Evaluation of the impact of rainfall on soil moisture variability

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The impact of rainfall on the spatial-temporal soil moisture variability is investigated by using a model of the soil moisture dynamics and two rainfall models, the noise-forced diffusive precipitation model and the WGR model. The study shows that the variability of the soil moisture field is impacted during the limited time of the storm period. During the interstorm period, the variability of the soil moisture field is closely related with the soil texture, as supported by the analysis of the Washita '92 data set. As the impact of rainfall on the variability of the soil moisture field is limited to the short time period of precipitation, the role of the rainfall is simplified as a source of water to the soil moisture field without any consideration of its variability and/or organization in space. A simulation study of the soil moisture field temporal evolution also supports this result, i.e. a strong relationship between the soil moisture field and the variability of its medium. Also, larger variability of the loss field coefficient result in easier removal of moisture from the soil. © 1993 Elsevier Science Limited. All rights reserved.

Key words: soil moisture, soil moisture variability, soil porosity, rainfall, soil moisture dynamics, stochastic model.

1 INTRODUCTION

The hydrologic components of current Earth system models include the effects of moisture transport and transformation, but the representations remain unsatisfactory due to a wide variety of reasons. Well-positioned programs are available for the gathering of data on various aspects of the water cycle including clouds, humidity and precipitation; however, there is a significant limitation to modeling efforts due to the lack of clean measurements or techniques in measuring moisture in the near-surface zone of the land surface (approximately tens of cm). The characterization of water in the near-surface zone has thus far eluded earth scientists.

Recent studies, both active and passive, with a microwave radiometer have shown some promise in measuring something related to soil moisture. The L-band instrument ESTAR (Electronically Scanned Array Radiometer) is believed to be capable of delivering accurate estimates of land surface soil moisture fields of the upper few centimeters of bare soil. Le Vine et al.\textsuperscript{11} describe a passive microwave remote sensing system, HMMR (High Resolution Multifrequency Microwave Radiometer) in detail, as a part of the Earth Observation System (EOS), one of whose components is ESTAR. ESTAR, an imaging radiometer operating near 1-4 GHz, is designed to sense soil moisture on a global scale with a resolution on the order of 10 km. Some aircraft experiments suggest that land surfaces have quite different signatures in some microwave bands after precipitation. These experiments further suggest the feasibility of using sensors, with a resolution of some tens of kilometers and mounted on low-orbiting satellites, to gather data sets on a global scope. Such data sets could be invaluable in verifying Earth system models and in initializing the models for various kinds of forecasts (weather, floods, droughts, etc).

One problem regarding the near-surface phenomena is their space/time variability over a broad band of scales. The depositing and removal mechanisms are highly variable and the medium itself is very heterogeneous. This study investigates the impact of rainfall
on soil moisture field variability and contributes toward understanding the impact of the rainfall as a forcing to the soil moisture field. Two stochastic models, the noise-forced diffusive precipitation model and the WGR (Waymire, Gupta and Rodriguez-Iturbe) model are used to represent the precipitation process. A zero-dimensional model for the soil moisture dynamics by Entekhabi and Rodriguez-Iturbe is used to represent the soil moisture field. The analysis of the WASHITA '92 data is carried out to support the findings in the analytical study based on the mentioned models. A simulation study of a soil moisture field to evaluate the effect of soil median variability on soil moisture variability is also carried out.

2 REVIEW OF SOIL MOISTURE AND RAINFALL MODELS

2.1 A model for soil moisture dynamics

Entekhabi and Rodriguez-Iturbe proposed a model for soil moisture dynamics by adopting the linear reservoir concept and considering the diffusion impact on the soil moisture propagation.

Based on the linear reservoir concept, where the input is the rainfall and the output is defined as loss due to surface run-off, evapotranspiration, and deep percolation, the soil moisture variation in time follows the expression

\[
ds = \text{input} - \text{output}
\]  

This expression was modified to satisfy the concept of mass conservation in considering the relative soil moisture \( s \), which is defined as the ratio of soil moisture in the total volume of void. The input in this expression is defined as rainfall rate (a stochastic variable with the dimension of \([\text{L/T}]\)) and the output is the soil moisture volumetric rate which leaves the control volume. The soil moisture storage is assumed to behave like a linear reservoir.

Based on dimensional considerations, the above expression can be rewritten as

\[
nZ_t \frac{\partial s}{\partial t} = P - \eta s
\]  

where \( n \) is the soil porosity [dimensionless]; \( Z_t \) is the depth of the soil top layer \([\text{L}]\); \( \eta \) is defined as the loss coefficient with dimension of \([\text{L/T}]\); and \( P \) is the rain rate \([\text{L/T}]\). The variation in \( s \), caused continuously in time and space by \( P \), is assumed to be spread out in space by a diffusion process

\[
\frac{\partial s}{\partial t} = \kappa \nabla^2 s
\]  

The diffusion coefficient \( \kappa \) is assumed to be independent of space with the dimension of \([\text{L}^2/\text{T}]\).

The above two equations constitute the components of the intrinsic dynamics of soil moisture driven by the stochastic rainfall process. Thus, it is assumed that the soil moisture field obeys the linear stochastic partial differential equation

\[
nZ_t \frac{\partial s}{\partial t} = -\nabla s + nZ_t (\kappa \nabla^2 s) + P
\]  

This equation, introduced by Entekhabi and Rodriguez-Iturbe, represents the dynamics of the soil moisture field. They also analyzed their model based on Fourier analysis and derived the relationship between the soil moisture spectrum, the noise-forcing spectrum, and the rainfall spectrum.

\[
\Phi_s(\nu, f) = G(\nu, f)\Phi_p(\nu, f)
\]  

where \( \Phi_s \) is the soil moisture spectrum, \( \Phi_p \) is the rainfall spectrum, and \( G(\nu, f) \) is the Gain Function of wave number \( \nu \) and frequency \( f \), which is

\[
G(\nu, f) = \frac{\left(\frac{1}{nZ_t}\right)^2}{\left(4\pi^2 \kappa^2 + \frac{\eta}{nZ_t}\right) + 4\pi^2 f^2}
\]  

where \( \nu^2 = \nu_x^2 + \nu_y^2 \). Figure 1 shows the shapes of the frequency and the wave number spectra of rainfall (based on the noise-forced diffusive precipitation model mentioned below), the shape of the gain function, and the soil moisture frequency and wave number spectra.

Entekhabi and Rodriguez-Iturbe concentrated on the changes in the statistical structure of the precipitation and soil moisture variables due to changes in the time-averaging period and length scales. For the parameters used in their work, the major impact of structured rainfall on soil moisture was found in the mesoscale range (1–10 km); beyond that aggregation level, it was assumed to be white noise. They also tried various parameters to see the change of the gain function and concluded that the gain function converges asymptotically.

2.2 Rainfall field models

One very simple and one very complex and realistic stochastic model of the rainfall process were used in our work as the forcing agent for soil moisture dynamics. A brief description of these two models, the noise-forced diffusive precipitation model and the WGR model, follows.

2.2.1 The noise-forced diffusive precipitation model

The noise-forced diffusive precipitation model, which is based on the diffusion equation with the noise-forcing term, has been used to represent rainfall in the context of estimation of sampling errors. The model represents a rain field \( \psi(r, t) \), generated by a stochastic process and
The space-time spectrum of the noise-forced diffusive precipitation model is given as

$$S(f, \nu) = \frac{\gamma}{4\pi^2 \nu_0^2 f^2 + (1 + 4\pi^2 \lambda_0^2 \nu^2)^2}$$  \hspace{1cm} (8)

where $\nu^2 = \nu_x^2 + \nu_y^2$ and $\gamma$ is a normalization factor such that

$$\iint S(\nu, f) \, d\nu^2 \, df = 1.0$$  \hspace{1cm} (9)

which satisfies $\rho(0,0) = 1.0$. The noise-forced diffusive precipitation model is attractive in that it follows a simple diffusion equation with a small set of parameters, but it cannot explain major physical features observed in rainfall, such as advection, in the precipitation propagation process and produces the homogeneous Gaussian field instead of the mixed lognormal distribution shown in observed precipitation fields.\(^\text{21}\) The parameters in this model can be easily estimated by comparing the model spectrum with the sample spectrum.

### 2.2.2 The WGR precipitation model

The WGR model was developed to represent mesoscale precipitation. As a conceptual model, it shows a good link between atmospheric dynamics and a statistical description of mesoscale precipitation.

The WGR model incorporates many observed features of rainfall at the mesoscale. As a space–time representation of the rainfall, this model is characterized by the arrival mechanism of storm events through time. It represents rainfall in a hierarchical approach with rain cells embedded in cluster potential centers, which, in turn, are embedded in rainbands. The Poisson process and the spatial Poisson process are introduced for the raingbands arrival scheme and to distribute the cluster potentials within a raingband, respectively. The occurrences of rain cells within the cluster potentials and the raingbands following are assumed to be random, independently and identically distributed in the space–time cylinder, with a common probability density function. Table 1 shows the parameters and their typical values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Order of Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_n$</td>
<td>rainband arrival rate</td>
<td>$2.2 \times 10^{-2}$ bands/hr</td>
</tr>
<tr>
<td>$\rho_t$</td>
<td>mean density of cluster potential</td>
<td>$4.0 \times 10^{-3}$ clusters/km$^2$</td>
</tr>
<tr>
<td>$E[\nu]$</td>
<td>mean number of cells per cluster</td>
<td>4.0</td>
</tr>
<tr>
<td>$\beta$</td>
<td>cellular birth rate</td>
<td>$3.5 \times 10^{-1}$ cells/hr</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>cell location parameter within a cluster potential region</td>
<td>5.4 km</td>
</tr>
<tr>
<td>$\alpha^{-1}$</td>
<td>parameter as a measure of mean cell life time</td>
<td>0.75 hr</td>
</tr>
<tr>
<td>$2\pi D^2$</td>
<td>spatial extent of cell intensity</td>
<td>30.0 km$^2$</td>
</tr>
<tr>
<td>$i_0$</td>
<td>rain cell intensity at cell center at the time of birth</td>
<td>60.0 mm/hr</td>
</tr>
<tr>
<td>$</td>
<td>U_b</td>
<td>$</td>
</tr>
<tr>
<td>$</td>
<td>U_c</td>
<td>$</td>
</tr>
</tbody>
</table>
Gupta and Waymire\textsuperscript{6} rewrote the representation of the ground-level rainfall intensity given by Waymire \textit{et al.}\textsuperscript{21} as follows

$$\psi(t, x) = \int_{-\infty}^{t} g_1(t-s)Z_x(s, x - v(t-s)) \, ds$$

(10)

where \(v\) is a uniform and steady drift velocity vector and \(Z(t, x)\) is given by

$$Z(t, x) = \int_{\mathbb{R}^3} g_2(x-y)X(t, y) \, dy$$

(11)

Waymire \textit{et al.}\textsuperscript{21} assumed \(g_1\) and \(g_2\) to be deterministic and of the form

$$g_1(t) = \begin{cases} \exp[-\alpha t], & t \geq 0 \\ 0, & t < 0 \end{cases}$$

(12)

$$g_2(r) = \begin{cases} \exp\left[-\frac{r^2}{2D^2}\right], & t \geq 0 \\ 0, & t < 0 \end{cases}$$

(13)

where \(\alpha^{-1}\) is a quantitative measure of the mean cell lifetime and \(D^2\) represents the spatial extent of a rain cell. The two-stage point cluster field \(X(t, y)\), a random field, governs the instantaneous generation of rain cells in time and space, and the kernel \(g_2(r)\) distributes the rainfall intensity in space around each cell. The kernel \(g_1(t)\) represents the temporal evolution of the life cycle of a rain cell.

The analytical form of the frequency-wave number spectrum of the WGR model was derived by Valdés \textit{et al.}\textsuperscript{20} This spectrum depends on all nine parameters of the reduced version of the model\textsuperscript{20} and has the following analytical form

$$S(f, \nu_x, \nu_y) = \theta_1 \frac{\alpha F(D, 0)}{\alpha^2 + \Theta^2} + \theta_2 \frac{2\alpha \beta (\beta^2 - \alpha^2)}{(\alpha^2 + 4\pi^2 \sigma^2) (\beta^2 + 4\pi^2 \sigma^2)} \delta(\nu_x) \delta(\nu_y) + \theta_3 \frac{\alpha \beta (\beta^2 - \alpha^2)}{(\alpha^2 + \Theta^2) (\beta^2 + \Theta^2)} \frac{F(D, \sigma)}{4\pi(D^2 + \sigma^2)}$$

(14)

where

$$F(D, \sigma) = 8\pi(D^2 + \sigma^2) \exp\left[-4\pi^2(D^2 + \sigma^2)(\nu_x^2 + \nu_y^2)\right]$$

$$\Theta = 2\pi(\nu_x u_x + \nu_y u_y + f)$$

$$\theta_1 = \frac{\lambda_m E[\nu] \rho_1 \pi D^2 \lambda^2}{2\alpha}$$

$$\theta_2 = \frac{2\lambda_m \beta E[\nu^3] \rho_1 \pi^2 D^4 \lambda^2}{\alpha(\beta^2 - \alpha^2)}$$

$$\theta_3 = \frac{2\lambda_m \beta E[\nu(\nu - 1)] \rho_1 \pi^2 D^4 \lambda^2}{\alpha(\beta^2 - \alpha^2)}$$

and where \(\delta(x)\) is the Dirac delta function, \(\nu_x\) and \(\nu_y\) are the spatial wave numbers, and \(f\) is the temporal frequency.

The parameters of the WGR model conceptually represent the physical features in mesoscale precipitation and can represent spatially-elongated precipitation fields, an observed characteristic of rainfall fields. This conceptual model also shows realistic stochastic representation of rainfall features in space and time, but has a complex framework which requires the estimation of many parameters. Islam \textit{et al.}\textsuperscript{7} Valdés \textit{et al.}\textsuperscript{20} and Koepsell and Valdés\textsuperscript{10} estimated the parameters for different fields through non-linear optimization techniques which minimized the sum of the square errors. Because of the large number of parameters and the large non-linearities, estimation has been a difficult task.

3 IMPACT OF RAINFALL VARIABILITY ON THE SOIL MOISTURE SPECTRUM

3.1 Analytical approach

The impact of rainfall on the soil moisture variability was first evaluated analytically by using the noise-forced diffusive precipitation model mentioned in the previous section. The rainfall model parameters used in this study were estimated by Graves \textit{et al.}\textsuperscript{3} tuned to the PRE-STORM (Preliminary Regional Experiment for STORM-Central), and the nominal values of the soil moisture model parameters were provided by Entekhabi and Rodríguez-Iturbe\textsuperscript{4} The WGR model parameters which were tuned to the PRE-STORM data are provided in Table 2.

To explicitly evaluate the impact of precipitation variability on the soil moisture field, the model by Entekhabi and Rodríguez-Iturbe\textsuperscript{4} is refined as follows

$$\tau_s \frac{\partial S(x, t)}{\partial t} - \lambda_s^2 \nabla^2 S(x, t) + S(x, t) = R(x, t)$$

(15)

where

$$R = \frac{P}{\eta}$$

(16)

$$\tau_s = \frac{n Z_i}{\eta}$$

(17)

$$\lambda_s = \sqrt{\frac{k n Z_i}{\eta}}$$

(18)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\lambda_m) (bands/hr)</td>
<td>0.01379</td>
</tr>
<tr>
<td>(\rho_1) (clusters/km(^2))</td>
<td>0.0015</td>
</tr>
<tr>
<td>(i_0) (mm/hr)</td>
<td>146.9</td>
</tr>
<tr>
<td>(\sigma) (km)</td>
<td>3.5</td>
</tr>
<tr>
<td>(\beta) (cells/hr)</td>
<td>0.209</td>
</tr>
<tr>
<td>(E[\nu])</td>
<td>3.963</td>
</tr>
<tr>
<td>(u) (km/hr)</td>
<td>25</td>
</tr>
<tr>
<td>(\alpha) (1/hr)</td>
<td>0.875</td>
</tr>
<tr>
<td>(D) (km)</td>
<td>2.0</td>
</tr>
</tbody>
</table>
and the new parameter, $\tau_s$, is calculated to be about 1300 hours and $\lambda_s$ has values ranging from meters to tens of kilometers. These values were estimated using the parameter values ($n = 0.15$, $Z_r = 1.0$ m, $\eta = 1.0$ m/year and $\kappa = 10^{-7} - 10^{-5}$ m$^2$/hr) provided by Entekhabi and Rodriguez-Iturbe. The wide range of the parameter $\lambda_s$ is mainly due to the wide variability of the diffusion coefficient $\kappa$, which depends on the water propagation velocity. The water propagation during the storm period is dominated by the surface water flow, but is also the result of diffusing water through the soil texture during the interstorm period. Thus the parameter $\lambda_s$ of the soil moisture field during the storm period has a much higher value than during the interstorm period.

It is also interesting to link the two parameters $\tau_s$ and $\lambda_s$ to the time scale and the length scale of the soil moisture field. By comparing these to the counterparts of the rainfall (about 12 hours and 40 km for the GATE Phase I), it is seen that the impact of rainfall on soil moisture is limited only to space. This is determined by investigating the soil moisture spectrum and the rainfall of the noise-forced diffusive precipitation model, which are

$$\Phi_{ss}(f) = \frac{\alpha'}{[4\pi^2\tau_s^2 f^2 + (1 + 4\pi^2\lambda_s^2 v^2)^2]} \times \frac{\alpha'}{[4\pi^2\lambda_0^2 f^2 + (1 + 4\pi^2\lambda_0^2 v^2)^2]} \tag{19}$$

where $\alpha' = \alpha/\eta$. At the beginning of the storm until the beginning of the surface flow ($\lambda_0 \gg \lambda_s \approx 0$), the wave number spectrum can be simplified as

$$\Phi_{ss}(v) \approx \frac{\alpha'}{1 + 8\pi^2\lambda_0^2 v^2 + 16\pi^4\lambda_0^4 v^4} \tag{20}$$

but the spectrum is changed as surface flow occurs ($\lambda_0 > \lambda_s \gg 0$)

$$\Phi_{ss}(v) = \frac{\alpha'}{(1 + 4\pi^2\lambda_0^2 v^2)^2 (1 + 4\pi^2\lambda_0^2 v^2)^2} = \frac{\alpha'}{1 + 8\pi^2(\lambda_0^2 + \lambda_s^2) v^2 + 16\pi^4(\lambda_0^4 + \lambda_s^4) v^4 + \cdots} \tag{21}$$

The effect of the rainfall decreases rapidly after the storm stops, especially when there is no more surface water flow. The soil moisture field then recovers its organization, and the spectrum becomes

$$\Phi_{ss}(v) \approx \frac{\alpha'}{1 + 8\pi^2\lambda_0^2 v^2 + 16\pi^4\lambda_0^4 v^4} \tag{22}$$

The frequency spectrum (when $v = 0$), which is negligibly affected by the rainfall ($\tau_s \gg \tau_0 \gg 0$), can be simplified as

$$\Phi_{ss}(f) = \frac{\alpha'}{1 + 4\pi^2(\lambda_0^2 + \tau_s^2) f^2 + 16\pi^4\lambda_0^2 \tau_s^2 f^4} \approx \frac{\alpha'}{1 + 4\pi^2\tau_s^2 f^2 + 16\pi^4\lambda_0^2 \tau_s^2 f^4} \tag{23}$$

Figures 2 and 3 clearly show the difference in the frequency and the wave number spectra during the storm and the interstorm period.

In summarizing the analysis, it may be concluded that the spatial variability of the soil moisture field is strongly affected by the rainfall, especially during the storm period. The soil moisture field recovers its organization, however, after widespread surface runoff diffusion during the interstorm period. The authors were unable to ascertain the duration of rainfall impact on the variability of the soil moisture field due to factors such as the duration and amount of rainfall, soil property, vegetation, weather conditions, etc. In the case of rainfall of relatively short duration, however, it is assumed as a source of water without any consideration.
used in this study is derived from the Washita '92 Data Sets (Jackson,\textsuperscript{8} version 12/20/93). Besides the ESTAR passive microwave data and the soil moisture data, it provides information on soil texture and land use that will be relevant for further research. All the image files are 228 pixels by 93 lines, covering an area of 45.6 km × 18.6 km (846 square km) with a grid of 200 × 200 m pixels.

The soil moisture data files\textsuperscript{8} provide the volumetric soil moisture (percentage of soil moisture in the total volume of soil) estimated mainly on the top of 5 cm of soil. The values represent the area averages over pixels of 200 m × 200 m with an image for each day of the experiment. The volumetric soil moisture data are converted into relative soil moisture data by dividing by the porosity of the characteristic soil of the pixel, which is also provided.

\subsection{Analysis of the correlation function}
The mean values of the relative soil moisture data decrease steadily from 53.48\% (10 June) to 28.37\% (18 June). Table 3 shows the change of the mean and standard deviations of relative soil moisture over the area.

The correlation structure of the data is estimated assuming stationarity in the field. Figure 4 shows the correlation functions of the 10 June, 12 June, 14 June, 16 June, and 18 June data in longitudinal and latitudinal observation directions. To eliminate the impact of the missing values and to estimate the correlation function, a normalization approach similar to Polvak and North\textsuperscript{16} is used. That is, each data set is normalized by dividing by the standard deviation after subtracting the mean. Correlation length is estimated in both the longitudinal and the latitudinal direction for each soil moisture data set and the soil porosity field (see Table 3). Although the correlation functions in the latitudinal direction seem to have quite long memory, the correlation length is estimated under the assumption of decay similar to the longitudinal direction. The rough estimation of the correlation length, as seen in Fig. 4, shows no considerable change in time. Rather, a noticeable result is

\begin{table}[h]
\centering
\caption{Mean, standard deviation (STDV), and correlation length (CL) of the Washita '92 soil moisture field and soil porosity field data}
\begin{tabular}{|c|c|c|c|c|}
\hline
Data & Mean  
(\%) & STDV  
(\%) & CL (Long.)  
(m) & CL (Lat.)  
(m) \\
\hline
10 June & 53.48 & 13.58 & 2556 & 1800 \\
11 June & 48.47 & 12.36 & 2440 & 1672 \\
12 June & 47.45 & 11.69 & 2612 & 1958 \\
13 June & 43.26 & 10.99 & 2330 & 2190 \\
14 June & 46.94 & 11.20 & 2490 & 1996 \\
15 June & --- & --- & --- & --- \\
16 June & 40.35 & 10.60 & 2648 & 1862 \\
17 June & 35.49 & 10.33 & 2992 & 1696 \\
18 June & 28.37 & 10.15 & 2024 & 1552 \\
Porosity & 0.4425 & 0.033 & 2418 & 1550 \\
\hline
\end{tabular}
\end{table}
found in the comparison of the correlation functions of the relative soil moisture field and the soil porosity field. These correlation functions are almost identical in both directions, as seen in Figs 4 and 5. This shows the possible link of the soil moisture field variability to its medium (soil porosity field in this study). This result is also supported by Rodriguez-Iturbe et al. Although this research concentrates on the spatial organization of the soil moisture and soil porosity fields based on self-similarity, the main concern is the possible link between soil moisture and its medium.

4 IMPACT OF THE VARIABILITY OF THE LOSS COEFFICIENT FIELD ON THE SOIL MOISTURE FIELD EVOLUTION

4.1 Spatial variability of the loss coefficient

The loss coefficient in the model by Entekhabi and Rodriguez-Iturbe represents various processes of run-off, evapotranspiration, percolation, etc. There are a significant number of studies in the literature on the individual component of the loss coefficient field, particularly on the evapotranspiration rate, which is dependent on various climate conditions. These are very limited, however, and focus mainly on the vertical processes. A large portion of recent research on the spatial organization of soil properties, land cover, and soil moisture uses the fractal theory, whose result can be effectively used although it provides very limited information.

In summarizing several research results, it may be concluded that the standard deviations of bulk density, soil porosity and water content are about 15% of their means, while assuming that topography, relief, aspect and vegetation cover provide a minor impact to the variability of the soil moisture field, (normally distributed with a standard deviation less than 15% of the mean). It is interesting to note that the standard deviation of the hydraulic conductivity is greater than 100% of the mean, which is used to quantify the
variability of the diffusion coefficient field during the interstorm period.

The loss coefficient field is assumed constant in several papers (e.g. Entekhabi and Rodriguez-Iturbe), but it seems worthwhile to investigate and characterize the loss coefficient field before following their assumption. It is assumed that the variability of the soil moisture field is very closely related with its medium variability rather than the precipitation field. This study also provides an approach towards attempting to link the soil field characteristics to the soil moisture field. The different mechanisms of soil moisture loss during interstorm and storm periods must first be considered. Evapotranspiration plays a major role in the removal during the interstorm period, as does run-off during the storm period. The loss rate during the storm must be much higher to remove the surface water quickly. The diffusion coefficient also varies greatly depending on surface flow, so its field should be modeled like the loss coefficient field. Entekhabi and Rodriguez-Iturbe also analyzed the diffusion coefficient separately for the storm and interstorm periods. During the interstorm period, the diffusion velocity of the soil water is governed by the hydraulic conductivity (so the diffusion coefficient is very small), but is governed during the storm period by the surface water flow with extremely high values of the diffusion coefficient. The diffusion coefficient field also varies depending on these situations. It is anticipated that the variability of the interstorm period will be higher than that of the storm period due to the high variability of the hydraulic conductivity field.

4.2 Impact of the loss coefficient field variability on the soil moisture field evolution

A simulation study is carried out to ascertain whether the parameters incorporated into the model effectively represent most of the medium properties, thereby saving considerable effort in dealing with complex models and their corresponding parameter characterization. More detailed consideration of parameter fields must be incorporated. If these are insufficient, this parameter sensitivity study will also help in understanding the impact of the medium heterogeneity on the soil moisture.

![Fig. 5. Correlation function of the porosity field in Washita '92 data.](image)

![Fig. 6. Sample loss coefficient field (STDV/Mean = 5% (top) and 1% (bottom)).](image)
First, the impact of the variability of the loss coefficient field is evaluated, setting up the constant diffusion field and the initial condition, and varying the variance of the loss coefficient field (Fig. 6). Although simulations are relatively simple, our result is very challenging. Figure 7 shows where a small variability of the loss coefficient field (less than 10% of the mean) led to a dramatic change of the soil moisture field organization, as well as its time evolution. This shows the importance of the soil moisture medium in studying the soil moisture field. As the variability of the soil moisture field appears mainly to be controlled by its medium characteristics, future studies of soil moisture should be performed along with its medium characterization. If the soil moisture field variability is quantified in relation to its medium variability, it will be very helpful in constructing a plan for the soil moisture field observation where the variability of the field plays an important role. Vegetation and its related evapotranspiration obviously are very important, but are not analyzed in this study.

5 CONCLUDING REMARKS

In this study, the impact of the rainfall on the variability of the soil moisture field is evaluated. The analytical study, using the model for the soil moisture dynamics developed by Entekhabi and Rodriguez-Iturbe and two rainfall models, shows the limited impact of the rainfall in time and space. That is, the impact of rainfall during the storm period is quite widespread, but decreases as the rain stops. It is also related to the correlation length change of the soil moisture field, which is dominated by the water-diffusing mechanism, surface run-off during the storm period, or diffusion through the medium during the interstorm period. It is also observed that the correlation time of the rainfall is much smaller than that of the soil moisture field. This obviously limits the impact of the rainfall on the soil moisture field variability.

This result directly indicates the importance of the soil texture, rather than rainfall, in quantifying the variability of the soil moisture field. After the storm ends, the variability of the loss field (surface run-off, deep percolation, evapotranspiration, etc.) diminishes the impact of the rainfall and recovers the organization of the soil moisture field. The Washita '92 data analysis shows the close link between the soil moisture and the soil porosity fields, which have almost identical correlation structures. The simulation study also supports this conclusion. Although the simulation is relatively simplified, the results obtained are sufficient to support the importance of the relationship between the soil moisture

![Fig. 7. Simulation results: the volumetric soil moisture field with different loss coefficient variability conditions after 150 days of evolution.](image-url)
field and its medium variabilities. The effect of the loss field variability on the soil moisture evolution is also seen, which is that more variability of the loss field causes easier removal of the soil moisture from its medium.

To fully prove the findings in this study, further data analysis is required. Although the Washita '92 data analysis shows the possible link of the soil moisture field to the soil, the effect of the rainfall on the soil moisture field is not seen. Future data analysis should concentrate, therefore, on the correlation change before and after a storm event, which would be very helpful for scheduling the sampling time. Also, discovery of a possible link between the soil moisture field and its medium would be beneficial for further investigations, especially for constructing an effective and economical sampling network.

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