

Evaluation of TRIGRS (transient rainfall infiltration and grid-based regional slope-stability analysis)'s predictive skill for hurricane-triggered landslides: a case study in Macon County, North Carolina

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Abstract The key to advancing the predictability of rainfall-triggered landslides is to use physically based slope-stability models that simulate the transient dynamical response of the subsurface moisture to spatiotemporal variability of rainfall in complex terrains. TRIGRS (transient rainfall infiltration and grid-based regional slope-stability analysis) is a USGS landslide prediction model, coded in Fortran, that accounts for the influences of hydrology, topography, and soil physics on slope stability. In this study, we quantitatively evaluate the spatiotemporal predictability of a Matlab version of TRIGRS (MaTRIGRS) in the Blue Ridge Mountains of Macon County, North Carolina where Hurricanes Ivan triggered widespread landslides in the 2004 hurricane season. High resolution digital elevation model (DEM) data (6-m LiDAR), USGS STATSGO soil database, and NOAA/NWS combined radar and gauge precipitation are used as inputs to the model. A local landslide inventory database from North Carolina Geological Survey is used to evaluate the MaTRIGRS' predictive skill for the landslide locations and timing, identifying predictions within a 120-m radius of observed landslides over the 30-h period of Hurricane Ivan's passage in September 2004. Results show that within a radius of 24 m from the landslide location about 67% of the landslide, observations could be successfully predicted but with a high false alarm ratio (90%). If the radius of observation is extended to 120 m, 98% of the landslides are detected with an 18% false alarm ratio. This study shows that MaTRIGRS demonstrates acceptable spatiotemporal predictive skill for landslide

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occurrences within a 120-m radius in space and a hurricane-event-duration (h) in time, offering the potential to serve as a landslide warning system in areas where accurate rainfall forecasts and detailed field data are available. The validation can be further improved with additional landslide information including the exact time of failure for each landslide and the landslide's extent and run out length.

Keywords Landslide · Hurricane · Hazard prediction · LiDAR

1 Introduction

Landslides triggered by rainfall pose significant threats to human lives and property worldwide (Hong et al. 2006; Kirschbaum et al. 2009). Landslide fatalities after the 2008 Wenchuan earthquake demonstrate how an increasing population in areas with a high landslide hazard has increased the risks from landslides and has highlighted the need to install effective early warning systems to help mitigate the risk. Current methods used for landslide analysis are highly varied. Empirical or statistical techniques generally are applicable to predicting landslide susceptibility at the regional scale, while more process-based approaches are applied at the local scale. Like any science discipline, empirical and descriptive landslide models, because of their easy implementation, have been developed for risk analysis and landslide monitoring (Caine 1980; Cannon and Gartner 2005). They have contributed much to identifying the key causal factors. To advancing the predictability of shallow landslides, it is encouraging to use physically based, slope-stability models that simulate the transient dynamical response of the pore water pressure to spatiotemporal variability of rainfall in complex terrains. Recent physically based landslide models have been developed to assess landslide risk using a range of topographic, geologic, and hydrologic parameters (Dietrich et al. 1995; Wu and Sidle 1995; Baum et al. 2002, 2008; Iverson 2000; Hong et al. 2007; Lu and Godt 2008; Godt et al. 2009; Ren et al., 2009). One such algorithm, the TRIGRS (transient rainfall infiltration and grid-based regional slope-stability analysis) model is coded in Fortran and is designed for modeling the potential occurrences of shallow landslides by incorporating the transient pressure response to rainfall and downward infiltration processes (Baum et al. 2008). Under assumption of saturated or tension-saturated initial soil conditions, the TRIGRS program computes transient pore-pressure changes to find analytical solutions to partial differential equations, representing one-dimensional vertical flow in isotropic, homogeneous materials due to rainfall infiltration from storms with durations ranging from hours to a few days. The TRIGRS program uses an infinite-slope model to compute a factor of safety (FS) calculation for each grid cell. Horizontal heterogeneity is accounted for by allowing material properties, rainfall, and other input values to vary from grid to grid.

In this study, we implemented a Matlab version of TRIGRS to model the rainfall-triggered landslides at regional scale (herein MaTRIGRS) since Matlab[®] offers unique computational efficiency in multi-dimensional Matrix data (<http://www.mathworks.com>). This version also offers real-time simulation visualization during the modeling and quantitative analysis tools after simulation. The aim of this research is to evaluate MaTRIGRS as a physically distributed landslide model to predict the spatiotemporal occurrences of the widespread landslides that were triggered by record rainfall over Macon County in the Blue Ridge Mountains, North Carolina during Hurricane Ivan in 2004. Although soil map for that study area is available, soil parameter values required by physical models are still difficult to achieve. Nevertheless, the values and parameters do

not always have a clear and direct relation with any physical aspect of a physical model (Montrasio and Valentino 2008). In this study, soil parameter values are determined by adjusting through a procedure of back analysis based on the soil map. If the objective of this study aims to map FS regionally as a suggestion tool for decision makers, the model with coarse soil information may still pose advantage in its large scale predicting ability. While only the shallow landslides are studied in this paper, the slip surface is assumed to be parallel to the ground surface, and the soil depth is ranged between 1 and 2 m (Meisina and Scarabelli 2007). The MaTRIGRS model outputs a set of landslide predictions that are evaluated using a local landslide inventory database collected by the NC Geological Survey. Results of this study will consider how the spatiotemporal predictability of landslide occurrences using the MaTRIGRS model may apply to regional landslide hazard assessment and potentially early warning during future hurricane seasons.

2 Study area and methodology

2.1 Study area and data sets

Macon is located in Blue Ridge Geologic Province of southern Appalachian Orogen. The inter-section of ductile structures (foliation, compositional layering, ductile shear zones, and intrusive contacts) with over-printing brittle structures (fractures, fracture systems) is reflected in the overall topography of the landscape (Wooten et al. 2008). In 2004, intense rainfall from the remnants of Hurricanes Frances (September 7–8) and Ivan (September 16–17) triggered at least 44 slope movements that caused 5 deaths, destroyed at least 27 homes, and disrupted transportation corridors throughout western North Carolina (Wooten et al. 2005, 2008). The distribution of the recorded slope movements is shown in Fig. 1. The above-normal record precipitation for the first 3 weeks of September in 2004 satisfies the MaTRIGRS model assumption of saturated or tension-saturated initial conditions and can be applied to study the effects of heavy rainfall on shallow landslide initiation. Several geospatial datasets were used to implement the MaTRIGRS model:

1. DEM was computed from light detection and ranging (LiDAR) data, which was obtained from the North Carolina Floodplain Mapping Program (www.ncfloodmaps.com). The 6-m grid cell spatial resolution provided by LiDAR greatly improves the spatial accuracy when mapping topographic variances compared with the Shuttle Radar Topography Mission (SRTM) DEM at 30-m resolution. Important topographic parameters were derived from the LiDAR DEMs, including elevation, slope angle, and spatial location.
2. Rainfall data were obtained from the 4-km (spatial resolution) Stage IV rainfall analysis product, which is calculated using the multi-sensor hourly Stage III analyses produced by the River Forecast Centers (RFCs) in CONUS (www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/stage4/). Hourly rainfall data from Hurricane Ivan were used as input to the model.
3. Soil data sets were obtained from the State Soil Geographic (STATSGO), distributed by the Natural Resources Conservation Service (NRCS) of the US Department of Agriculture (www.nrcs.usda.gov). The data set consists of 16 defined soil texture classes using a broad-based inventory of soil areas over the continental United States at a 1-km resolution. In this region, soil type referring to STATSGO is 3, sandy loam, which relatively homogeneously covers from east to west. Due to lack of detailed soil

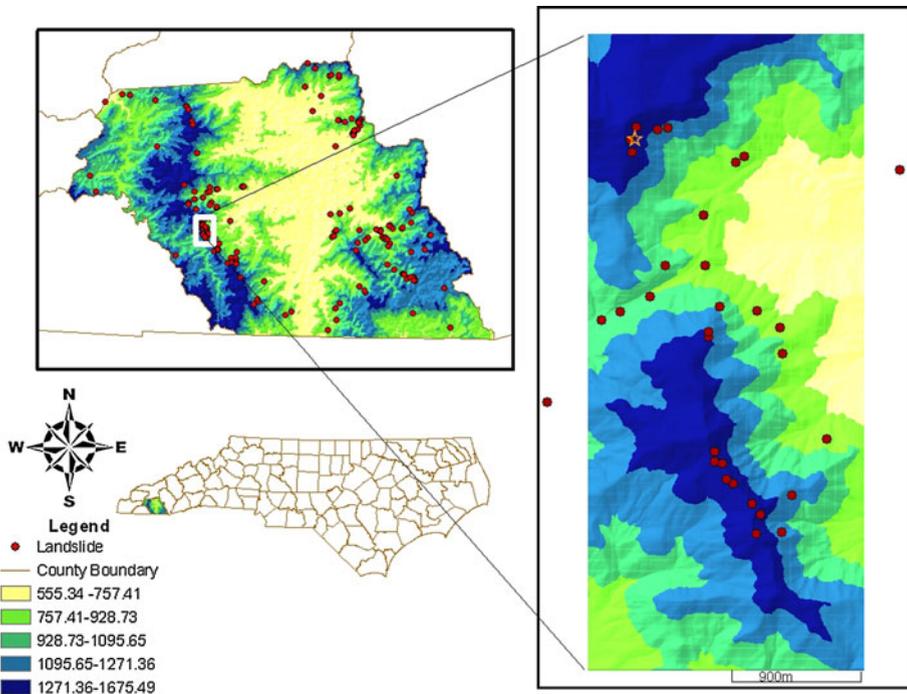


Fig. 1 Location of study area in Macon County, North Carolina, showing study boundaries, elevation, and landslides triggered by Hurricanes of Ivan in Poplar Cove mountainous region. The grid shown as a *yellow star* is selected for grid analysis in application section (based on 6-m LiDAR DEM)

information, soil cohesion, friction, and conductivity were derived by adjusting through a procedure of back analysis within a relatively large range. The depth used to calculate FS in this paper is assumed to be 1.5 meters, as a fact that most shallow landslides range from 1 to 2 m (Meisina and Scarabelli 2007). It is also the best soil thickness we can get due to limitation of better soil information regionally and remotely.

4. Landslide inventory information was obtained from the North Carolina Geological Survey and was mapped through field investigation. The inventory contains more than 44 shallow translational slope failures (i.e., earth slides). The inventory is used for evaluating the MaTRIGRS simulation results.

2.2 Transient rainfall infiltration and grid-based regional slope-stability analysis

Iverson (2000) provides a theoretical framework for understanding how hydrologic processes influence the location, timing, and rates of landslide occurrence based on a solution to the boundary problem posed by Richard's equation. Transient pressure, which is a function of changing rainfall rates, is introduced with the assumption that shallow landslides are tension-saturated. This solution assesses the effects of transient rainfall on the timing and location of landslides by modeling the pore water pressure of a steady component, represented by the first term in Eq. 1, and a transient component. The Iverson (2000) model requires only three parameters to predict the magnitude and timing of the

transient pressure: rainfall intensity, duration, and soil hydraulic diffusivity. Baum et al. (2002) generalizes Iverson’s original infiltration model solution by developing the TRIGRS program for cases of variable rainfall intensity and duration. The generalized solution used in TRIGRS is given by:

$$\begin{aligned} \phi(Z, t) = & [Z - d]\beta \\ & + 2 \sum_{n=1}^N \frac{I_{nz}}{K_z} \left[H(t - t_n) [D_1(t - t_n)]^{\frac{1}{2}} \operatorname{ierfc} \left[\frac{Z}{2[D_1(t - t_n)]^{\frac{1}{2}}} \right] \right] \\ & - 2 \sum_{n=1}^N \frac{I_{nz}}{K_z} \left[H(t - t_{n+1}) [D_1(t - t_{n+1})]^{\frac{1}{2}} \operatorname{ierfc} \left[\frac{Z}{2[D_1(t - t_{n+1})]^{\frac{1}{2}}} \right] \right] \end{aligned} \tag{1}$$

where, $\phi(Z, t)$ is the ground-water pressure head at time t and at depth Z , which is positive in the downward direction.

$Z = z/\cos \alpha$, z is normal to the slope angle α ; α is slope angle; d is the steady water table in z -direction; $\beta = \epsilon \cos \alpha$, in which $\epsilon = \cos \alpha - [Iz/Kz]_{LT}$; K_z is hydrological conductivity; I_z is initial surface flux in the Z -direction; I_{nz} is the surface flux for the n th time interval; LT means long term; $H(t - t_n)$ is the heavy-side step function; $D_1 = D_0 \cos^2 \alpha$, in which D_0 is the saturated hydraulic diffusivity; D is the total number of intervals.

The function ierfc is

$$\operatorname{ierfc}(\eta) = \frac{1}{\sqrt{\pi}} \exp(-\eta^2) - \eta \operatorname{erfc}(\eta) \tag{2}$$

where, $\operatorname{erfc}(\eta)$ is the complementary error function. Incorporating Eq. 1 into the classic infinite slope-stability equation yields a factor of safety (FS) estimation:

$$FS = \frac{c}{\gamma_s Z \sin \alpha \cos \alpha} + \frac{\tan \phi}{\tan \alpha} + \frac{(-\phi \gamma_w) \tan \phi}{\gamma_s Z \sin \alpha \cos \alpha} \tag{3}$$

in which ϕ is friction angle of soil, c is soil cohesion, γ_s is the unit weight of soil, and γ_w is the unit weight of water. Factor of safety (FS) is defined as the ratio of resisting forces over driving forces on a hill slope. A FS value at or below one suggests that the slope is unstable and a landslide is predicted. The first term in Eq. 3 is soil cohesion, which contributes to a larger FS value. The second term, friction angle, also increases the FS value. The third term identifies the transient pressure due to surface fluxes, which decreases the FS value as pressure increases.

2.3 Matlab version of TRIGRS

We have rewritten a Matlab version of TRIGRS (MaTRIGRS) and implemented it on a gridded digital elevation model in Macon County, NC. Figure 2 outlines the three main components of the MaTRIGRS modeling framework: input, model, and output.

- Input accepts a list of input files, including precipitation, DEM-derived parameters, soil property data, etc. The mechanical and hydraulic properties of the soil data are derived from empirical values based on the definition of different soil classes. The grid resolution of input data is all downscaled from larger resolution to match the 6-m LiDAR DEM.
- The model component serves as the core function to calculate a FS value at each grid cell with a user-defined time step corresponding to the rainfall inputs. Parameter values

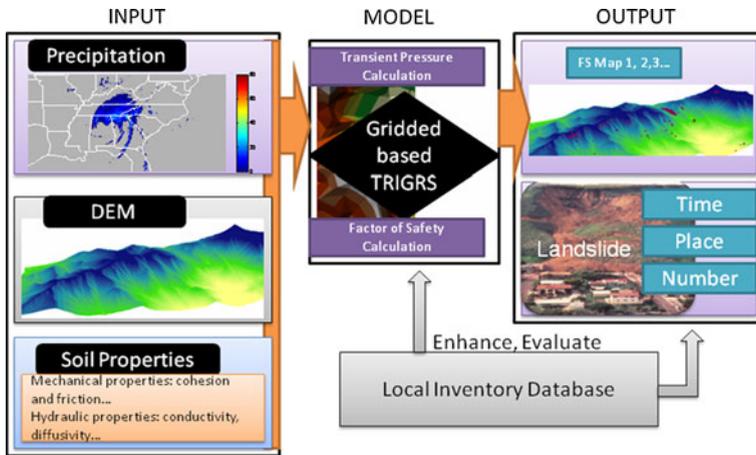


Fig. 2 Conceptual framework of applying the Matlab version TRIGRS (MaTRIGRS) for prediction of rainfall-induced shallow landslides in Macon County, NC

Table 1 Parameters, symbols, and values are used for MaTRIGRS application

Property	Symbol	Unit	Value\Range
Slope angle	α	$^{\circ}$	Variable
Landslide depth	Z	m	1.5
Water table	L	m	1.3
Soil cohesion	c	KPa	2–25
Soil friction	ϕ	$^{\circ}$	10–35
Soil unit weight	γ_s	N/m ²	16–20
Hydraulic conductivity	K	m/s	10 ⁻²
Hydraulic diffusivity	D	m ² /s	10 ⁻⁴
Rainfall intensity	I	mm/h	0–250 (peak average: 25)
Rainfall duration	t	h	30

for the model are summarized in Table 1. Hydraulic parameters including conductivity and diffusivity are obtained from Iverson 2000 and derived according to soil classes and empirical reference tables. The depth z used to calculate FS in this paper is assumed to be 1.5 meters, as most shallow landslides in the study area range from 0.5 to 1.5 m according to inventory information in Macon County. A more detailed description of the TRIGRS model is available in Baum et al. (2002).

- Output files include FS maps and intermediate variables and parameters for deriving the FS maps, which are all generated at time steps consistent with designated modeling time intervals (e.g. the temporal resolution of rainfall inputs). The output intermediate parameters could be used for process-based analysis of the slope failure for each grid. The output files can be analyzed in visualization software such as ArcGIS. Collectively, all intermediate processes and final output files can be used to evaluate the spatiotemporal dynamics of the FS maps and identify the time, location, and number of failed grid cells. Landslide inventory data can be used to improve the modeling processes and parameterization of the MaTRIGRS.

3 Application results and analysis

3.1 Rainfall analysis of hurricane events

Eight tropical cyclones made landfall in the southeastern United States during the 2004 hurricane season (Fig. 3a). In western North Carolina, particularly across Macon County and nearby portions of the southern Appalachians, the first 5 months of 2004 were characterized by below-average rainfall, followed by above-average rainfall in both June and July. Precipitation data from the mountainous highlands (Fig. 3b) illustrate the general spatial characteristics of rainfall across the area. The June and July precipitation totals and departures from average were 211 mm (+30 mm) and 314 mm (+147 mm), respectively. The precipitation total for August was 165 mm, 3 mm below average; however, the soil had already been saturated due to substantial precipitation in June and July.

Heavy rainfall associated with the passage of the remnants of Hurricanes Frances (September 7–8) and Ivan (September 16–17) dominated the precipitation record during the first 3 weeks of September, 2004 across the entire southern Appalachian region. Both storms developed from tropical waves that moved westward off the coast of Africa. They followed similar tracks across the Atlantic along the southern periphery of the Bermuda High, and into the Gulf of Mexico (Fig. 3a). In both storms, the right side of the cyclonic circulation passed over Western North Carolina (relative to the northeastward storm motion), resulting in significant orographic enhancement of the precipitation as the south, southeast, and eastern winds encountered the higher terrain (Wooten et al. 2008). Observations indicated that the higher elevation stations had greater rainfall totals than stations at lower elevations (Wooten et al. 2007). Major floods occurred in the French Broad, Swannanoa, Pigeon, and Little Tennessee River valleys in North Carolina.

These consecutive storms with heavy rainfall constitute dangerous scenarios for regional flooding (Witt 2005) and damaging slope movements (Wooten et al. 2007) in western North Carolina. High-intensity rainfall from a single storm such as Hurricane Ivan (as high as 356 mm in portions of southern Macon County) can trigger landslides, especially when antecedent moisture conditions are high, as true this case. Thus, the tension-saturated conditions in the Macon County region were assumed for the MaTRIGRS modeling as a result of the hurricanes, and the 3 weeks of record rainfall in September. The MaTRIGRS is used to predict the 30 slope failures triggered by Hurricane Ivan in Poplar Cove mountainous region from 6 a.m. to 12 p.m. on September 17 (Fig. 1). Figure 3c shows the precipitation intensity over Macon County at the 21st hour of the storm's passage, when the maximum number of landslides was predicted by MaTRIGRS.

3.2 Analysis of the temporal evolution of MaTRIGRS modeling results

Using the NOAA/NWS Stage IV combined radar and gauge rainfall as a forcing input, the parameterized MaTRIGRS model was run hourly and a FS value was generated every hour throughout the 30-h duration of the Hurricane Ivan event at every 6-m grid cell (Fig. 4). Three intermediate FS maps were selected for comparison to the landslide inventory before, during and at the peak of the modeled landslide occurrences (Fig. 5). The FS values in each map range from 0 to 5 (values above 5 are regarded as 5). A slope failure is predicted when the FS value is below 1 as indicated as pink circles in Fig. 5.

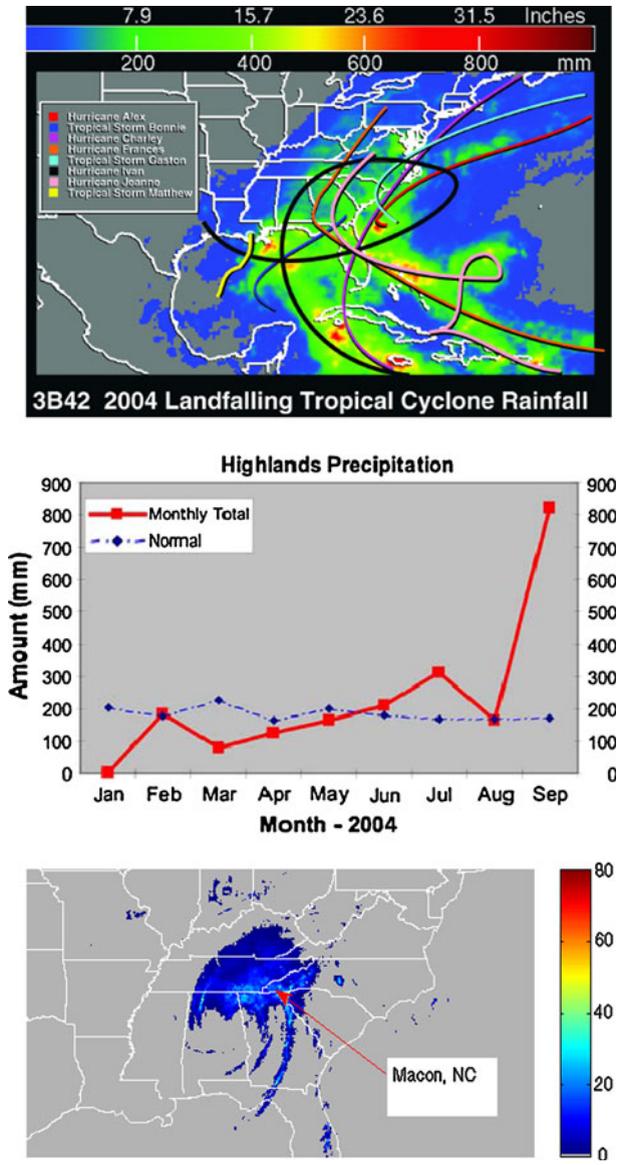


Fig. 3 **a** Tropical cyclones paths and rainfall accumulation from NASA TRMM-based Multi-satellite Precipitation Analysis in Southeast USA during the 2004 Hurricane season (CITATION); **b** monthly rainfall in Macon County highlands in 2004 versus climatology (after Wooten et al. 2008); and **c** Stage IV radar analysis shows heavy precipitation (mm/h) crossing Macon County at EST 02 a.m., September 17, 2004 (21st hour of the 30-h simulations)

3.2.1 Grid-based analysis

In each simulation time step, FS values are calculated for each grid at a 6-m resolution. We selected one failure grid, shown as the yellow star in Fig. 1, in order to demonstrate

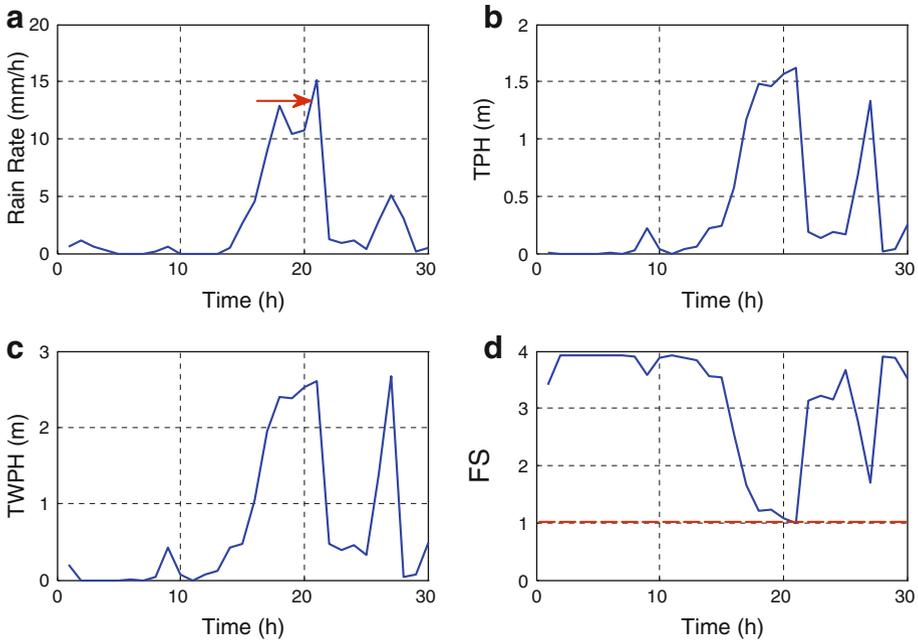


Fig. 4 Graphs for grid analyses along time series of hurricanes. **a** Hourly rainfall observed by radar at the study grid, **b** hourly transient pressure head (TPH) due to downward surface flux as a response calculated by MaTRIGRS, **c** hourly total water pressure head (TWPH) by Eq. 1 (the y label in **b** and **c** is the same), and **d** factor of safety calculated by Eq. 3 for the period EST 6:00 a.m., September 16, 2004 to 12:00 a.m., September 17, 2004. Red arrow in **a** indicate time of the occurrence of slope failure at this grid. The red dash line in **d** is line of FS values of 1. Any value reaches to below one indicates a potential slope failure

the behavior of water pressure head values in response to hurricane rainfall. This grid was predicted to fail (i.e. $FS < 1$) at the 21st hour of the storm (shown as the red arrow in Fig. 4a) and corresponds to the location where a landslide was observed in the validation dataset (indicated by a yellow star in Fig. 1). Fig. 4a shows the rainfall peak period between the 16th and 21st hours of the hurricane. Fig. 4b illustrates the response feature of the transient pressure head through the simulation process. The last two terms of Eq. 1 could be regarded as a response function to rainfall. Before the rainfall rate peak, transient pressure remains close to zero and then proceeds to increase consistently until rainfall intensity declines after the first peak in Fig. 4a. The transient pressure then exhibits a relatively slow increasing rate during the second rainfall peak until reaching a peak at the 21st hour of the storm. Figure 4c shows the total pressure head distributed along the hurricane time series at the test grid cell, which illustrates the profound influence of transient pressure from Fig. 4b. Figure 4d predicts the slope failure at the 21st hour of the hurricane, when the FS is 0.9, resulting from an increase in the water pressure head.

From the first term of Eq. 1, the total water pressure is determined by the water table and slope failure surface. Transient pressure varies with rainfall intensity, duration, and soil conductivity. Figure 4b, c demonstrates that FS depends on the total water pressure head, which is influenced by transient pressure as a response to rainfall intensity. In summary, Fig. 4 shows the time evolution of a slope failure as a function of pressure which is

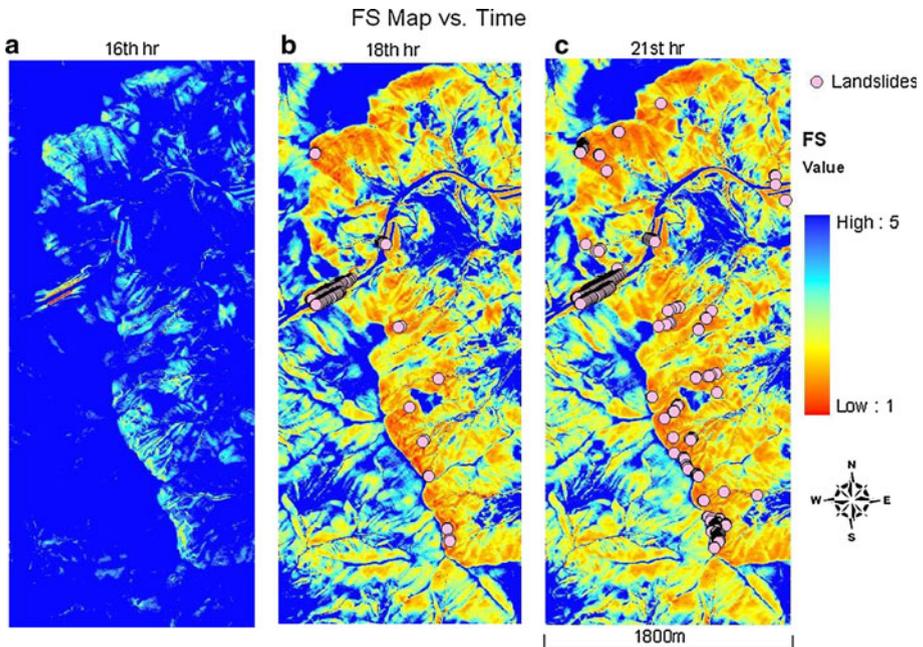


Fig. 5 **a** Left, factor of safety map at 16th hour (EST 22 p.m., 16 September) of hurricanes Ivan before landslide initialization, **b** middle, FS map at 18th hour (EST mid-night of 16 September) in the middle of landsliding, **c** right, FS map at 21st hour (EST 3 a.m., September 17) at peak of landsliding at Macon County, NC. Note that in the color scheme $FS \geq 5$ shows as blue and $FS < 1$ (failure prediction) as indicated by the *light pink circle* marks

determined by influencing factors such as rainfall intensity and duration, soil conductivity, and hydrologic infiltration capacity.

3.2.2 Regional analysis of intermediate FS maps

One main objective of this research is to evaluate the spatiotemporal predictability of landslide occurrences in Macon County using the MaTRIGRS model for regional landslide hazard assessment and potentially early warning during future hurricane seasons. The gridded FS map series calculated by MaTRIGRS predicts the location and time of landslide occurrences by monitoring when the grid FS values approach the critical value 1.

Figure 5 depicts the temporal and spatial dynamics of FS values induced by Hurricane Ivan during the 30-h duration (i.e. 6 a.m., 16 September through 12 p.m., 17 September) in 2004. The three intermediate FS maps for the 16th, 18th, and 21st hour of the storm are shown in Fig. 5, corresponding to 10 p.m., 12 a.m. and 3 a.m. on September 16–17, respectively. When comparing these three maps, FS values tend to decline as rainfall intensity increases to the storm peak. At the 18th hour of the hurricane, MaTRIGRS predicted that 175 grid cells failed, shown by the pink circle markers in Fig. 5b. After another 3 h of heavier precipitation, a total of 418 failed grids are detected including the previous failed grids (Fig. 5c). Figure 5c also illustrates regional differences in landslide initiations during intense rainfall. Areas in the eastern portion of the mountains have lower FS values, while the west remains fairly safe ($FS > 1$). Failure zones are generally associated with higher slope angles in the east.

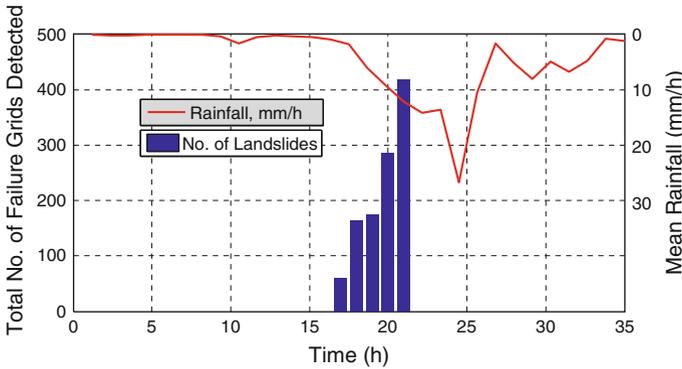


Fig. 6 Time series plots of total failed grids predicted by MaTRIGRS and average rain rates during the Hurricane Ivan event, September 16–17, 2004 in Macon County, NC

Figure 6 illustrates the relationship between the number of failure grid cells and mean rain rates during Hurricane Ivan. Rain rates were averaged within the study area for each hour as the hurricane crossed Macon county over a 30-h period. Initially, the maximum rain rate was 2 mm/h. The rate then quickly increased to a peak of 25 mm/h in the following 10 h. Fifty-nine grid cells began to fail at the 17th hour of the hurricane. The grid cells continued to fail during the passage of the storm and reached a maximum of 418 failure grid cells detected at the 21st hour of the storm. After this point, the rain rate continued to increase, but no additional failed grid cells were detected. One explanation of this finding is that by the 21st hour of the storm, most grid cells exhibiting potential to be induced by rainfall had already been triggered.

3.3 Statistical evaluation of the results

Figure 7a shows that areas at high elevation have preferentially more failed grid cells compared with grid cells at lower elevations. Figure 7b illustrates that most of the failed grids and observed landslides occurred in areas with higher slope angles. Both the observed and predicted landslides primarily occur on the eastern side of the mountain range.

In this study, a total of 418 failed grid cells are predicted by MaTRIGRS during the 30-h Hurricane Ivan event, whereas 30 landslides were observed from field surveys. It is likely that many adjacent failed grids could be considered as one prediction with a large aerial extent. However, due to program limitations in regional analysis of large number of the landslides, each grid is analyzed as individual on the spatial extent or severity. In addition, the landslide inventory does not provide the exact time of initiation for each landslide occurrence during the 30 h of the Hurricane Ivan event. We utilized the contingent tables (Ebert et al. 2007) to evaluate the model prediction results. In general, it is common for landslide to range in size from square meters to kilometers. We evaluated the model predictions using an incremental radius from 6 meters to maximum 120 m from the landslide location to better account for variability in the size of the landslide.

Table 2 provides definitions of the statistical indices used for validating the MaTRIGRS model within a specified radius of confidence from the observed landslide location. Probability of detection (POD) defines how well the predicted results compare to observations, using a value ranging from 0 (poor performance) to 1 (perfect model results). In the MaTRIGRS prediction for Hurricane Ivan, the POD value increases from 0.06 at a

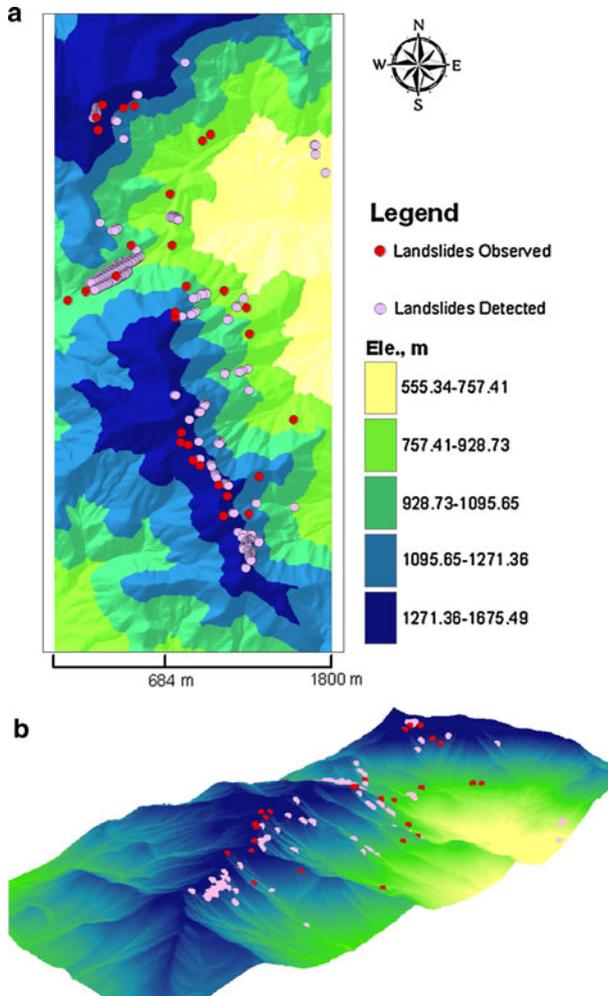


Fig. 7 **a** Two-dimensional and **b** three-dimensional plots of landslides detected (light color circles) by MaTRIGRS and surveyed observations (red circles) after the event

Table 2 Statistical analysis indices for evaluation of model predictions

Statistical index	Unit	Equation	Perfect value
Probability of detection (POD)	N/A	$POD = \frac{H}{H+M}$	1
False alarm ratio (FAR)	N/A	$FAR = \frac{F}{H+F}$	0
Critical success index(CSI)	N/A	$CSI = \frac{H}{H+M+F}$	1

H observed landslide correctly detected within specified radius, *M* observed landslide but not detected within specified radius, *F* landslide detected but not observed within specified radius

radius of 6 m to 0.67 at a radius of 24 m, and finally to 0.98 at a radius of 120 m (Fig. 8 and Table 3). The false alarm ratio (FAR) indicates the tradeoff between a prediction that matches the observed data and one that does not correspond to observed landslides, with a

Fig. 8 Schematic of probability of detection (POD), false alarm ratio (FAR), and critical successful index (CSI) for comparison between landslide observations and predictions as a function of detection radius from center of the landslides

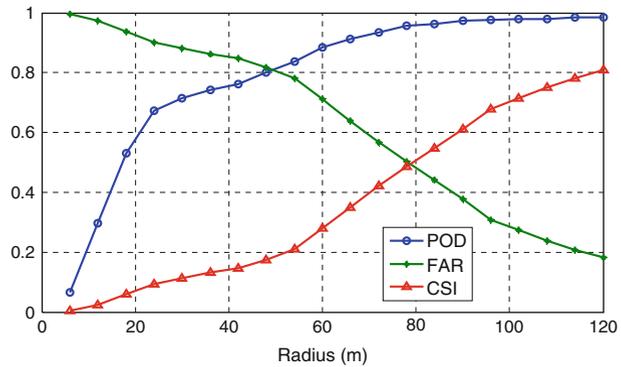


Table 3 POD, FAR, and CSI for evaluation of the MaTRIGRS predicted landslide locations within in incremental distances from the center of landslide observations

Radius (m)	POD	FAR	CSI
6	0.065	0.995	0.004
12	0.297	0.974	0.025
18	0.530	0.938	0.059
24	0.672	0.902	0.093
30	0.714	0.881	0.114
36	0.744	0.862	0.132
42	0.762	0.847	0.146
48	0.800	0.819	0.174
54	0.836	0.781	0.210
60	0.885	0.711	0.279
66	0.911	0.639	0.348
72	0.935	0.566	0.421
78	0.956	0.502	0.487
84	0.961	0.440	0.547
90	0.972	0.377	0.612
96	0.976	0.309	0.679
102	0.978	0.274	0.714
108	0.980	0.237	0.751
114	0.984	0.208	0.781
120	0.985	0.182	0.808

value of 0 indicating that the modeled predictions match the observed data exactly. Figure 8 illustrates that within a 60-m radius, the FAR value is as high as 0.71. However, as the radius of confidence extends to 120 m, the FAR is reduced to a value of 0.18. The critical success index (CSI) is a combined effects of both FAR and POD, at a range from 0 (no skill at all) to 1 (best predictive skill). The CSI value is very low (up to 0.2) within 60 m, whereas both the POD and FAR are high. However, after 60 m, the CSI value increases to 0.71 at a radius of 102 m, mainly due to a decrease in the FAR values. Table 3 provides the POD, FAR, and CSI values for each radius (m) from the observed landslide locations. The validation can be further improved with additional landslide information including the failure time of each landslide and its area and volume.

4 Summary and discussion

A Matlab version of TRIGRS has been implemented in Macon County, NC, where widespread landslides were triggered by Hurricane Ivan in mid-September 2004. High resolution LiDAR DEMs, soil database, and gauge-corrected radar precipitation data are used as inputs to evaluate the MaTRIGRS model, using a local landslide inventory database to evaluate the modeling results.

MaTRIGRS outputs hourly factor of safety maps, which are analyzed to assess the spatial distribution and timing of potential landslide events. Results from Macon County indicate that within a 24-m radius of the observed landslide locations, about 67% of the landslides were successfully predicted but with a relatively high FAR (0.90). When the detecting radius is expanded to 120 m, 98% of landslides could be successfully predicted with a relatively low FAR (0.18), which we consider is acceptable for a landslide warning system. Furthermore, the evaluation can be further improved if additional landslide observation information was available (e.g. the time of failure for each landslide, the area and volume).

Results of this study demonstrate that the MaTRIGRS model has the potential to become a new tool for early warning of landslide disasters where comprehensive field data and fine-scale precipitation observations and forecasts are available. However, several areas should be improved for future applications of the MaTRIGRS model: (1) the current MaTRIGRS simulation assumes there to be a uniform ground water table depth (1.5 m) as initial conditions, which could lead to modeling errors as well as limited predictability for deep-seated landslide prediction; (2) over-prediction (i.e. high false alarm) as indicated along roadsides (figure not shown here) illustrates the difficulty in predicting landslides along artificial or man-made slopes where extra cautions should be taken; and (3) discrepancies between predicted and observed landslides could be further reduced with higher spatiotemporal resolution of rainfall inputs and soil database to account for the high geomorphologic variations of landslide-prone regions. Though with rooms to improve, MaTRIGRS demonstrates acceptable spatiotemporal predictive skill for landslide occurrences within a 120-m radius in space and a hurricane-event-duration (h) in time, offering the potential to serve as a landslide warning system in areas where accurate rainfall forecasts and high-quality field data are available. Additionally, in order to better apply soil topography and vegetation, etc., integrating recently constructed dynamic/thermodynamic model (e.g., SEGMENT-landslide, Ren et al. 2008, 2009), which accounts explicitly for soil mechanics, root distribution, a full cycle of hydrological processes involved, would optimistically improve the MaTRIGRS. Future work also includes applying the MaTRIGRS model to unsaturated slopes during a single heavy storm after long-time drought conditions.

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References

Baum RL, Savage WZ, Godt JW (2002) TRIGR—a Fortran program for transient rainfall infiltration and grid-based regional slope-stability analysis. U.S. Geological Survey Open File Report

- Baum RL, Savage WZ, Godt JW (2008) TRIGRS—a Fortran program for transient rainfall infiltration and grid-based regional slope-stability analysis, version 2.0: US Geological Survey Open-File Report, 75 p
- Caine N (1980) The rainfall intensity duration control of shallow landslides and debris flows. *Geogr Ann Ser A* 62:23–27
- Cannon S, Gartner J (2005) Wildfire related debris flow from a hazards perspective. In: Jacob M, Hungr O (eds) *Debris-flow hazards and related phenomena: Springer-Praxis Books in Geophysical Sciences*, pp 321–344
- Dietrich WE, Reiss R, Hsu ML, Montgomery DR (1995) A process-based model for colluvial soil depth and shallow landsliding using digital elevation data. *Hydrol Process* 9:383–400
- Ebert EE, Janowiak JE, Kidd C (2007) Comparison of near-real-time precipitation estimates from satellite observations and numerical models. *Bull Am Meteor Soc* 88:47–64
- Godt JW, Baum RL, Lu N (2009) Landsliding in partially saturated materials. *Geophys Res Lett* 36
- Hong Y, Adler R, Huffman G (2006) Evaluation of the potential of NASA multi-satellite precipitation analysis in global landslide hazard assessment. *Geophys Res Lett* 33:L22402. doi:[10.1029/2006GRL028010](https://doi.org/10.1029/2006GRL028010)
- Hong Y, Adler RF, Huffman GJ (2007) Use of satellite remote sensing data in the mapping of global landslide susceptibility. *Nat Hazards* 43(2):245–256. doi:[10.1007/s11069-006-9104-z](https://doi.org/10.1007/s11069-006-9104-z)
- Iverson RM (2000) Landslide triggering by rain infiltration. *Water Resour Res* 36(7):1897–1910
- Kirschbaum DB, Adler R, Hong Y, Hill S, Lerner-Lam AL (2009) A global landslide catalog for hazard applications—method, results and limitations. *J Nat Hazards*. doi:[10.1007/s11069-009-9401-4](https://doi.org/10.1007/s11069-009-9401-4)
- Lu N, Godt JW (2008) Infinite-slope stability under steady unsaturated conditions. *Water Resour Res* 44:W11404. doi:[10.1029/2008WR006976](https://doi.org/10.1029/2008WR006976)
- Meisina C, Scarabelli S (2007) A comparative analysis of terrain stability models for predicting 478 shallow landslides in colluvial soils. *Geomorphology* 87(3):207–223
- Montrasio L, Valentino R (2008) A model for triggering mechanisms of shallow landslides. *Nat Hazards Earth Syst Sci* 8:1149–1159
- Ren D, Leslie LM, Karoly D (2008) Mudslide risk analysis using a new constitutive relationship for granular flow. *Earth Interact* 12:1–16
- Ren D, Wang J, Fu R, Karoly D, Yong Yang, Leslie LM, Fu C, Huang G (2009) Mudslide caused ecosystem degradation following Wenchuan earthquake 2008. *GRL* 36. doi:[10.1029/2008GL036702](https://doi.org/10.1029/2008GL036702)
- Witt AC (2005) A brief history of debris flow occurrence in the French Broad River Watershed, western North Carolina. *NC Geogr* 13:58–82
- Wooten RM, Reid JC, Latham RS, Medina MA, Bechtel R, Clark TW (2005) An overview of the North Carolina Geological Survey's Geologic hazards program-phase 1: In: *Proceedings of the 56th highway geology symposium*, Wilmington, NC, 4–6 May 2005, pp 291–307
- Wooten RM, Latham RS, Witt AC, Gillon KA, Douglas TD, Fuemmeler SJ, Bauer JB, Reid JC (2007) Landslide hazards and landslide hazard mapping in North Carolina: In: Schaefer VR, Schuster RL, Turner AK (eds) *Conference presentations 1st North American landslide conference*, Vail Colorado, AEG Special Publication 23, pp 458–471
- Wooten RM, Gillon KA, Witt AC, Latham RS, Douglas TJ, Bauer JB, Fuemmeler SJ, Lee LG (2008) Geologic, geomorphic, meteorological aspects of debris flows triggered by hurricanes Frances and Ivan during September 2004 in the southern Appalachian Mountains of Macon County, North Carolina (southeastern USA). *Landslides* 5(1):31–44
- Wu W, Sidle RC (1995) A distributed slope stability model for steep forested basins. *Water Resour Res* 31:2097–2110