SPATIAL AND TEMPORAL INFLUENCES ON SOIL MOISTURE ESTIMATION

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Abstract: The effect of diurnal cycle, intermittent visit of observation satellite, sensor installation, partial coverage of remote sensing, heterogeneity of soil properties and precipitation to the soil moisture estimation error were analyzed to present the global sampling strategy of soil moisture. Three models, the theoretical soil moisture model, WGR model proposed Waymire *et al.* (1984) to generate rainfall, and Turning Band Method to generate two dimensional soil porosity, active soil depth and loss coefficient field were used to construct sufficient two-dimensional soil moisture data based on different scenarios.

The sampling error is dominated by sampling interval and design scheme. The effect of heterogeneity of soil properties and rainfall to sampling error is smaller than that of temporal gap and spatial gap. Selecting a small sampling interval can dramatically reduce the sampling error generated by other factors such as heterogeneity of rainfall, soil properties, topography, and climatic conditions. If the annual mean of coverage portion is about 90%, the effect of partial coverage to sampling error can be disregarded. The water retention capacity of fields is very important in the sampling error. The smaller the water retention capacity of the field (small soil porosity and thin active soil depth), the greater the sampling error. These results indicate that the sampling error is very sensitive to water retention capacity. Block random installati on gets more accurate data than random installation of soil moisture gages. The Walnut Gulch soil moisture data show that the diurnal variation of soil moisture causes sampling error between 1 and 4 % in daily estimation.

Key Words: soil moisture, sampling error, partial coverage, temporal gap, spatial gap

INTRODUCTION

Soil moisture plays an important role in several ranges of hydrological processes including geomorphic processes (Beven and Kirkby, 1993), runoff and flooding processes (Kitanidis and Bras, 1980), soil moisture-rainfall feedback mechanisms (Eltahir, 1998), land-atmosphere interactions (Entekhabi et al., 1996), and linkage between the hydraulic cycle and the energy cycle through evapotranspiration (Lin *et al.* 1994). This is particularly true in the mid-latitudes and Rind (1982) concluded that, "*knowledge of the ground moisture at the beginning of the summer might allow for improved summer temperature forecasts*".

During the last decade, several experiments have been conducted to collect and analyze time series of point and spatially distributed hydrologic data, focusing on soil moisture and evaporative fluxes using both conventional and remote sensing methods. Recent advances in low- frequency microwave remote sensing may provide direct measurement of surface soil moisture under various topographic and land cover conditions within reasonable error bounds (Engman, 1990; Jackson and Le Vine, 1996). To estimate the hydrologic variables such as soil moisture or rainfall in global-scale the satellite remote sensing is essential. The sampling errors depend on the observation design and on the spatial and temporal variability of the soil moisture field itself. Therefore to design the appropriate sampling strategies, it is necessary to analyze those factors which impact soil moisture sampling. In this study, the impact of diurnal cycle, topography, soil properties, vegetation, and climatic condition on the sampling of the soil moisture field was analyzed to decide a convincing approach to the global measurement of soil moisture field.

Densely measured soil moisture data shows a definite diurnal cycle, which causes critical sampling error in daily sampling. The Walnut Gulch data were used to analyze the diurnal impact on daily sampling of the soil moisture field. Even though there are enough point measurement within the soil moisture field to analyze the diurnal impact on daily sampling of soil moisture, we do not have two-dimensional soil moisture data to analyze the spatial and temporal sampling effect. Even though the SGP '97 soil moisture data were gathered in large experimental domain for 29days, thirteen days' soil moisture data of them are not available since weather condition and calibration problem. Therefore SGP '97 soil moisture data is not suitable to analyze the spatial and temporal sampling design of soil moisture field. Three models, the theoretical soil moisture model, WGR model proposed Waymire *et al.* (1984) to generate rainfall, and Turning Band Method to generate two dimensional soil porosity, active soil depth and loss coefficient field were used to construct sufficient two-dimensional soil moisture data based on different scenarios.

2. IMPACT OF DIURNAL CYCLE ON THE MONSOON '90 SOIL MOISTURE MEASUREMENT

The Walnut Gulch experimental watershed is explained in chapter 2. More extensive information on the experimental data and watershed can be found in Schmugge *et al.* (1994). Two main experimental subwatersheds, Lucky Hills and Kendall were more intensely monitored. The Kendall study area is grass dominated and the Lucky Hills study area is covered predominantly with brush. The remotely sensed soil moisture data obtained on a daily basis does not mimic the diurnal cycle. The half-hourly measurements of soil moisture from resistance sensors were used to analyze the diurnal impact.

Ground-based measurements of soil moisture, ten at Lucky Hill, three at Kendall North, and two at Kendall South were used to analyze the diurnal impact and the effect of the temporal gap on soil moisture sampling. The data contaminated by noise were discarded for this study. The diurnal cycle on the Lucky Hills study area presented a very clear diurnal cycle. The Kendall experimental site dominated by grass did not show the apparent diurnal cycle.

Fig. 1 shows that the error of daily sampling has a cyclic pattern between 1 % and 4 %, and the error of daily sampling (remote sensing from satellite or airplane) is affected by the diurnal cycle. The daily sampling error between 5 am and 8 am is at a low of 1% while the daily sampling between 1 p.m. and 3 p.m. indicate a sampling error on the order of 4%. The impact of the temporal gap to the soil moisture sampling was also analyzed from the Walnut Gulch data.

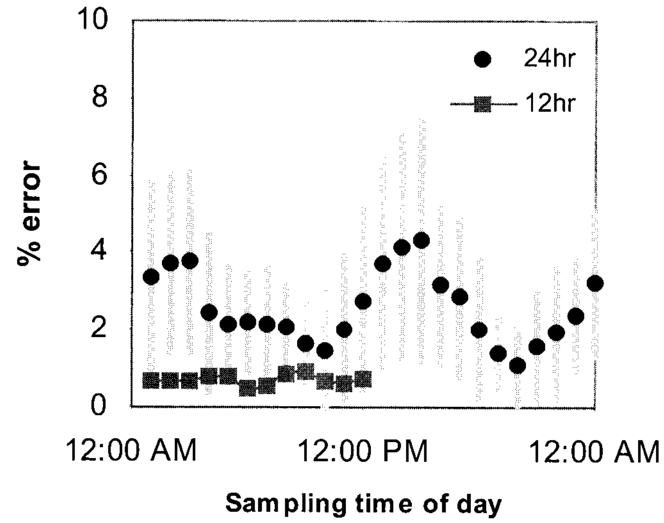


Fig. 1. The impact of diurnal cycle on daily sampling of soil moisture data (use Walnut Gulch data)

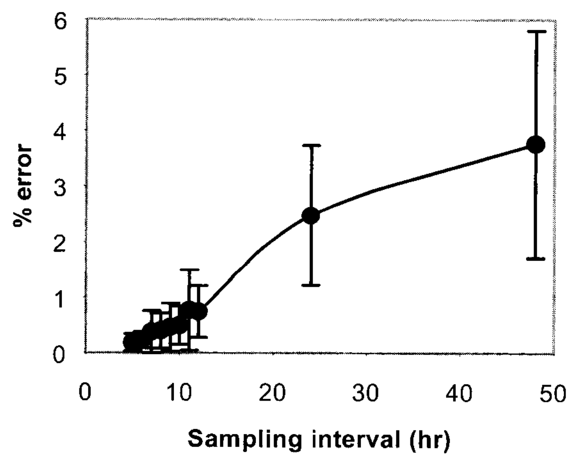


Fig. 2. The impact of temporal gap on sampling of soil moisture data (Walnut Gulch data)

Fig. 2 shows that the mean and standard deviation of sampling error increased linearly by increasing temporal gap.

3. SIMULATION STUDY

To analyze the effect of topography, soil properties, vegetation, climatic condition and partial coverage on the sampling of the soil moisture field, a substantial amount of soil moisture data sets are required for each case. There are actually insufficient data on two dimensional soil moisture to conduct a spatial and temporal sampling analysis. The lack of temporal coverage of the SGP '97 soil moisture data has limitation in analysis of the spatial-temporal sampling design of soil moisture field. We used three different models to generate sufficient two dimensional soil moisture filed with different hydrometeorological scenarios.

3.1 Model for the soil-moisture dynamics

Entekhabi and Rodríguez-Iturbe (1994) had proposed a theoretical model of soil moisture based on the linear reservoir concept, which considered the diffusion effect on soil moisture propagation in space. The model for the soil moisture field consists of three major factors. The loss term represents the temporal evolution dominated by decay process caused by various processes such as evapotranspiration, infiltration, and surface runoff. The diffusion term represents the spatial interaction of the soil moisture field through both the porous media as well as the surface water flow. The diffusion effect is significant during storm periods and is almost negligible during an inter-storm period. The movement of soil moisture by diffusion is not a process similar to that of omni-directional diffusion of pollutants in a lake. The diffusion of soil moisture during storm period is affected by the topography. Therefore direction parameter was introduced, which decide the direction of diffusion behavior from digitized elevation model (DEM) data. The direction parameter can consider the topographic effect on spatial characteristic of soil moisture behavior. The diffusion process is divided to two states 1) where the soil moisture approaches saturation 2) where surface flows directly above the already saturated soil. The direction parameter is used to handle the amount of the spatial movement of surface flow above saturated soil moisture. The Monsoon '90 data showed the clear diurnal cycle in temporal behavior of soil moisture field. Therefore, a diurnal cycle term is introduced to analyze the diurnal impact of the soil moisture field. The fourth term, rainfall forcing is a unique source of soil moisture field. This model followed the stochastic differential equation, where stochasticity was introduced by considering the random rainfall field as driving force. The equation was as follows

$$nZ_r \frac{\partial s}{\partial t} = -\eta s + nZ_r(\kappa\, d\, \nabla^2 s) + A\, s \sin(\omega t + \tau) + P \tag{1}$$

where n is the soil porosity, Z_r is the depth of the surface soil layer, η is loss coefficient, κ is diffusion coefficient, d is direction parameter, $A\ s\ \sin(\omega t+\tau)$ and P is the rainfall field as a noise forcing.

Soil moisture dynamics has the same form as the spatial evolution for crop yield (Whittle, 1962). Entekhabi and Rodríguez-Iturbe (1994) statistically analyzed the model with the assumption of constant parameters, but weather conditions, topography, vegetation and land use affect both parameters. In this research, loss coefficient, soil porosity and active soil depth fields were generated by the model parameter estimated from the SGP '97 and Washita '92 data.

Multivariate regression analysis was used to estimate the loss coefficient and diffusion coefficient. Loss coefficient, η=0.03m/day with porosity, n=0.46 was tuned from SGP '97 data. Active soil depth is used as Z_r=0.5m assumed by

Table 1. Description of the WGR model parameters and (a) the estimates of the WGR model parameter from June to August 1997 on the selected sites of the SGP '97 experimental region, (b) the estimates of the WGR model parameter over winter season on the Brazos Valley, Texas.

Parameters	Definition	Unit	Range
D	Rainfall intensity spatial attenuation parameter.	Km	1.0-5.0
σ	Cell location parameter	Km	-
u	Rain band speed relative to ground	Km/hr	30
ρ	Mean density of cluster potential	cluster/km2	0.01-0.001
v	Mean number of cells per cluster	-	2.0-8.0
β	Cellular birth rate	1/hr	0.06-6.0
α	Mean cell age	1/hr	0.6-6.0
λ	Mean rain band arrival	1/hr	0.06-0.0006

Parameter set	λ (storms/hr)	ρ (CPCs/km2)	ν (cells/CPC)	α (1/hour)	β (cells/hour)	i_o (mm/hr)	SSQ
				El Reno (SGP '97)			
(a)	0.0153	0.0055	6.50	4.90	0.7886	71.8	0.0429
				Wheelock (Texas)			
(b)	0.0078	0.0034	5.10	2.04	0.3840	60.0	0.0100

Table 1. Georeferencing information of selected porosity and DEM fields (Projection : Universal Transverse Mercator Zone 145)

	Site 1	Site 2	Site 3
Upper left corner	543600 E 3914600 N	567600 E 4017000 N	591600 E 4119400 N
Upper right corner	646000 E 3914600 N	670000 E 4017000 N	694000 E 4119400 N
Lower left cornet	543600 E 3812200 N	567600 E 3914600 N	591600 E 4017000 N
Lower right cornet	646000 E 3812200 N	670000 E 3914600 N	694000 E 4017000 N

Entekhabi and Rodríguez-Iturbe (1994). The soil moisture field behavior is dominated by precipitation forcing and decay process caused by evapotranspiration and infiltration. The regression analysis shows the spatial interaction represented by diffusion term is very small. The resented by diffusion term is very small. The estimates of the diffusion parameter κ under two different hydrologic conditions, storm period and inter-storm period are calculated by using $\kappa = (v^2 t)/4$. Typical velocity associated with the front advance is about 20cm/day. The interstorm period, t, is about 48hours. From these values, the lower bound of the parameter κ is $10^{-3}m^2/h$. The velocity of the overland flow ranges about few to tens of cm/s. Storm duration was assumed to be approximately 6hours. From these values, the upper bound of parameter κ was $10^5m^2/h$ (Entekhabi and Rodríguez-Iturbe, 1994). The diffusion coefficient, κ=0.001m^2/hour was applied for unsaturated region and κ =$10^5m^2/h$ was used to treat moisture over porosity.

3.2 Rainfall model

The WGR model (Waymire *et. al.*, 1984) was developed to represent mesoscale precipitation. As a conceptual model, this model shows a good link between atmospheric dynamics and a statistical description of mesoscale precipitation. The description of the rainfall model was described in chapter 4. The parameters of the WGR model represent the physical features in mesoscale precipitation and can also represent spatially elongated precipitation field, which is an observed characteristic of rainfall fields. This conceptual model also shows good stochastic representation of rainfall events in space and time, but has a complex framework, which requires the estimation of many parameters. The WGR model parameters were estimated from Oklahoma Mesonet data during the SGP '97 experiment. The WGR model parameters estimated over the Brazos Valley in Texas were also used to generate rainfall field (Koepsell et al., 1989). The WGR model parameters in Table 2 were used to generate the rainfall field.

3.3 Turning bands method

Generation of multidimensional random fields via the Turning Bands Method (TBM) was presented by Mantoglou and Wilson (1982). The basic concept of this method is to reduce a multidimensional simulation into the sum of a series of equivalent unidimensional simulation. The mean, m, the variance, s^2, and the spatial covariance function, $C(x_1, x_2)$, of the parameter to be generated are pre-specified in this methods and second order stationarity is assumed in this process, i.e.,

1. the mean is independent for all position of each point in space R^n

$$E[Z(x)] = m(x) = m, \quad \forall x \in R^n \tag{2}$$

where R^n is n dimensional space

2. the covariance function $C(x_1, x_2)$ is dependent on the vector difference d = $x_1 - x_2$ and not on any particular vector of each point

$$C(x_1, x_2) = C(x_1 - x_2) = C(d) \tag{3}$$

Let P is the region in which it is desired to simulate a two-or three-dimensional field, Turning Bands lines are generated at any origin, O, in R^n.

Turing Band lines are generated such that the corresponding direction unit vectors, u, are uniformly distributed on a unit circle or sphere depending on whether a two- or three- dimensional field is generated. Along each line, a second order stationary one-dimensional process is generated with zero mean and covariance function $C_1(\delta)$, where δ is the coordinate on line i. The points in region P where values are to be generated are projected orthogonally onto the line i and the corresponding values of the one dimensional discrete process are assigned. If $Z_i(\delta_{Ni})$ is the assigned value for any point N in the region P from the line process and if L lines of simulated value for point N is given by :

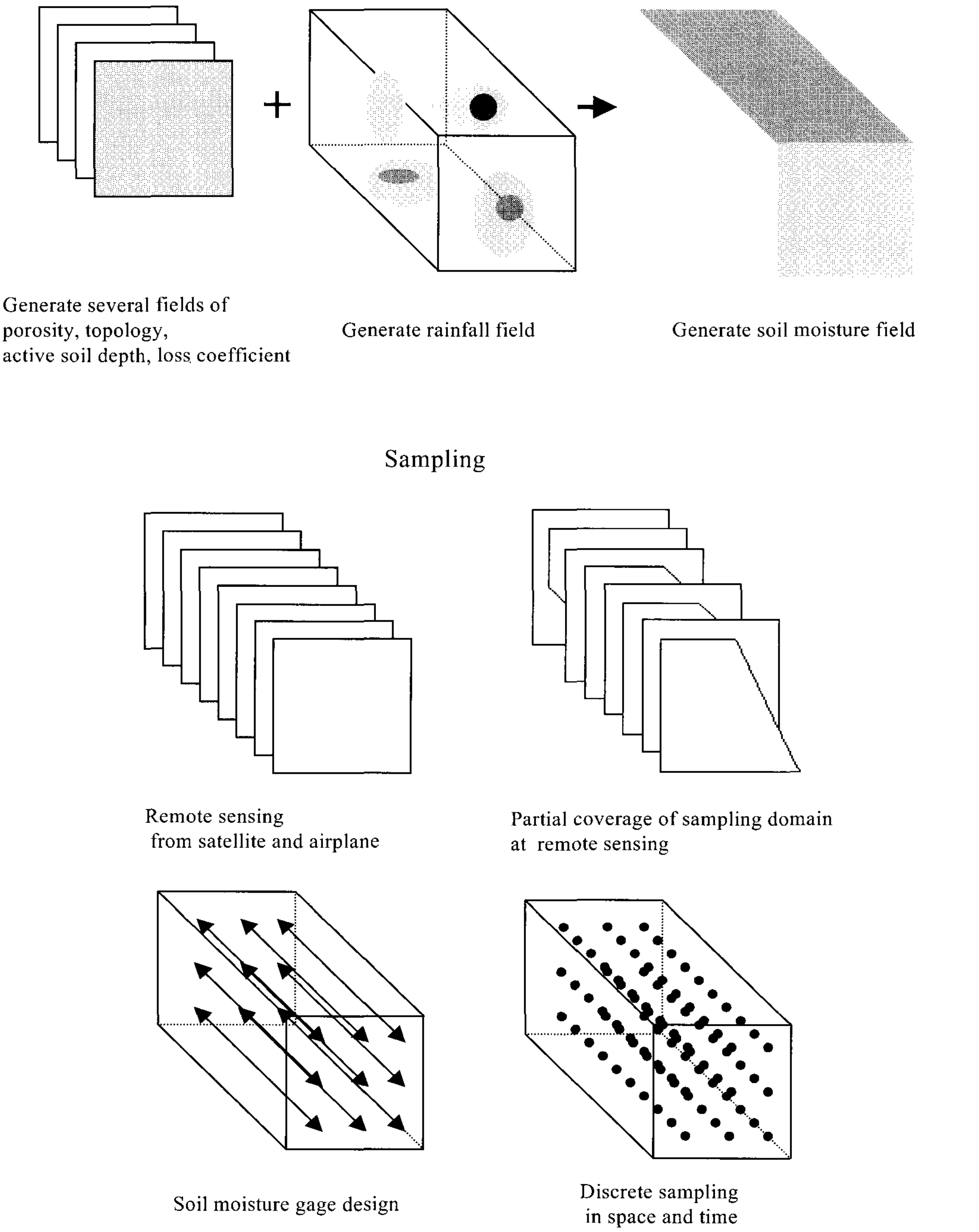


Fig. 3. Schematic diagram of simulation study, The standard procedure is 1. to generate the soil properties, elevation, loss coefficient and diffusion coefficient 2. to generate rainfall data with tuned parameter from experimental data 3. to generate soil moisture field 4. to analyze the impact of field conditions, sampling design, partial coverage by using simulated soil moisture field

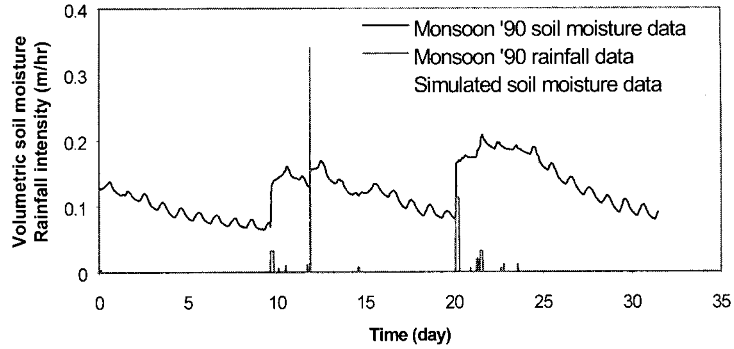


Fig. 4. For soil moisture model verification, the Monsoon '90 soil moisture data and simulated soil moisture were compared

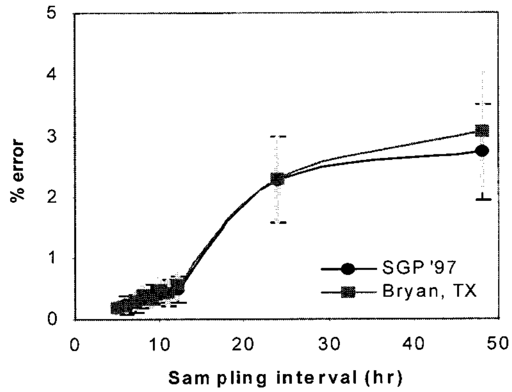
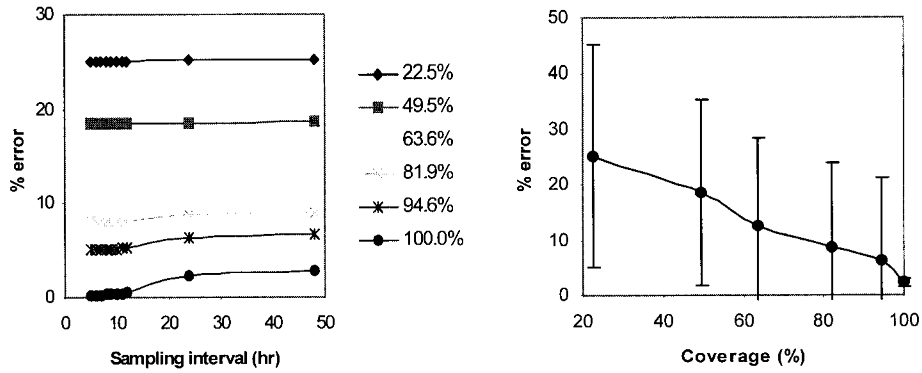


Fig. 5. Sampling error regarding intermittent visit with different rainfall field



(a) (b)

Fig. 6. (a) Sampling error regarding partial coverage between 23% and 95%, (b) Sampling error regarding partial coverage with daily sampling

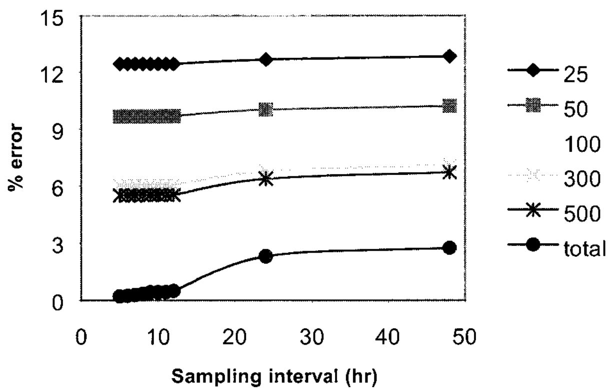


Fig. 7. Sampling error regarding random soil moisture gage installation

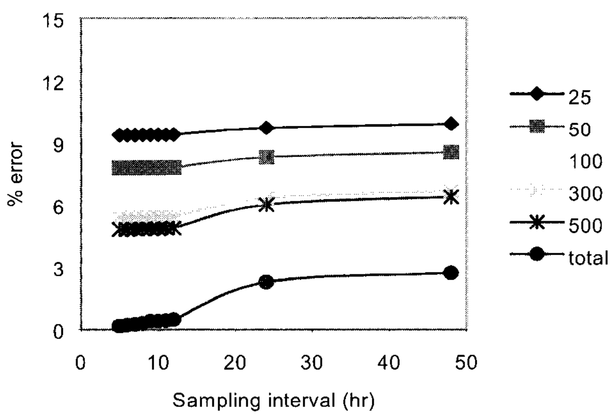


Fig. 8. Sampling error regarding block random soil moisture gage installation

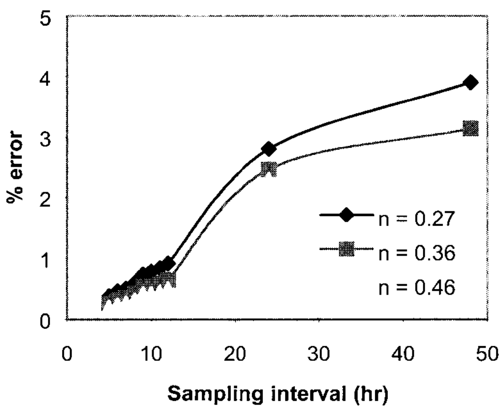


Fig. 9. Sampling error regarding different porosity field

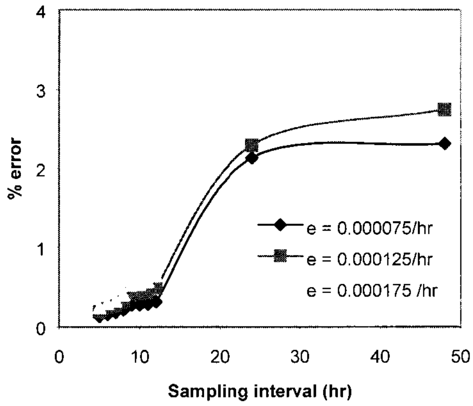


Fig. 10. Sampling error regarding different loss coefficients

$$Z_s(X_N) = \frac{1}{\sqrt{L}} \sum_{i-1}^{L} Z_i(x_N \cdot u_i) \quad (4)$$

where x_N is the location of the point N, u_i is the vector on line i, and $x_N \cdot u_i$ is the projection of the vector x_i onto the line i.

Several forms of the covariance function such as exponential, exponential spherical, Bessel and Telis function were used in TBM (Mantoglou and Wilson, 1982). The exponential covariance function, which has been used in this study, is of the form

$$C(\delta) = \sigma^2 \exp\left\{ -\left\{ \left(\frac{\delta_1}{\rho_1}\right)^2 + \left(\frac{\delta_2}{\rho_2}\right)^2 + \left(\frac{\delta_2}{\rho_3}\right)^2 \right\}^{1/2} \right\} \quad (5)$$

where δ_1, δ_2, and δ_3 are the separation vectors, ρ_1, ρ_2 and ρ_3 are the correlation lengths and σ^2 is the variance of the field.

Porosity, active soil depth, amplitude of diurnal impact and loss coefficient fields were generated by using the TBM. This method was chosen due to its computational efficiency in generating large fields and its ability to preserve field statistics such as mean, covariance and correlation structure. The accuracy of TBM depends on an appropriate choice of model parameters.

Porosity data of SGP '97 experimental field were used in this study. Basic data to generate loss coefficients are calculated by using the SGP '97 soil moisture data with 0.8 km by 0.8 km resolution. The estimate of loss coefficient is 0.0000125 m/hour with same correlation length of soil moisture data. The amplitude of diurnal cycle and active soil depth field were generated by using TBM method.

4. SOIL MOISTURE FIELD GENERATION AND SAMPLING STUDY

The construction of sufficient two dimensional soil moisture data and precipitation data under several soil properties, vegetation characteristics, topographic characteristics and climate conditions is necessary to analyze the field characteristic in soil moisture sampling. Fig. 3 shows the schematic diagram of simulation study. The standard procedures are: 1) to generate the soil properties, elevation, loss coefficient and diffusion coefficient; 2) to generate rainfall data with tuned parameter from experimental data; 3) to generate soil moisture field; 4) to analyze the impact of field conditions, sampling design, partial coverage by using simulated soil moisture field.

The dimension of analysis field was 128×128 with 800 m pixel resolution. Soil moisture and rainfall fields were generated hourly for a year with an extra 30 days data, which was introduced to remove the effect of initial condition. The porosity field with 0.8 km × 0.8 km resolution was estimated using CONUS data whose resolution is 1 km × 1 km. Simulation field elevation is extracted from DEM data. Table 2 shows the UTM coordinate of porosity and DEM field. Initial soil moisture is assumed constant value of 0.5 and more generated by using TBM method with mean of 0.5 and standard deviation is 0.05. Actual soil depth field was held at constant a value i.e. 0.5m or 0.05m and generated by using the TBM method. Loss coefficient and amplitude of the diurnal impact field was computed by use of the TBM.

The Monsoon '90 soil moisture data and simulated soil moisture were compared to verify the soil moisture model in fig. 4. Values obtained for simulated soil moisture exhibits a close to the experimental data. In the Monsoon '90 experiment, the rainfall gage and soil moisture gage were not located in same the spot so which caused a difference between simulated soil moisture and field soil moisture during day 10 to day 20. Fig. 5 shows the effect of intermittent visit of the observation satellite under different climatic condition. Trend of sampling error is linearly increased with increase of sampling interval and the diurnal variation caused dramatic increase of sampling error between sampling interval 12 hour and 24 hour. The WGR model parameters for those two cases are shown in Table 2. This figure depicts a similar pattern to that of fig. 2. Sampling twice per day can remove the sampling error caused by the diurnal cycle.

Different sensing radius, 50km, 70km, and 90km, were used to realize the effect of partial coverage of remote sensing. Each sensing radius has an annual mean of coverage portion, equal to 23%, 50%, 64%, 82% and 95% of the observation area. Figure 6 shows that partial coverage can cause an increase in sampling error over that of the diurnal impact. Decreasing the coverage portion decreases the impact of diurnal cycle in sampling error. The sampling error caused by temporal gap is also decreased by decreasing the coverage portion. If the annual mean of coverage portion is about 90%, the effect of partial coverage to sampling error can be disregarded.

In attempting to characterize a soil moisture field, the installation of soil moisture gages, both number and location are relevant to this process. Fig. 7 and 8 show the sampling error introduced by soil moisture gage installation. Those figures show that block random installation can provide a more accurate measurement than from random installation of soil moisture gages. Those patterns in the figures are very similar to that of partial coverage. The impact of diurnal cycle on sampling error is decreased and can not affect the sampling error if the sampling gage network is sparse. Fig. 9 indicates that sampling error decreases with an increase in soil porosity. Water retention capacity of fields is very important to sampling error. The smaller the water retention capacity of the field (e.g. small soil porosity and small active soil depth) the greater the sampling error. Fig. 10 shows sampling error for the field with a large loss coefficient is greater than that for the field which has a small loss coefficient. The effect of heterogeneity of soil properties and rainfall to sampling error is smaller than that of intermittent visit. If we choose a small sampling interval we can dramatically reduce the sampling error generated by other factors such as heterogeneity of rainfall, soil properties, topography and climate conditions.

5. RESULTS AND DISCUSSION

The error of daily sampling has the cyclic form between 1 % and 4 %. Figure 1 shows the error of daily sampling (remote sensing from satellite or airplane) is affected by diurnal cycle. The daily sampling between 5 am to 8 am shows the lowest value of 1 % and between 1 p.m. to 3 p.m. the sampling error shows the highest value of 4%. The impact of the temporal gap to the soil moisture sampling was also analyzed from the Walnut Gulch data. The mean and standard deviation of sampling error linearly increased with increase of sampling interval. The error of daily sampling linearly increases with increase of the amplitude of diurnal cycle.

Soil moisture model, rainfall model and random field generation model with model parameters estimated from experimental data such as the SGP'97 data were used to generate two dimensional soil moisture fields. 13 months long hourly two dimensional soil moisture data and precipitation data under several soil properties, topographic conditions, loss fields and climate conditions were generated to use sampling error analysis. One hundred months were randomly selected to analyze sampling error. Each sampling error represents an ensemble mean of 100 months.

Partial coverage or block random installation is superior to random installation. The water retention capacity of fields is very important in the sampling error. The smaller the water retention capacities of the field, small soil porosity and thin active soil depth, the greater sampling error. These results indicate that the sampling error is sensitive to water retention capacity. Ensemble mean and standard deviation of sampling error with change of statistical parameters of porosity field, active soil depth, loss coefficient, partial coverage and sensor installation, must be estimated.

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