# An analytical method for predicting surface soil moisture from rainfall observations

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[1] A simple analytical method for estimating surface soil moisture directly from rainfall data is proposed and studied. Soil moisture dynamics are represented by a linear stochastic partial differential equation [*Entekhabi and Rodriguez-Iturbe*, 1994]. A diagnostic equation is derived from the soil moisture dynamics equation by eliminating the diffusion term. The derived daily soil moisture function is a time-weighted average of previous cumulative rainfall over a given period (e.g., >14 days). The advantage of this method is that information on the initial condition of soil moisture, which is often not available at all times and locations, is not needed. The loss coefficient in the diagnostic equation for soil moisture can be estimated from land surface characteristics and soil properties. The method for determining the averaging window size, the loss coefficient, and the infiltration coefficient are described and demonstrated. The soil moisture data observed during three field experiments, i.e., Monsoon'90, Washita'92, and SGP'97, are compared to the calculated soil moisture. The results indicate that the proposed method is robust and has the potential for useful soil moisture predictions. *INDEX TERMS:* 1655 Global Change: Water cycles (1836); 1704 History of Geophysics: Atmospheric sciences; 1719 History of Geophysics: Hydrology; 1866 Hydrology: Soil moisture; 1854 Hydrology: Precipitation (3354); 1818 Hydrology: Evapotranspiration; *KEYWORDS:* soil moisture, precipitation, Antecedent Precipitation Index (API), loss coefficient

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## 1. Introduction

[2] Soil moisture is often defined as the water content in the upper several meters of soil that is available for plant growth. It affects land surface-atmosphere interactions by influencing the partition of incoming radiation into sensible and latent heat fluxes, and the separation of precipitation into infiltration and surface runoff. Understanding of the spatial and temporal patterns of soil moisture is critical for many applications and for answering various science questions [e.g., *Hornberger et al.*, 2001; *Houser*, 1996]. The important roles of soil moisture in Earth system dynamics include: (1) atmospheric dynamics, where soil moisture can influence large-scale atmosphere circulation [*Dastoor and Krishnamurti*, 1991; *Delworth and Manabe*, 1993; *Castelli and Rodriguez-Iturbe*, 1995; *Koster et al.*, 2000; *Ducharne et al.*, 2000; *Hong and Pan*, 2000]; mesoscale dynamics [e.g., *McCumber and Pielke*, 1981; *Ookouchi et al.*, 1984; *Mahfouf et al.*, 1987; *Lynn et al.*, 1995]; and boundary layer development [e.g., *Zhang and Anthes*, 1982; *Betts et al.*,1993; *Lynn et al.*, 1995; *Quinn et al.*, 1995]; (2) water resource availability, where soil moisture is an important variable for water resource management, reservoir design and operation [*Mehrotra*, 1999], drought assessment, flood forecasting [e.g., *Viterbo and Betts*, 1999], hydrologic processes and water-balance studies; (3) agriculture, where crop production, irrigation, pest detection and control are all related to soil moisture information [e.g., *Dinar et al.*, 1986]; (4) forestry, where soil moisture is important for forest yield estimation, harvest management and forest fire prediction; (5) civil engineering, where soil moisture is useful in hazardous assessments in construction; (6) ecosystem dynamics, where soil moisture states influence biogeochemical cycles [e.g., *Weitz et al.*, 1999; *Lindberg et al.*, 1999]; and (7) soil science, where soil moisture plays an important role in erosion, mass movement, and land slides [e.g., *Govers*, 1991; *Fecan et al.*, 1999].

[3] Although soil moisture data have many applications, the observations of soil moisture are often sparse. Unlike soil moisture, precipitation is measured routinely at weather stations. Besides the routine point measurements, satellite (e.g., TRMM) and ground radar systems (e.g., NEXRAD) are utilized for measuring rainfall over large areas at long period and at high sampling frequency. Since precipitation is the primary force controlling the state and evolution of soil moisture [*Entekhabi and Rodriguez-Iturbe*, 1994], we want to develop a new, relatively simple method for estimating surface soil moisture over large areas and long periods, that can be applied with readily available atmospheric forcing data including rainfall, land cover, and soil characteristics.


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[4] Several attempts have been made to link precipitation to soil moisture using Antecedent Precipitation Index (API) [e.g., *Saxton and Lenz*, 1967; *Blanchard et al.*, 1981; *Choudhury and Blanchard*, 1983; *Wetzel and Chang*, 1988; *Shaw et al.*, 1997]. However, *Saxton and Lenz* [1967] indicated that accuracy in selecting the initial API is critical for successful estimation of subsequent values. Therefore the beginning date for computing API was often chosen a few days after a heavy rain, because the initial condition of API or soil moisture is easy to define, i.e., near field capacity [*Saxton and Lenz*, 1967]. Although the effect of the initial condition decays with time, the dependence on the initial condition is a serious limitation to the API method. Finally, the API method can only be applied when soil moisture is less than field capacity [*Saxton and Lenz*, 1967].

[5] *Farago* [1985] derived a stochastic model for the estimation of soil moisture distribution based on daily rainfall and an initial value of the soil moisture. However, similar to the API method, the requirement of initial information on soil moisture condition makes Farago's method less generally applicable. *Capehart and Carlson* [1994], along with many others, have used observed precipitation and surface radiation to derive soil moisture based on soil hydrology models; however, this approach requires initial and boundary conditions, specification of radiative, thermal and hydraulic parameters, as well as significant computational resources.

[6] *Findell and Eltahir* [1997] found that the correlation of soil moisture with the moving average (with a 21-day window size) of rainfall actually is less than that of soil moisture with the subsequent precipitation. Their results imply that we could predict rainfall from soil moisture, rather than predict soil moisture from rainfall. *Entekhabi and Rodriguez-Iturbe* [1994] (hereinafter referred to as ER94) proposed a stochastic partial differential equation to represent soil moisture dynamics. This equation was utilized only to study the characteristics of the space-time variability of soil moisture in frequency and wavelength domain, rather than to derive soil moisture directly from rainfall. *Yoo et al.* [1998] used the same equation to study the impact of rainfall on soil moisture variability. Their study showed that rainfall is less important than soil texture in controlling the variability of the soil moisture field, because surface runoff, drainage, and evapotranspiration reduce the impact of rainfall and make the soil moisture field similar to soil texture field after the storm ends.

## 5. Conclusions

[33] A simple analytical method for estimating soil moisture directly from rainfall data is proposed and studied. A diagnostic soil moisture equation is derived from the linear stochastic partial differential equation, first proposed by *Entekhabi and Rodriguez-Iturbe* [1994], by dropping the diffusion term. The derived soil moisture is a function of the time-weighted average of previous cumulative rainfall over a period (e.g., >14 days), rather than a moving average of previous cumulative rainfall. Although the concept behind this method is similar to the API method [*Saxton and Lenz*, 1967], this method is directly derived from soil moisture dynamic equation. On the other hand, it overcomes three weaknesses involved in the API method: (1) no initial condition of soil moisture is needed, because as the window size increases, the contribution of the associated cumulative rainfall to the current soil moisture decays due to dry-down processes (i.e., evapotranspiration and percolation); (2) it can be applied to the whole dynamic range of soil moisture, because an exponential relationship between the time-weighted of the ratio of rainfall to the loss coefficient (i.e., *B*) and soil moisture is introduced, i.e., as *B* reaches a threshold, soil becomes saturated; and (3) it can predict soil moisture at any time.

[34] The method for estimating a loss coefficient is critical for this method. In this study, we have shown that the loss coefficient can be determined from land surface and soil characteristics. Through comparisons of observed and estimated soil moisture during three field experiments, it is shown that the proposed method is simple and able to capture some spatial and temporal structures of soil moisture fields. The errors in the estimated soil moisture are partially due to neglecting spatial and temporal variation of atmospheric conditions and solar radiation when we compute the loss coefficient. More research on the loss coefficient is needed for eventually developing a loss coefficient function that depends on soil, vegetation, and atmospheric conditions.

[35] As we discussed in section 4.4, using only one relationship between B and soil moisture could produce a large error in the estimated soil moisture, especially during wet periods. Therefore, before we apply this simple method to any location, further effort is needed to develop a family of *B* versus soil moisture functions that depend on soil hydraulic properties. On the other hand, without considering capillary rise, we could underestimate soil moisture especially where the water table is close to surface, because when *B* is equal to zero, soil moisture is also zero according to equation (14). It seems that capillary rise does not contribute much to surface soil moisture in our study areas. One possible reason is that water table is deep. Preliminary results from analyzing ground-measured soil moisture data taken at Soil Climate Analysis Network (SCAN) sites (http://www.wcc.nrcs.usda.gov/scan) managed by Natural Resources Conservation Service (NRCS) of United States Department of Agriculture (USDA) indicate that a general relationship between *B* and soil moisture can be given as:

$$\theta = c_1 + \theta_r + (\phi - \theta_r - c_1)\left(1 - e^{-c_2 B}\right) \tag{17}$$

where $c_1$ is the contribution to the surface soil moisture due to capillary rise, $\theta_r$ is residual soil moisture content, $\phi$ is saturated soil moisture content, and $c_2$ is a parameter related to soil hydraulic properties. This work will be discussed in a forthcoming paper.

[36] Although significant progress has been made in the microwave remote sensing of soil moisture [e.g., *Jackson and Schmugge*, 1989; *Engman*, 1990, 1995], the attenuation of microwave signals by dense canopies [*Ulaby and Wilson*, 1985] makes the soil moisture measurements in forest regions unreliable [*Njoku*, 1999]. Unlike remote sensing of soil moisture, vegetation covers do not produce any adverse effects on remote sensing of rainfall above canopies. With increasing global precipitation measurements (e.g., TRMM, NASA Global Precipitation Measurement (GPM) and land surface characteristic observations (e.g., AVHRR, Landsat, MODIS), this simple diagnostic method could become very useful for retrieving surface soil moisture especially over forests, from a remote sensing point of view.