Revista Brasileira de Cartografia (2017), Nº 69/1, Edição Especial Geotecnologias e Desastres Naturais: 13-22
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto
ISSN: 1808-0936

# ON THE PRECIPITATION HOMOGENEITY HYPOTHESIS IN TOPMODEL APPLICATIONS

*Sobre a Hipótese de Homogeneidade da Precipitação em Aplicações TOPMODEL*

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***Received on November 12, 2015/ Accepted on September 18, 2016***
***Recebido em 12 de Novembro, 2015/ Aceito em 18 de Setembro, 2016***

## ABSTRACT

The objective of this work is to analyze the asymptotic conditions of similarity of soil water distribution over complex terrain and propose a relaxation of the rainfall spatial homogeneity, which is considered in the hydrological distribution TOPMODEL. The result is a generalization based on the conservation of material properties over the asymptotic drain paths of the complex terrain. The similarity hydrological conditions are here considered to be weak restrictions on the variational problem. In practice, a numerical application was built to assist weather forecasters in the diagnosis and prognosis of hydrometeorological conditions of increased risk, such as landslides and flash floods. These events can occur in much smaller time scales that provided by the usual weather forecasts in the synoptic scale.

**Keywords:** Hydrologic Distribution, TOPMODEL, Heterogeneous Rainfall, Modeling Risk of Flooding.

## RESUMO

O objetivo deste trabalho é analisar as condições assintóticas de similaridade de distribuição de água do solo em terrenos complexos e propor um relaxamento da hipótese de homogeneidade espacial das chuvas, considerada na versão original da distribuição hidrológica TOPMODEL. O resultado é uma generalização baseada na conservação de propriedades materiais sobre caminhos de drenagem assintóticos do terreno complexo. As condições de similaridade hidrológicas são aqui consideradas como restrições fracas do problema variacional. Na prática, uma aplicação numérica foi construída para auxiliar os meteorologistas previsores no diagnóstico e prognóstico das condições de maior risco hidrometeorológico, tais como deslizamentos de terra e inundações repentinas. Esses eventos podem ocorrer em escala de tempo muito menor que as disponibilizadas pelas previsões meteorológicas usuais de escala sinótica.

**Palavras-chave:** Distribuição Hidrológica, TOPMODEL, Distribuição Heterogênea da Precipitação, Modelagem do Risco de Inundação.

## 1. INTRODUTION

In general, there are large spectral and temporal heterogeneity into the distribution of sizes and properties of rainfall hydrometers (e.g., PRUPPACHER & KLETT, 1997). Particularly, both convective and orographic precipitation show larger horizontal gradients of rainfall in relation to stratiform precipitation. Beyond that, the time scales of rainfall decreases dramatically of stratiform clouds to convective clouds (BARRY & CHORLEY, 2010; MARKOWSKI & RICHARDSON, 2010). In order to consider all the spatial and time scales present in atmospheric precipitation, today the large centers of prediction usually have employed three dimensional mesoscale numerical models, in higher resolution compared to the forecast in synoptic scale. The state of the art in Quantitative Precipitation Forecast (QPF) is considered in the WPC (2015).

There is a spin-up period right at the beginning of forecast run lasting up to several hours to the mesoscale prediction model to achieve satisfactory performance. This spin-up time may be as large as 12-hr. This large gap can be filled with nowcasting methods up to 6-hr in advance applied to severe weather related to flash floods and , mudslides (DE BLASIO, 2011), lightning strikes and other major risk hydrometeorological phenomena. The atmospheric phenomena have spatial and temporal scales ranging from seconds (e.g., turbulence) to several years (e.g., El Niño Southern Oscillation). Dutton (1986) brings a comprehensible review. In particular storms associated with cumulonimbus clouds have a spatial scale of 10 km in diameter lasting 20-minute develop in dynamic convective vertical structure and the warm microphysics larger droplets (ROGERS & YAU, 1989; PRUPPACHER & KLETT, 1997).

The surface hydrology model TOPMODEL is capable of responding to time variations of rainfall, but not to the spatial rainfall heterogeneities (BEVEN & KIRKBY, 1978). In its original version, this model is able to compute the asymptotic state of water distribution in the soil layer of a future time (i.e., make a forecasting), along the strips of draining of the complex terrain, where the catchment area and drainage network are physically connected (BEVEN, 2000). The theory used in the TOPMODEL implies the existence of a universal function of similarity, that is usually found by dimensional analysis (i.e., using the theorems of the similarity theory). These functions are obtained under constraints hypothesis, first, of horizontally homogeneity of rainfall and second, the horizontal homogeneity of the deep infiltration (BEVEN, 2000). This sounds very appropriated to mid-latitude countries with some deep soils, for forecasting of soil wetness in consequence of stratified rainfall, during the winter. But seems inappropriate to use in tropical catchments during summertime, when convective events of precipitation occur frequently, well featured by large horizontal gradients and time variations as also by multi-scale events.

Several researchers have published in-depth discussions on the computational models used to simulate the humidity conditions of river basins, with the inclusion of discussions on the advantages and limitations of TOPMODEL (BEVEN *et al.*, 1995). First, the original code was written in FORTRAN 77 (BEVEN & KIRKBY, 1970). Then, it was encoded in MATLAB (ROMANOWICZ, 1995). Following, it was included as an available tools of a GIS, the GRASS (Cho, 2000). Later, the model was rewritten in language C from the original version f77, becoming available as R-library (Buytaert, 2009). Romanowicz (1995) exemplifies the application of TOPMODEL in MATLAB for accomplished a simulation of a small mid-latitude catchment, inside a rectangle topographic terrain domain of 6 km by 8 km. This later presented graphical outputs, showing the distribution over the terrain of the variables: topographic index, the soil moisture and the evapotranspiration, at the final time of the simulation. The rainfall catches were transported to valleys and low plains of the terrain, where the drainage network (of a very small watershed) appears naturally highlighted, as a place where the soil becomes saturated after rainfall ended. This makes evident the role of topography to reduce the fractal dimension of the problem from the catchment to the drainage network, under the listed constraints explained above.

According to Pappenberger *et al.* (2006), flood inundation prediction is sensitivity to uncertainties on upstream boundary conditions as the goodness of the model verified by holistic sensibility tests with 1D St. Venant equations as well as due to bridges along the river within the modeled region. Indeed, the understanding of such uncertainties is showed to be essential to improve flood forecasting and floodplain mapping. Uncertainties of the upstream boundary have significant impact on model results, exceeding model parameter uncertainties in some areas. The multiple sources of uncertainty in flood inundation models are: 1) choice of model structure as a simplification of reality (e.g., 1D or 2D flood inundation model and features such as bridges); 2) the numerical solution approximation; 3) boundary conditions uncertainties, including input forcing data and; 4) choice of effective parameters, including scaling and incommensurability effects (PAPPENBERGER & WERNER, 2015).

Nowadays, the uncertainty of the input forcing data is usually associated to an incomplete representation of the rainfall field in hydrological models. This is an important research issue, considering the mesoscale structure and time scale of convective storms in tropical watersheds. There is many applications and scientific research carried out with the classic version of TOPMODEL in Brazil and three are highlighted. Dos Santos & Kobiyama (2008) applied TOPMODEL to determine saturated areas of Rio Pequeno, a 104 km2 watershed in São José dos Pinhais, Paraná State, Brazil. They showed a good correlation between estimated and observed runoff. The coefficient of variance of R2=0.75 indicates good model performance for flatter watershed within tropical climates.

Calvetti and Pereira Filho (2014) obtained probabilistic stream flow forecasts using simulated rainfall with WRF model as input data of TOPMODEL, applied to Iguaçu River catchment, in Paraná State, Southern Brazil. They showed that large phase uncertainties of the simulated input rainfall data were responsible by decreasing the general Nash-Sutcliffe Efficiency (NSE) of the simulations. In this study, the WRF simulations was built without a 4D assimilation of rainfall (from radar or satellite) in sub-grid, but only defined the initial condition from the analysis of GPS model.

Rocha Filho (2010) in a very comprehensible work employed data from weather radar as input of the TOPMODEL, in high space-time resolution. He has showed showed that mistakes in estimation of precipitation typically resulted in discrepancies of flow simulations in relation to observations. These discrepancies can be minimized by integrating telemetric data in the analysis. He also suggested that further research can implement the representation of spatial variability of rainfall in TOPMODEL, but without a formal indication how this might be done. These three instances did not consider the spatial variation of rainfall. So, the present work is to taken into account rainfall variability.

In the present work, the conditions of similarity associated to the asymptotic water distribution of mesoscale catchments are analyzed to propose a relaxation of homogeneity hypothesis of the original equations of TOPMODEL. Indeed, the original solution is maintained as the asymptotic limit in the catchment basin, though transient solutions area allowed to actually obtain a consistent way with water conservation and the asymptotic similarity. Section 2 presents details of the proposed method. Results are shown in Section 3, and main findings of this work in Section 4.

## 2. METHODS

The theoretical development of the proposed method is presented next. The idea is to start with the original TOPMODEL formulation on soil moisture deficit and constraints applied on rainfall and deep infiltration yields by incorporating kinetic and advection effects into a variational function. A numerical procedure and an alternative Lagrangian view of proposed method are briefly introduced and discussed.

### 2.1 Theoretical Formulation

Using a exponential transmissivity infiltration factor in the soil vertical, Kirkby (1997) derived the following equation

$$\partial D/\partial t = a\ (\partial j/\partial x) - (i-j) \qquad (1)$$

consistent with *water mass conservation*, D being the saturation deficit of soil water (dimensionless), (a) the catchment contributing area by unit of width of flow strip (w) on the topography, with both (a) and (w) in units of (m), j is the deep infiltration (recharging through water table, a function of time only), by unit of w, in units of ($s^{-1}$), and i the precipitation rate by unit of w, in ($s^{-1}$). From the similarly analysis Kirkby (1997) rewrite Eq. (1) as

$$m\ (\partial \ln(j)/\partial t) = a\ (\partial j/\partial x) - (i-j) \qquad (2)$$

So $m = \partial D/\partial \ln(\gamma)$ is a *invariant similarity catchment parameter*, and $\gamma = (aj/\Lambda)$ *the topographic index*, where $\Lambda$ is the *slope inclination*. Therefore, the *asymptotic distribution model* of (D) and $\lambda=\ln(\gamma)$, can be written consistently by

$$D-D_m = m\ (\lambda-\lambda_m) \qquad (3)$$

Here suffix *m* indicates the median value. The *horizontal homogeneity hypothesis* applied in Eq. (2) yields

$$m\ (\partial \ln(j)/\partial t) = (j-i) \qquad (4)$$

Hence, the difference *(i-j)* forces the humidity of the superficial soil layer, where *j* is responsible by the aquifer recharge.

## 2.2 Relaxing Homogeneity Hypothesis

The relaxation of the spatial homogeneity of the rainfall and deep infiltration yields along the draining path

$$d(i)/dt = \partial(i)/\partial x + c\ .\ \nabla i \qquad (5)$$

where *i* is the rainfall rate, considered the local source of runoff, $\boldsymbol{c} =(c_x,c_y)$ is the flow kinematic wave celerity vector equal to $c = (c_x,c_y)=[-c(\Lambda_x/\Lambda), -c(\Lambda_y/\Lambda)]$, where $c=(aj_{med}/m)$ is the module of $\boldsymbol{c}$ and $-(\Lambda/\Lambda)=[-(\Lambda_x/\Lambda),-(\Lambda_y/\Lambda)]$ is the flow direction, i.e., opposite to the slope gradient. $j_{med}$ is the *j* median. The second term in the right hand side of the above equation is the advection along the draining path. The duration of transient effects can be followed through. Consistently, the relationship between the Lagrangian total variation of the Kirkby topographic index and the material derivate of the natural logarithm of the rainfall rate can be expressed by,

$$d\lambda = - (\gamma_m)^{-1}\ d \ln(i) \qquad (6)$$

In this work we propose the application a variational functional associated with a Lagrangian multiplier ($\lambda_E$). That is

$$F=\iint_S \{\ \alpha(\lambda-\lambda_\infty)^2+\lambda_E\ (\delta t/\gamma_m)[\partial \ln(i)/\partial t+c\ .\nabla \ln(i)]\}ds \qquad (7)$$

$\lambda_\infty$ being the prior distribution (i.e., due to the stratiform precipitation, only function of time), $\lambda$ is the corrected topographic index, which indeed is continuously relaxed in direction to the asymptotic state, using the basin response time, i.e., 10800 (s) = 3 (h) in the simulation, $\delta t$ *is* the time step, in (s) and, $ds = dxdy$ is the area of on grid element in *($m^2$)* . Without convective rainfall perturbation, a asymptotic stationary solution can be achieved in a time period of $T \geq min\{\Delta x, \Delta y\}/max\{c\}$, $\Delta x$ and $\Delta y$ being grid lengths in directions *x* and *y*, respectively. Minimizing *F* in relation to $\lambda$ yields

$$\lambda = \lambda_\infty + (2\alpha)^{-1}\ |\ \nabla\lambda_E\ .\ \delta\ | \qquad (8)$$

where $\boldsymbol{\delta}=(\Delta x, \Delta y)$. The summation of the partial derivate of equation (8) in x and y direction implies in the following Euler-Lagrange equation

$$\nabla^2\lambda_E = -\ 2\ \alpha\ (\delta t/\gamma_m)\ [\ \partial \ln(i)/\partial t + c.\nabla \ln(i)\ ] \qquad (9)$$

where $\nabla^2$ is the Laplacian operator. Inside the brackets, in the Eq. (9), there are two terms: the first, it is the local forcing, and the second is the non-local forcing. On the other hands, the first is associated with the local time variation of input data (i.e., rainfall), and the second term is associated with the kinematic wave advection, or runoff flux. Both terms are responsible for driving the soil humidity distribution in this proposed generalization. In this manner, by relaxing the prior constraints applied on the atmospheric forcing data, it is possible to obtaining a posterior distribution of *D,* in a physically consistent way. Here, in the simulation test, we applied a time step of 1 h (3600 s), but for nowcasting operations seems to be appropriated a time step of 5 min (300 s).

## 2.3 Numerical Implementation

The numerical implementation was done in octave, following the Eulerian approach with the steps below:

- a) Get the Kirkby topographic index, from the digital elevation model (DEM) (BEVEN, 2000).

- b) Solve the Eqs. (9) and (8) to update the saturation deficit distribution with Eq. (3).
- c) Plot the successive states of soil saturation deficit, considering the composite forcing.
- d) Analyzing the potential risk of floods and landslides, as a function of time and space.

The derivative operators are coded by finite differences in a Arakawa grid type A. The Euler-Lagrange equation was solved by sequential relaxation. Numerical solution were coded in octave (and Fortran-90), with a shell script used to control the compilation and execution. The major computational cost was expended with the prior distribution (i.e., in building the topographic index), really a numerical procedure of relatively higher cost up to now.

Further optimization seems to be indicated for further massive DEM data, addressing high resolution hydrological and risk assessment, e.g., using MPI.

## 2.4 Lagrangian Interpretation

The method can also be interpreted in terms of a Lagrangian approach:

- a) At initial time apply a deconvolution on the observed rainfall field for decreasing dispersion associated to the remote sensing observation by radar, satellite, etc. This deconvolution precedes a bijective application built with Lagrangian advection driven by topographic gradient and catchment areas;
- b) Obtain, once and for all, the bijection operators were defined relating the successive times, and
- c) Apply the results from the first step to compute the atmospheric surface forcing each time, to thereby obtain its successive states f(x,y,t+dt). This is accomplished with Barnes interpolation followed by convolution, leading the field toward the observation.

This Lagrangian approach can be useful for operational applications, since the advective bijection operator can be defined once and for all. The role of the convolution on sparse data precipitation, for example, associated with the distribution of gauges, or radar pixels, is to generate a continuous field of precipitation.

In general, operational meteorology, this is done by applying a filter function as given by Barnes interpolation. On the other hand, in a complementary manner, deconvolution can be applied to maximize the details or reduce scattering errors. Considering the degree of defocussing precipitation found in satellite images and radar in the S band, it seems plausible the use of deconvolution and convolution on the initial forcing data: i) to take in account the dispersion of observations, as well as, ii) to improve the detail focus of the simulations obtained from data initially unfocused. In practice, convolution can be applied to dispersed data to obtain a continuous but without focus field, followed by a deconvolution applied to results, thus getting focus on details that actually are present, but which are dispersed, considering the effect of a Point Spread Function (PSF). Deconvolution need prior knowledge of the PSF (i.e., the blurring function) and of its inverse, which can be built following Dalitz *et al.* (2015).

# 3. RESULTS

An arbitrary 3D topographic feature together with a 2D rainfall rate distribution are used for testing the method introduced in Section 2. Afterwards, it is applied to Tijuca mountain within the Metropolitan Area of Rio de Janeiro (MARJ), a realistic and more complex topographic feature.

## 3.1 Preliminary Test (Gaussian Hill)

In the test a convective cell Gaussian with maximum rainfall of 50 (mm h-1) spreads from NW to SE, on the Gaussian hill, 1000 m high and near 10km width, which is quite similar to the hills found on the Metropolitan Area of Rio de Janeiro (MARJ), but only with a shape more circular. Three numerical tests were carried out successfully:

- 1) First, with only local corrections;
- 2) Second, with nonlocal corrections, and
- 3) Third, including both local and non-local corrections.

The corrections were obtained by variational analysis, assuming that draining paths is given by a prior distribution, obtained by similarity, asymptotically. In the case of a horizontally homogeneous rainfall all draining paths are activated and carry rain water. Otherwise, for the heterogeneous case, only the paths that originate where the precipitation falls are activated. This is solved by a quadratic PDE, as can be derived by variational analysis. Here, the solution of the PDE was obtained numerically in finite differences, by sequential relaxation. For accomplishing the job, a octave script was encoded.

Figura 1 shows the idealized topography used in the simulation, consisting of choline Gaussian superimposed on an inclined plane rising from west to east. The area to the west is more favorable to the presence of moisture in the soil. Figura1 shows a rainwater catchment area associated with soil moisture conditions for each point of the domain. The hill's presence changes the overall pattern of distribution of water catchment area that increases from east to west. The slope equal to the topography of the gradient module is shown in Figura 2. The gradient vector components are used to control the direction of the runoff in each point of the domain.

The Kirkby topographic index is shown in Figura 4 Values between 19.3 and 24.3 are present. The topography of the hill has an important role in defining the distribution conditions of rainfall water collected in the field.

Figures 5 shows the distribution of precipitation at 3-hr of simulation time. This distribution corresponds to precipitation produced by a convective storm moving along the main diagonal of the area from NW to SE at a speed of 10 (m s-1). The storm goes across the intere area in a 12-hr simulation.

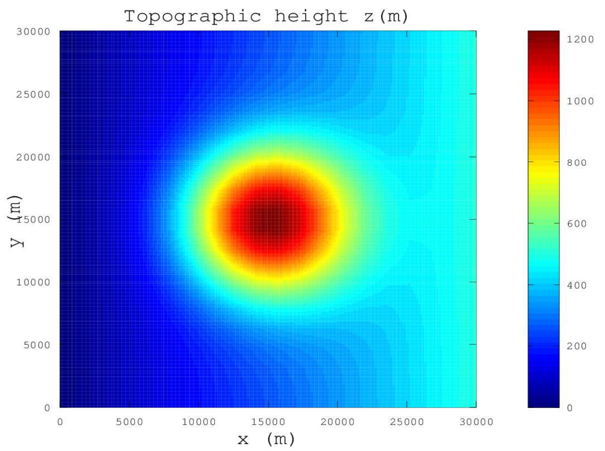


Figura 1 - Idealized topography used in the simulation, constituted of a sloped terrain and a high hill in the domain center.

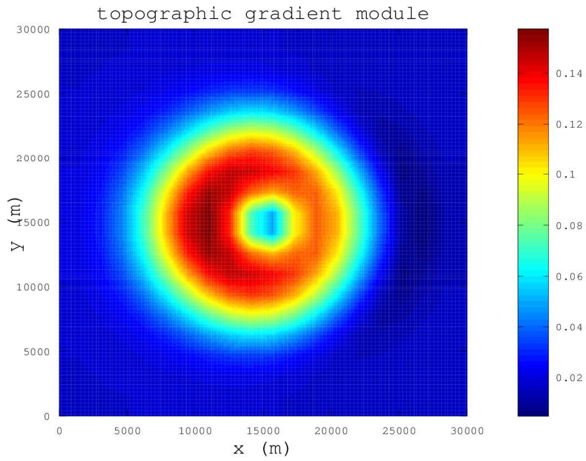


Figura 2 - Terrain inclination for the test topography

The distributions of the local and non-local forcing are shown in Figures 6 and 7, respectively, for the simulation time 6-hr. At this time, there is the passage of the maximum precipitation over most elevated area of the topography, which is the top of the hill. The effect of NW storm movement appears as an increase of the local forcing to leeward and a decrease of the local forcing windward. At the same time, the non-local forcing leads to a distribution around the hill, inducing the transport of water collected in the area downhill, mainly to the west of the hill, i.e., toward the plain.

Figures 8, 9 and 10 show the distribution of water saturation deficit in soil in 3 different simulation times, at 3-hr, 6-hr and 9-hr, respectively, for which it is considered a mixed forcing (i.e., an average local and non-local forcing was used). What can be observed in these simulation results are local and non-local effects, that is, either the precipitation is used to soil saturation locally, where was the storm, as well as to transport and even humidify distant points along the drainage paths.

An estimate of the probability flood plot was made considering the mapping of saturation deficit. First, it takes the minimum value of the negative deficits as a range for normalizing the degree of saturation. According defines a linear proportionality between the likelihood of flooding and the normalized degree of saturation, where the deficit is negative. The resulting is shown in Figura 11. Note the water accumulation trend in points subject to both local distribution, to the east, and non-local to West.

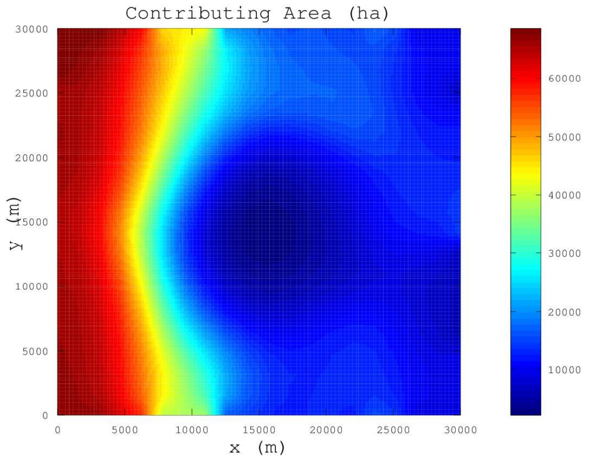


Figura 3 - Uphill area contributing to the catchment of any grid point, in units of (ha), for the test topography.

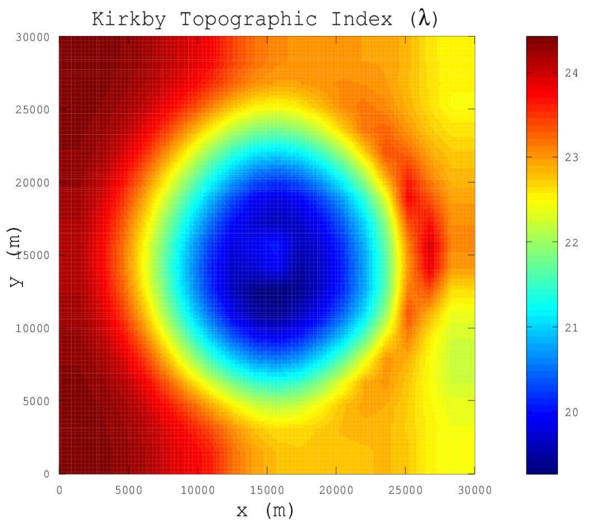


Figura 4 - Topographic index for the test topography.

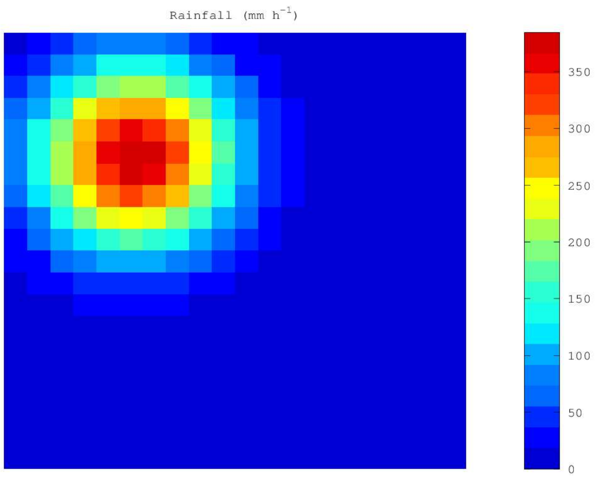


Figura 5 - Simulated rainfall distribution at 3-hr of simulation time. The rainfall distribution pattern was moving at uniform speed of 10 (m s-1) from NW to SE.

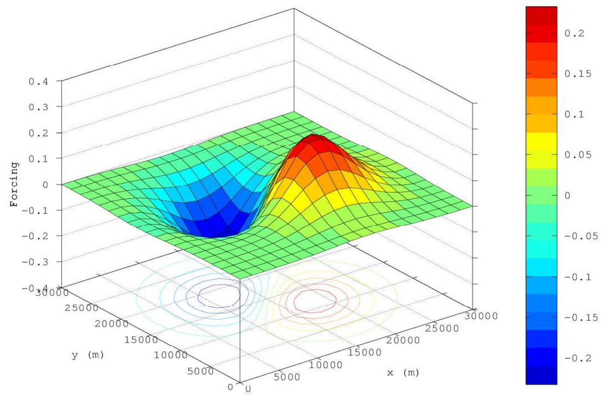


Figura 6 - Local rainfall forcing at 6-hr of simulation time.

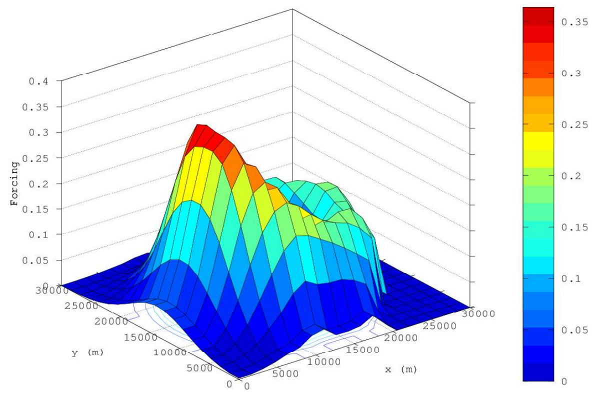


Figura 7 - Non-local rainfall forcing at 6-hr of simulation time

Some uncertainties in the distribution of the initial forcing and model parameters can be assessed by comparison with the observation of the areas actually flooded during operational nowcasting. Additionally, deconvolution of the initial conditions can be used for targeting of wetland areas.

### 3.2 Application to realistic topography (Tijuca outcropping)

The method will be applied to evaluate the temporal evolution of the landslide risk potential in the Metropolitan Region of Rio de Janeiro, whose complex topography is shown in Figure 12, where the topography of the Tijuca outcrop stands out.

Initially, the potential will be evaluated considering the maximum value of precipitation observed in the area. This assessment will consider observations of rainfall by a network 32 rainfall stations.

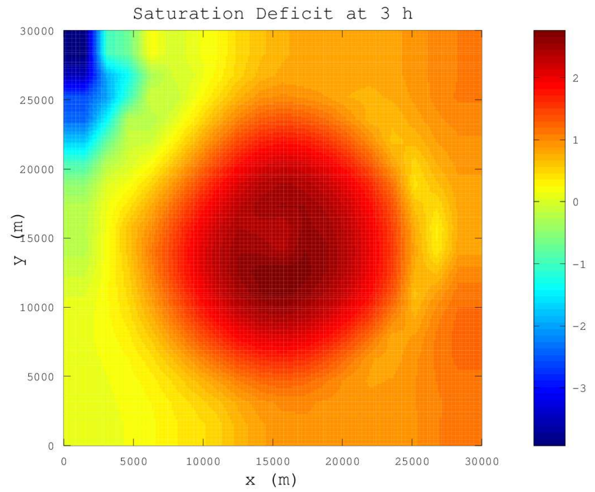


Figura 8 - Soil saturation deficit at 3-hr of simulation time, for mixed forcing.

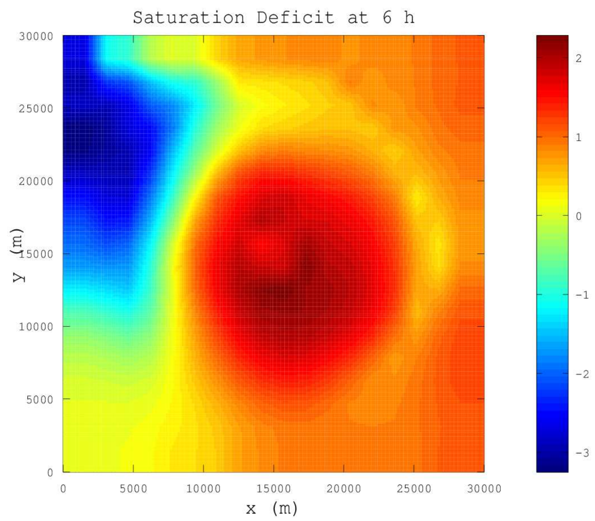


Figura 9 - Soil saturation deficit at 6-hr of simulation time, for mixed forcing.

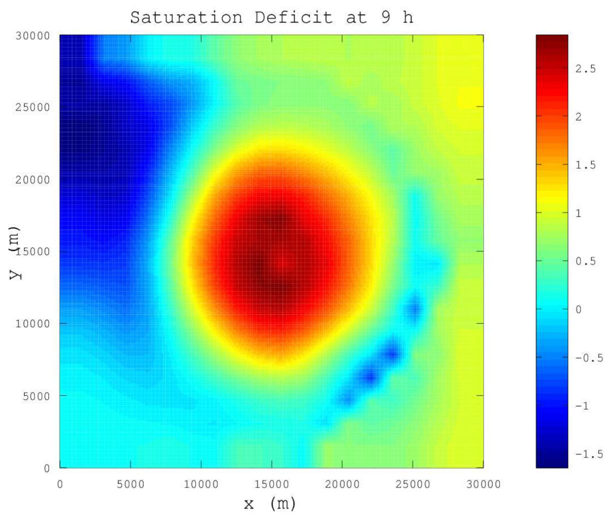


Figura 10 - Soil saturation deficit at 9-hr of simulation time, for mixed forcing.

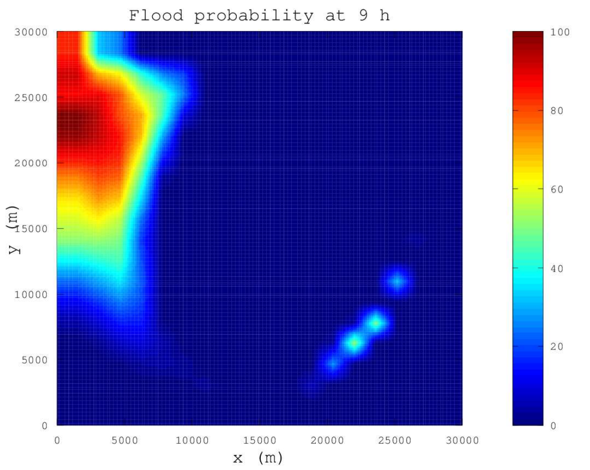


Figura 11 - Flood probability at 9 h of simulation time, based linearly on the water soil excess, for mixed forcing simulation.

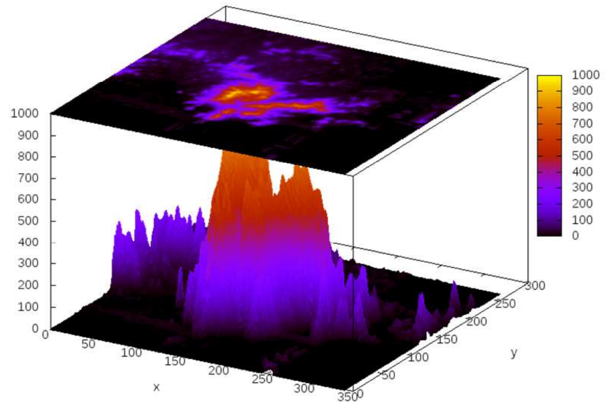


Figura 12 - Tijuca outcropping topography and neighborhoods in the city of Rio de Janeiro-RJ, Brazil. The horizontal coordinates are given in 100-meter units, and the vertical in meters. Data source: CGIAR-CSI SRTM 90m Database (JARVIS *et al.*, 2008).

A clustering analysis will allow to evaluate the occurrence of homogeneous groups from a statistical point of view. A priori, two or three groups are considered, one of plains and the other associated to sloping terrain of the hills, actually with features of orographic rainfall and convergence of flow. In a second moment, heterogeneities of the precipitation field will be considered, since the MARJ area is large enough to contain storm clusters and their mesoscale movement. The risk can be assessed using the potential value of risk as well as its temporal tendency at selected points of observation. A case study period will be selected, for example, the year 2010 when many scars from landslides were observed in the area. An observation operator (H) will be used to assess the value of risk on points where slips were observed. In this way, it will be possible to verify the statistical performance of the proposed method, evaluating its uncertainty for operational purposes for nowcasting.

## 4. CONCLUSIONS

This work is a contribution addressed to the setup of Quantitative Precipitation Forecasts (QPF) in high resolution need to an effective assessment of the environmental hydrometeorological risks expected to RJ State-Brazil. The main conclusions obtained here are: 1) A set of asymptotic trajectories was determined uniquely based on the assumption of similarity on a complex terrain; 2) Local and non-local forcing were considered in a variational optimization of the topographic index under constraint of null total derivate of the forcing and ; 3) Alternatively, a bijection application between successive times can figure out a series of coherent hydrological distributions, relaxing the initial homogeneity assumption on atmospheric forcing.

Preliminary results obtained in a test schedule indicates the possibility of using the proposed method in hydrometeorological prediction centers. The next steps for the development of this work is to carry out a series of case studies employing rainfall as observed by a mesoscale rain gage network kept by Rio de Janeiro municipality.

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