogr.* 28 (3), 210–223.
- Wu, J., Loucks, O.L., 1995. From balance of nature to hierarchical patch dynamics: a paradigm shift in ecology. *Q. Rev. Biol.* 70 (4), 439–466.
- Wu, J., Shen, W., Sun, W., Tueller, P.T., 2002. Empirical patterns of the effects of changing scale on landscape metrics. *Landscape Ecol.* 17 (8), 761–782.
- Wu, M.Y., Xue, L., Jin, W.B., Xiong, Q.X., Ai, T.C., Li, B.L., 2012. Modelling the linkage between landscape metrics and water quality indices of hydrological Units in Sihui Basin, Hubei Province, China: An Allometric Model. *Procedia Environ. Sci.* 13, 2131–2145.
- Zhang, J.X., Chang, K.T., Wu, J.Q., 2008. Effects of DEM resolution and source on soil erosion modelling: a case study using the WEPP model. *Int. J. Geogr. Inf. Sci.* 22 (8), 925–942.
- Zhang, X., Liu, Y., Zhou, L., 2018. Correlation analysis between landscape metrics and water quality under multiple scales. *Int. J. Environ. Res. Public Health* 15 (8), 1606.
- Zhang, W., Montgomery, D.R., 1994. Digital elevation model grid size, landscape representation, and hydrologic simulations. *Water Resour. Res.* 30 (4), 1019–1028.
- Zimmermann, P., Tasser, E., Leitinger, G., Tappeiner, U., 2010. Effects of land-use and land-cover pattern on landscape-scale biodiversity in the European Alps. *Agric. Ecosyst. Environ.* 139 (1–2), 13–22.