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Temporal and Spatial Prediction of Rainfall-Induced Landslidesusing the Specialized TRIGRS Model

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Abstract

Landslides as natural phenomenon occur every year in many parts of the world, especially in hilly areas, andpose considerable life and property losses. Given the temperate and humid climate in northern Iran, most landslides occurred in this area are triggered due to rain. In this study, in order to predict the time and location of shallow landslides caused by rainfall, TRIGRS model was applied inNekarood area in the Alborz mountain range in northern Iran and its sensitivity to a number of effectiveparameters in the landslide was assessed. After preparation of all required parameters, TRIGRS model wasimplemented to predict alandslidewithin the study area induced by a rainfall intensity of 1.27 mm/h lasting for 24 hours. The results showed that the model predicted landslides accurately.Also, the effect of rainfall duration on increasing the number of unstable cells isalso evident.In this regard, within the first hour, 0.19% of cells indicate a safety factor (FS) less than 1 while after 24 hoursit reaches 4.08%. To evaluate the model sensitivity to initial ground water level, some adjustments were made in the water table level. The result showed that, unlike the changes in precipitation, modelresponse to watertablefluctuation is not significant.

Keywords: temporal and spatial prediction, landslide prediction, TRIGRS, Nekarood

1. Introduction

Landslides as natural phenomenon occur every year in many parts of the world, especially in hilly areas, and pose considerable life and property losses. The negative consequences of the landslidesaremostly the destruction of homes and infrastructure, loss of productivity in the affected area, unpredictable changes in alocal watercourse, and decreasing habitable and arable lands.Landslides are caused by natural internal and external factors, as well as humanfactors. Internal factors are inherent environmental properties in a particular area, such as the characteristics of topography, geology, soil, hydrology, and vegetation. On the other hand, external factors that directly or indirectly trigger landslides include factors such as earthquakes, rain, andsnowfall. Human factors such as roads construction in steep forested areas and changes in land use in hilly areas are effective in the landslides. Landslidesaremostly triggered by external and human factors.However, internal factors have a significant impact on the initiation and development of landslides (Kim et al. 2013).

Landslides are part of geomorphological cycles in the development of natural landscapes. Once they become directly hazardous they interfere with human activities. The major motivationfor landslide studiesis the prevention and adjustment of accidents and mitigation of risk.Landslides in developing countries where environmental management is less of concern might cause a higher risk.More than 95% of accidents and fatalities is related to mass movements, especially landslides in developing countries (Hansen 1984, Chung 1995). Iran is covered byvastmountainousregions that constitute more than half of the country. Due toits geology, seismicity, rainfall, and climatic conditions, and topographical variations, Iran is among the countries that have experiencing numerous landslides and suffering from the consequent losses.ShariatJafari (2011) estimated that 28443 landslides in this country caused approximately half a billion $US.Northern slopes of the Alborz Mountains (northern Iran) are exposed to small and large landslides that bring much damage in the region annually (e.g., Manjil (1990), Absek (1993), Kiasar (1999), and Karaj-Chalus road landslides (2007)) (Onagh et al. 2012). Due to the temperate and humid climate of northern Iran, most of the landslides that occur in this region are triggered by rainfall events. Significant economic and social damage of landslides hasmadethe understanding of spatial and temporal distribution as well as the prediction of the phenomenona great challenge.

A variety of experimental and numerical methods are applied to estimate the landslides hazard. Experimental methods include the methods for determining the threshold of precipitation, probabilistic methods based on historical records, statistical analysis (multivariate and the informational value), mathematical analysis (artificial neural networks and fuzzy logic), heuristic, and definitetechniques. Multivariate statistical analysis and artificial network analysis are often used to assess landslide potential on a regional scale (Tan et al. 2008). Moreover, in the last decade, multivariate statistical method are used to assess landslide potential (Meusburger and Alewell 2009).In heuristic or direct method, theexpertiseof landslide hazard zonation plays a key role (Niemann and Howes, 1991; Anbalagan, 1992; Turner and Schuster, 1996; Atkinson and Massari, 1998; VanWesten et al. 1999). The problem in this method is that itrequires many geological and environmental information about landslides and the factors involved.

Gaining this volume of information and data is very difficult. Other defects of this method are renewable results, the uniqueness of the used weighting system, and the ranking and clustering of variables in the study (Dai et al. 2001). The definite method is used to assess the large-scale landslidesif the following conditions are met:firstly, geological and geomorphological properties across the region are homogeneous and uniform; and, secondly, the type and nature of the landslide are simple and well known (Dai et al. 2001 Turner and Schuster, 1996). The main advantage of this method is that factor of safetyis separately calculated for each slope. In small areas, slope stability cannot be calculated with good accuracy using other methods;however, thedefinitemethod would solve the problem well (Van Westen, 1993; Terlien et al. 1995; Wu and Slide, 1995). Definite methods offer the best quantitative information about the occurence of landslides, which can be directly used in determining the hazard value.However, these methods need highly accurate input data from laboratory experiments and field measurements and only used in small areas and large scale (Van Westen 2004).Statistical methods do not offer agoverning mechanism forthe slope and do notprovide a mechanical sense.However, it is assumed that measuring the variable involved in thelandslides in the past, regions prone to landslide can be predicted (Lee et al. 2004; Zhou et al. 2003; Ohlmacher and Davis 2003). Experimental methods, in general, are simple and relatively easy to use. Information required by these methods is usually readily available. When there is a local historical landslide data center, experimental relations can be developed easily; nevertheless, experimental methods just offer anearly estimation of travel path features (Dia et al. 2002). Experimental methods for predicting alandslide, due to being time-consuming and costly and usable in a small area, are not economically justified. Distribution models of physical features assess a stable landslide based on the factor of safety (FS). Using the same values for each input parameter in calculating the FS would make these methods more appropriate for small-scale regions; because in larger areas, the range of impacts and effective parameters on soil analysis is significantly wide (Burton et al. 1998; Haneberg 2004). With the progress made in combining GIS and DEM technology in modeling the distribution of physical characteristics, prediction of a landslide at the basin scale has become easier (Montgomery and Dietrich 1994; Wu and Sidle, 1995; Dhakal and Sidle 2003; Iida 2004). Although previous versions of the distribution models of landslide physical characteristics could assess aspects of the spatial distribution,they could not evaluate dynamic response to the heavy rains. Models of physical distribution are potentially powerful tools in analyzing landslide particularly when combined with DEM data based on LIDAR (Dietrich et al. 2001), real rains input (Baum et al. 2002; Dhakal and Sidle 2004) and long-term land use scenarios (Dhakal and Sidle 2003). However, the widespread use of these models is limited, because they need some distributed input data (including DEM) and specialized software such as GIS, and some computer modeling.In this research, to predict the time and location of rainfall-inducedlandslides, TRIGRS, as a distribution model of physical features, is implemented. The model is evaluatedin Nekarood basin, eastern Alborzrangeinnorthern Iran and its sensitivity is tested to the parameters in the investigated landslide.The aim of this study is to investigate the possibility of applying this model in the study area, consideringthe weather conditions and geomorphology of the study area.

2. Study area

The study area covers an area of approximately 6.2 km2in Safal-Mian village and 30 km south-southeast ofNekacounty, located in Mazandaran Province. The study area iswithin thelongitudes of 53 30 24 and 53 32 12, and latitudes of 36 29 03 and 36 30 070 (Fig. 1). The study areaconsists of limestone (calcarenite) to marl bedrock, a cover of forest vegetation, and anaverageprecipitation of 760 mm/year. Basin slope angels varybetween 1° to 28° and the maximum altitude is 1160 ma.s.l.Sincethis area experiences frequent rainfall and the road construction along steep slopes, it is posed tofrequent landslide hazards. However, due to low soil thickness and relatively steep slopes, landslides aregenerally shallow type.

3. Index Landslide

To calibrate the TRIGRS model,a landslidemust be selected in the field with aknown time of occurrence.

Thus, it will be feasible to correlate the time with the corresponding rainfall. A landslide occurredon December 20, 2012, at the longitude of 29 31 53 and latitude of 55 29 36 within the study area waschosen as the index landslide. The rainfall responsible for this slope failure wasan event with the total precipitation of about 30 mm (1.27 intensity and duration of 24 h). The depth of this shallow roadside landslide (Fig. 2) was between 2 to 2.5.

4. Materials and Methods

4.1. Foundations of the model

TRIGRS model was designed by the United States geological survey (USGS) for modeling time and spatial distribution of shallow rainfall-induced land-

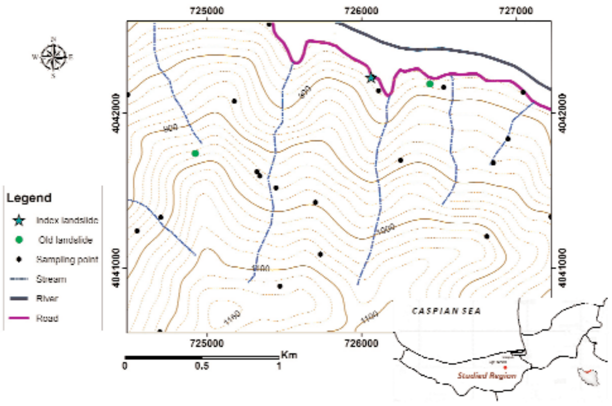

Figure 1. study area and sampling points

slides (Baum et al. 2002). This program is written in FORTRAN language based on models and solutions offered by Iverson (2000). TRIGRS contains a penetration model, with the governing equation based on the linear equation of Richard (Baum et al. 2002, Iverson 2001).The model calculates the fluctuations of transient pore water pressure and FS due to the influence of rainfall for each cell. TRIGRS models the influence of rainfall during a storm with a few hours to a few days by partial differential equations (PDEs) for one-dimensional flow in thehomogeneous and isotropic material in both saturated and non-saturated conditions. Using a series of stepwise functions allows the model to receive the variable rainfall input and divert excess water from impermeable areas to areas down the slope with the more penetration in a simple runoff routing model (Montrasio 2011). This solution evaluates the transient rainfall effect at the time and location of landslides with fixed component modeling of pore water pressure in Equation 1 and the transient component. ToPredict the time and amount of pore water pressureIverson's model needs threeparameters: the intensity and duration of rainfall and soil hydraulic diffusion coefficient. Bavem et al. 2002 developed Iverson's penetra-

Figure 2.Dec.20, 2012 landslide observed in the study area (landslide index)

tion model by developing TRIGRS model for items with variable rainfall intensity and duration.The other inputs of the model are water table level, soil depth, cohesion (C), internal friction angle *(φ)*, hydraulic conductivity coefficient, weight per unit volume of soil, the number of rainfall periods, rainfall duration, infiltration rate, and topographical conditions. To improve usability as well as simplify the model inputs, some soil properties (features) zones, each one with different mechanical and hydraulic characteristics, have been defined in the new version of TRIGRS model. The solution of Iverson (2000) used in TRIGRS is presented in Equation 1:

(Z,t)=[Z-d]β

$$+2\sum_{n=1}^{N}\frac{I_{nz}}{K_z}\left[H(t-t_n)[D_1(t-t_n)]^{\frac{1}{2}}ierfc\left[\frac{Z}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]\right. \quad 1$$

$$\left.-2\sum_{n=1}^{N}\frac{I_{nz}}{K_z}\left[H(t-t_{n+1})[D_1(t-t_{n+1})]^{\frac{1}{2}}ierfc\left[\frac{Z}{2[D_1(t-t_{n+1})]^{\frac{1}{2}}}\right]\right.\right.$$

where, $\psi_{(Z,\,t)}$ is underground water head at time t and depth z; Z=z/cosα and z are proportional with the slope angle α; D is water table fixed in the direction *β*=€cosα,z where €=cosα-$[I_Z/K_Z]_{LT}$,$K_z$is hydraulic conductivity, $I_Z$isinitial surface penetration in the direction Z,$I_{nZ}$is surface penetration for the n-th time, and LT means long-term.H(t-t_n) is Heaviside function; and D1=D_0cosα, where $D_0$is saturated hydraulic penetration coefficient andDis the total number of intervals. In this hydraulic conductivity model,K*(ψ)*, Equation 2, and moisture contentθ, Equation 3,are dependent to the pressure head.

(2) $K(\psi)=K_s\exp(\alpha^*)$

(3) $\theta=\theta_r+(\theta_s-\theta_r)\exp(\alpha^*)$

In the relationships, ψ, pressure head;*=–$_0$where $\psi_0$is a constant;$K_S$issaturated hydraulic conductivity; $K_{(\psi)}$ is hydraulic conductivity function; θ isvolumetric water moisture;$\theta_r$risradialmoisture; and θ_S saturated moisture content.Also, α is obtained from Equation (2) and soil characteristic curve. Moreover, Ierfc function in Equation 1 is obtained using Equation 4:

$$Ierfc(\eta)=\frac{1}{\sqrt{\eta}}\exp(-\eta^2)-\eta erfc(\eta) \quad (4)$$

$$FS(Z,t)=\frac{c}{Z\sin\alpha\cos\alpha\gamma s}+\frac{\tan\varphi}{\tan\alpha}+\frac{-(Z,t)\gamma_W\tan\varphi}{Z\sin\alpha\cos\alpha\gamma_S} (5)$$

Ierfc is the complementary error function. By combining Equation (1) with the stabilityrelationship of theclassical infinite slope, a factor of safety (FS) is obtained (Equation 5).

$$FS(Z,t)=\frac{c}{Z\sin\alpha\cos\alpha\gamma s}+\frac{\tan\varphi}{\tan\alpha}+\frac{-(Z,t)\gamma_W\tan\varphi}{Z\sin\alpha\cos\alpha\gamma_S} (5)$$

where,φ is internal friction angle, C is soil cohesion, γsisweight per unit volume of soil, and y_W weight per unit volume of water. Factor of safety (FS) defined as the ratio of displacement resistant forces to driving forces on a given slope. If FS is 1 or less, the slope is unstable and a landslide is probable to occur.

The first term in Equation (5) isthecohesion of soil that leads to larger values of FS; in the second term, the angle of friction *(φ)* also increases FS; and in the third term, transient pressure caused by penetration level determines thatthe increase in transient pressure increasing leads to a decrease inFS (Liao 2010). The model has been successfully used in some parts of the world for quantitative assessment of rainfall-induced landslides:

1. TRIGRS was used at acase study to explain transient rain effect onthe landslide initiation and was compared with experimental basins such as those in the Seattle area in America (Godt et al. 2008) and Tenliao in Taiwan (Chen et al. 2005) and Yangju in South Korea (Kim et al. 2010).

2. TRIGRS was implemented for landslide stability analysis and compared with the other physical models such as SLIP (Montrasio 2011), SHALSTAB (Sorbino 2010), SINMAP and LISA (Morrisey et al. 2001). The results showed that Iverson's model (2000) as the base of TRIGRS is preferred to the other mentioned four models because the hydrological model transient response of Iverson can provide a stable condition as a function of time and depth on a regional scale in areas prone to rainfall-induced landslides.

3. Some researchers focused on parametric analysis to estimate the material properties (Salciarini et al.

2006, Vieira 2010) and produced asatisfactory approximation of soil parameters based on a limited number of measurements in their study areas.

4. TRIGRS model was integrated with other statistical techniques such as Monte Carlo simulations. The results showed that the susceptibility maps of simulated landslidesare similar to those obtained from field observations (Liu and W_u, 2008).

5. TRIGRS code was reviewed and modified for specific purposes.in this regard, there is a probabilistic version of TRIGRS-P (Raia 2013) and a version of MATLAB MaTRIGRS (Liao et al. 2011) for specific purposes. TRIGRS-P adopts a random method to calculate and sample input parameters through a probability distribution. MaTRIGRS offers unique computational capabilities in real-time simulation and visualization of multi-dimensional matrix data during modeling.

5. Parameters preparation

According to the described foundations of the model shown in Table 1, TRIGRS model requires different parameters as input information. To provide the required parameters of the model, field investigations and laboratory tests were performed in the study area. In this regard, DCP test wascarried out at 25 points to determine the depth of soil. Then, undisturbed soil samples were extracted from each point in order to estimate the weight per unit volume of soil,perform shear tests to determine the angle of internal friction *(φ)* and cohesion (C) of samples saturated for 12 hours, and also the texture and type of studied soil.To determine soil hydrological parameters, soil particle gradation test was performed. Next, Ks, α, θ_r, and θ_s were obtained based on thefrequency of particles (sand, silt, and clay) and natural weight per unit volume of soil, using Rosetta lite v.1.1 (Schaap et al. 2001) software and Van Genoghten model (1980). According to required parameters of TRIGRS for each zone, the area is divided into three zones including MH, CH, and CL.

D_0 (diffusion coefficient) in studies conducted earlier is considered 10 to 500 times for the saturated hydraulic conductivity. Accordingly, D_0 (Liu and W_u 2008) was assumed 200 times of the saturated hydraulic conductivity; however, information about Iz (early penetration rate) in the conducted studies is very low. Izis affected by soil properties including porosity, storage capacity, and transfer rates.Type of vegetation, soil content, and soil temperature also play a role in controlling the amount of penetration. If the soil is saturated, Iz can be considered equivalent to hydraulic conductivity of the soil while for dry soil this parameter will be zero. In this study, Iz was considered one-tenth (0.1) of the saturated hydraulic conductivity (Salciarini et al. 2008; Liu and W_u, 2008; Kim et al. 2010).

Necessary topographic Information including digital altitude maps of 20 m × 20m, slope angle and direction of flow of topography maps were prepared in ArcGIS (ESRI, Inc., Ver. 9.3) environment for the south-southeast of Safal-Mianvillage.Also, a soil depth map was prepared using interpolating of 25 sampling points for the entire study area. The initial-

Table 1. The necessary input parameters of the TRIGRES model.

Geological parameters	**Rainfall parameters**	**Soil mechanical parameters**	**Morphological parameters**	**Soil hydraulic parameters**
γ_s weight per unit of volume of soil Soil depth Underwater ground water	Rainfall intensity Rainfall duration	Cohesion (c) Internal friction angle *(φ)*	Digital elevation model(DEM) Slope Flow direction	(Ks) saturated hydraulic conductivity (D_0) the hydraulic diffusion coefficient Saturated volume moisture(θ_s) Remained volumemoisture(θ_r) (Iz)early penetration rate

groundwater level in this model was assumed to be constant; which is acceptable since the running time of model is relatively short. According to field observations, the slope of the area and thickness of soil, the groundwater level in the model was considered 10 cm above the bedrock. The output files were rasterized in ArcGIS software and the output was finally obtained in ASCII format.

6. Results and discussion

DCP test results in the field studies show that soil depth in the area varies between 1 and 3.5 m. In addition, regarding that the TRIGRS allows different zones to be determined by the spatial variations of soil characteristics, based on experimental results, three zones in the region definedfor the soil typeincluding zones 1 (MH), 2 (CH), 3 (CL). The corresponding soil cohesion for zones 1, 2, and 3 is 5-15, 15-20, and18-24 kPa, respectively. According to these results, thec and φhavea valuerange and those presented in Table 2 indicatethe best response and appliedin the model.Other required values are presented as well.

TRIGRS model evaluates the slope stability and determines time and place of instability using precipitation influence simulation and runoff routing. The aim of this study is to evaluate TRIGRS model to predict landslides occurred within the Nekarood basin (especially in Safal-Mianvillage). Index landslide occurred in the region was caused by a rainfall with theintensity of 1.27 mm/hour and duration of 24 hours. Therefore,the simulation was performed based on these rainfall parameters and parameters related to soil propertiesobtained from field observations and laboratory experiments. The results obtained after analyzing the data and penetration modeling and runoff routing show that the cells predicted as unstable (FS<1)are consistent with the location of occurred landslides (Fig. 3).

As can be seen in the figure, at the end of a 24 hours rainfall, the unstable points with FS<1are located mainly in zone 1 (MH) rather than two other zones (CH, CL). These points indicate lower resistance parameters as well as a hydraulic conductivity and hydraulic diffusion coefficient. Thus, the rainwater during rainfall penetrates more in the soil of this region and causes soil saturation.Furthermore,it increases pore water pressure and reduces shear strength and finally increasesslope instability.

It is noteworthy that during low-intensity rainfalls small soil collapses make the slope around forest streams stable. Hence, these areas show relatively high stability in larger precipitations.

Generally, it can be stated that in the forest area landslides generally occurwith slope angle changes.In thestudied area, almost all unstable points indicate landslide occurrence andpoints predicted as unstable are on slopes greater than 19°, which stimulates the instability driving forces. Because of using Google feature maps to prepare topography maps in this study,the topography data used to run the model with an accuracy of 10 m are related to before the recent landslide in the area. For this reason, in addition to the area where the index landslide occurred, the model also indicates two other unstable points that were surveyed in the field observations as slightly older landslides. So, the instability in these points is not associated with the studied rainfall period.

To investigate the effect of duration of precipitation on changes of the FS predicted by TRIGRS, the model was run at the first, sixth, twelfth, eighteenth and twenty-fourth hours after rainfall (Fig. 5). The results show that after the onset of rainfall and with the passage of time, the FS in some places decreases-

Table 2. The input values of applied parameters in TRIGRS model.

α	θ_s	θ_r	Ks(m/s)	D0(m^2/s)	φ	c(kpa)	γ_s(N/m^3)	Zone
1.36	0.472	0.091	3.6×10^{-7}	7.2×10^{-5}	10	9	1.61×10^{4}	1
1.59	0.39	.09	2.09×10^{-7}	4.18×10^{-5}	11	17	1.72×10^{4}	2
1.2	0.36	0.076	1.42×10^{-7}	2.8×10^{-5}	15	20	1.79×10^{4}	3

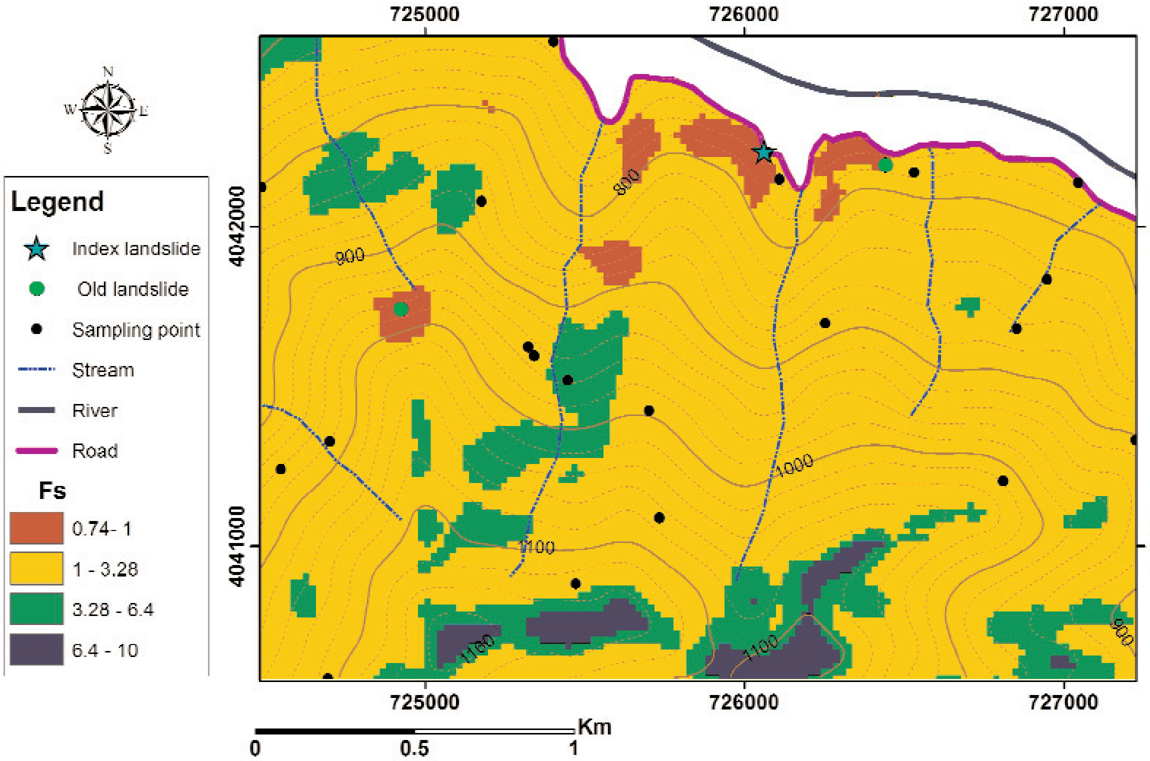

Figure 3.The factor of safety at the end of a 24hour precipitation (drawn circles represents observed landslides that are also predicted by the model).

Table 3. The percentage and number of cells with FS<1 with the rainfall time period.

Cell percentage with FS<1	Cell number with FS<1	hour
0.19	26	1
0.4	56	6
1.37	19	12
2.73	379	18
4.08	569	24

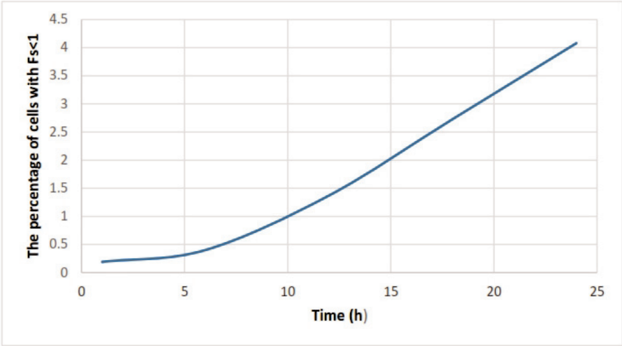

Figure 4. Percentage change of cells with FS<1 during the rainfall hours.

Table 4. percentage and the number of cells with factor of safety by increasing penetration time

The percentage of cells with FS<1	The number of cells with FS<1	Penetration period
4.08	569	24
3.32	464	48
1.1	154	72

significantly and the slopebecomes unstable at the end of precipitation.

As presented in Table 3 and can be seen in Fig. 4, six hours after arainfall, the percentage of cells with a FS<1 is0.4% in the study area which is increased compared tothe first hour that is 0.19%, but the increase is not sharp. This case could occur in the early hours of precipitation, during which infiltration continues but is not severe and soil is not saturated yet.

With the passage of time, rain causes soil saturation and thus the increase in the number of cells with FS<1indicates an almost exponential trend from12 to 24 hours. These changes areillustrated in Fig. 5.

However, if the soil is allowed to drain the water penetrated to the soil and excess water in the soil, saturation and weight gain of soil mass occurs as well as an increase in penetrated water pressure emitted from inside, leading to the reduced number of unstable cells predicted by TRIGRS (Table 4).

When performing the model foradurationof 48 hours

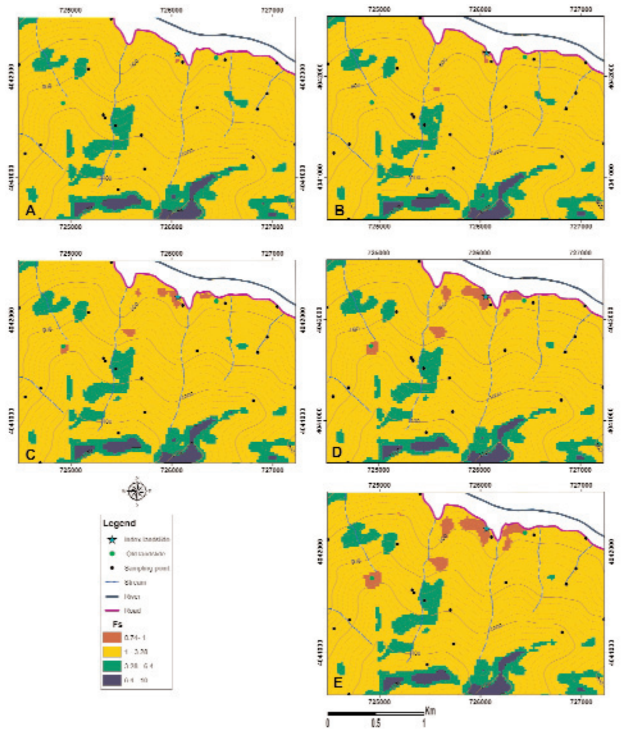

Figure 5. FS in: a) one hour, b) six hour, c) 12 hours, d) 18 hours, and e) 24 hours after rainfall.

Table 5. Percentage and the number of cells with afactor of safety with the rise ofwater table.

The percentage of cells with FS<1	The number of cells with FS<1	Water level of floor(cm)
0.19	26	10
0.30	42	20
0.38	53	30

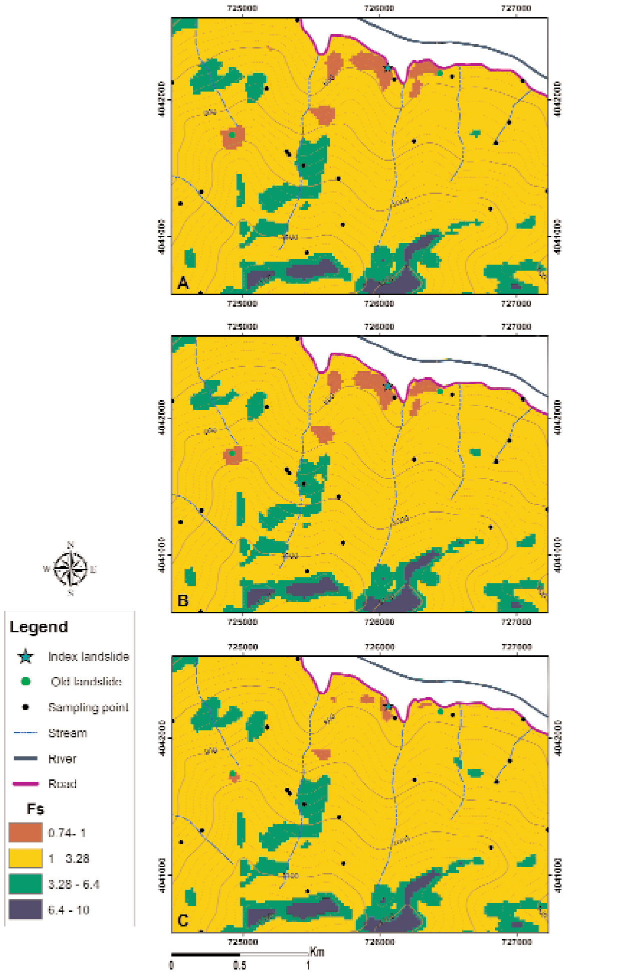

Figure 6. The impacts of penetration period increase on FS: a) an FS for 24 hours precipitation with the rainfall intensity of 1.27 mm/h; b) an FS for 48 hours rainfall with two periods of rainfalls with an intensity of 1/27 mm/h and 0 mm/h; and c) an FS of 72 hours rainfall with periods of 24 hours and intensity of 1.27 mm/h and penetration for 48 hours.

and two 24-hour rainfall periods with the intensity of1.27 mm/hour (Fig. 6 (a)), the results indicated a lower instability than the case ofapplying only one 24-hour period, with the same rainfall intensity (Fig. 6 (b)).In the case where the duration of the penetration period continues for 48 hours, the reduction trend also continues (Fig. 6 (c)).As mentioned earlier, by increasing the drainage period, the reducer factors of FSareweakened and its changes indicate a considerable increase.

To investigate the effect of initialgroundwater level and the sensitivity to changes in water table, the models were run with water tables of 0, 10, 20, and 30 cm above bedrock.As expected, it was observed that the FS fell with as water table rises (Table 5 and Fig. 7), because of the increased pore water pressure; leading to an increase in the driving forces of slope instability, and its resistance decreases. Nevertheless, the FS changes are not high, implying the more effect of rainfall compared to underground level on slope instability.

7. Conclusion

In order to predict time and location of a landslide, TRIGRS model was applied as a tool capable of modeling the influence of precipitation, runoff, and finally the slope stability. The aim of this study is to investigate the possibility of using this model for predicting landslides in Iran. For this purpose, the

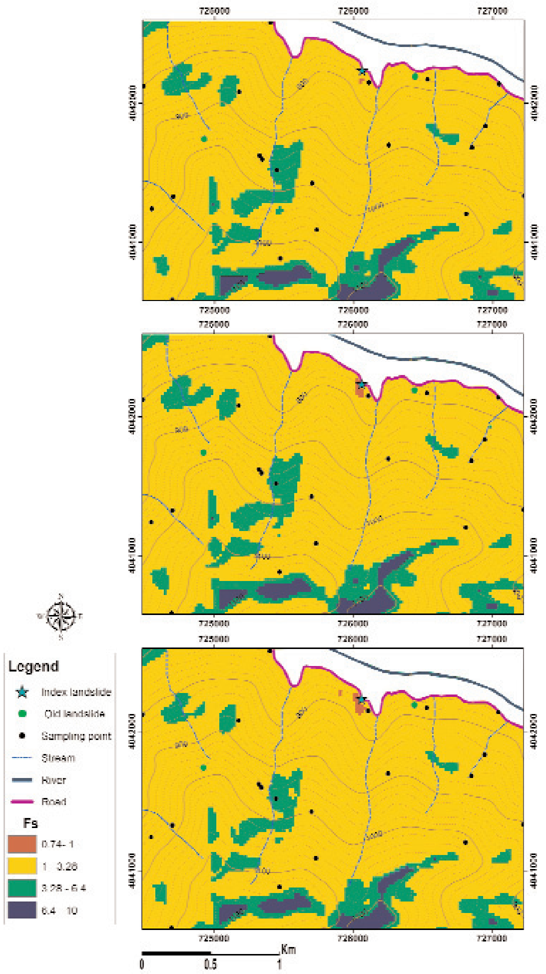

Figure 7. The FS for different water table levels: a) 10 cm b) 20 cm, andc) 30 cm above the floor.

requiredinput parameters were determined through the field and laboratory studies.The rainfall simulation results and its impact on slope instability indicated that thepredicted instabilities and theoccurred instabilities after 24 hours of rainfall all fall in zone 1 (MH) thatcompared with the other two zones (CH, CL) has alower resistance and higher hydraulic conductivity and the diffusion coefficient.Moreover, in zone 1 the unstable areas are those with aslope greater than 19° and also thickersoils. The rainfall effect on the instabilities predicted by the modelis presented by the soil mass weight gain due to soil saturation. The impact ofwater table variations on the created instability, unlike the effect of rainfall, is not significant and the changes in the factor of safety(FS) are not significant due to the rise of thewatertable. It is noteworthy that TIRGRS can accurately predict the space development of regional characteristics such as slope, soil depth, water table depth, and soil type and simulate theoccurrenceof landslidesthat few numerical models are capable of. Accordingly, and considering the ability of TRIGRS to predict landslide on a regional scale, it can be implemented to predict the time and location of landslides and prevent the occur-

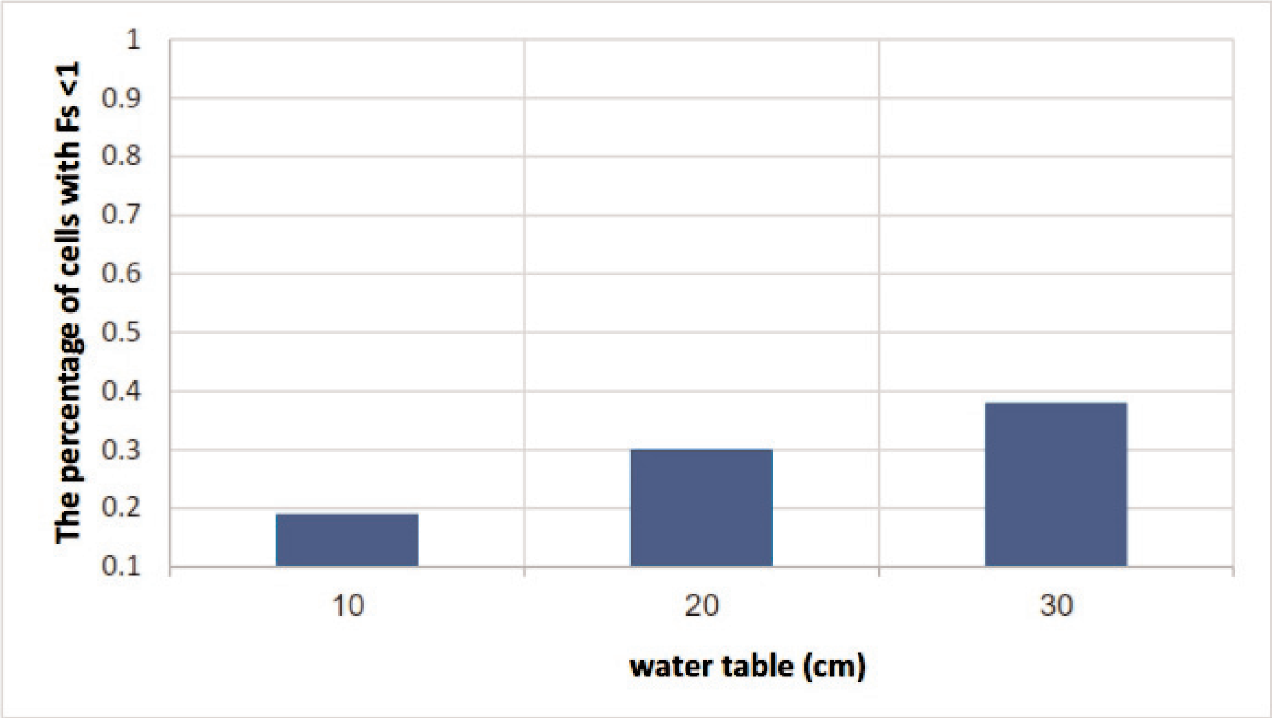

Figure 8. The percentage changes of cells with FS<1.

rence of damage such as the loss of forests, increased sedimentation, destruction of homes, blocked roads, and disconnection between villages by slope stabilization. Furthermore, by applying slope stability reinforcements it would be possible to prevent landslides and preserve agricultural soils that are the natural assets and the only available soils in hilly areas.

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