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SPATIAL DISTRIBUTION OF POINT SOIL MOISTURE ESTIMATES USING LANDSAT TM DATA AND FUZZY-C CLASSIFICATION[1]

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ABSTRACT: Many hydrologic models have input data requirements that are difficult to satisfy for all but a few well-instrumented, experimental watersheds. In this study, point soil moisture in a mountain watershed with various types of vegetative cover was modeled using a generalized regression model. Information on surficial characteristics of the watershed was obtained by applying fuzzy set theory to a database consisting of only satellite and a digital elevation model (DEM). The fuzzy-c algorithm separated the watershed into distinguishable classes and provided regression coefficients for each ground pixel. The regression model used the coefficients to estimate distributed soil moisture over the entire watershed. A soil moisture accounting model was used to resolve temporal differences between measurements at prototypical measurement sites and validation sites. The results were reasonably accurate for all classes in the watershed. The spatial distribution of soil moisture estimates corresponded accurately with soil moisture measurements at validation sites on the watershed. It was concluded that use of the regression model to distribute soil moisture from a specified number of points can be combined with satellite and DEM information to provide a reasonable estimation of the spatial distribution of soil moisture for a watershed.

(KEY TERMS: remote sensing; infiltration and soil moisture; forest hydrology; evapotranspiration.)

INTRODUCTION

Some knowledge of the moisture content of soils is necessary for planning and management in a variety of disciplines. In agriculture, irrigation demands, application schedules and amounts, potential crop yields, and detection of crop water stress all depend to some extent on the soil moisture in the upper layer. Rangeland and forest management decision are likewise benefitted by a knowledge of soil moisture content and the spatial distribution thereof. Hydrologic forecasts are highly dependent on a knowledge of antecedent soil moisture when predicting runoff and infiltration resulting from a rainfall event. Recharge of groundwater aquifers is influenced by soil moisture conditions, which affect or govern quantities which are (1) returned to the atmosphere through evaporation and evapotranspiration, (2) absorbed and converted to plant mass, or (3) percolated to the underlying ground water.

In order to adequately predict temporal and spatial distributions of soil moisture, enormous quantities of data are required, and the cost of acquiring these data by conventional means (such as field surveys) is often prohibitive. In addition, management requirements for operational use of such data may be such that the time lag between collection, delivery, and processing of data before using them in a model can make the data obsolete. In this study, data that are available on a large-scale basis will be used in conjunction with existing methodology to provide a spatial and temporal distribution of soil moisture in a mountain watershed with an arid climate.

The use of remotely sensed data to represent the spatial distribution of hydrologic processes has been discussed at length, but the utility of the technique for hydrologic models has not yet been well demonstrated (Price, 1980; Rango and O'Neill, 1982; Jackson, 1985; Johnson *et al.*, 1985; Owe *et al.*, 1988). This study describes a procedure for estimating soil moisture in both space and time dimensions by utilizing available remotely sensed data in conjunction with point measurements. Extrapolation from point estimates to watershed scale is made possible by the fuzzy-c classification algorithm, which defines class centers, as well as the competing influence of each data vector on the various classes.

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The objective of the research was to develop and verify a simple procedure for accurately representing the spatial distribution of soil moisture in a mountain watershed with a reduced and cost-effective amount of data collection. The relationship between the spatial distribution of soil moisture and the spatial distribution of vegetative cover types was examined. To accomplish this objective, the temporal distribution of soil moisture was determined through measurement and modeling at various points within the watershed. The sites selected for installation of access tubes represented all of the major ground cover classes. A Landsat-DEM database for the watershed was classified, and the information from that classification was used in a generalized regression model to distribute the point soil moisture estimates over the entire watershed.

METHODS AND PROCEDURES

Study Site

For this study, the Tony Grove Creek watershed in northern Utah was selected as a test site (shown in Figure 1). Landsat TM data collected on July 1, 1986, were used to provide information on the surficial characteristics of the watershed. USGS topographic maps were digitized to provide information on pertinent topographic variables such as elevation, slope, and aspect. In addition, a weather station was installed at the base of the watershed to measure important meteorological data, particularly those needed to predict soil moisture change.

Access tubes were installed throughout the watershed, and soil moisture was measured at various soil depths during the years 1989 and 1990. Soil moisture measurements were collected at 31 sites at depths ranging from 45 to 75 cm. One site was instrumented with eight access tubes while the other sites had one access tube each. No soil maps of the area have been published, but unpublished research indicated associations of mollisols and alfisols. From field data, the soil types in the area were mostly loam and clay loam with bedrock close to the surface in many places. A number of access tubes were located randomly as a check on the accuracy of the spatial extrapolation of soil moisture. These sites will be referred to as validation sites. Soil moisture measurements were gathered at all of the sites as previously described.

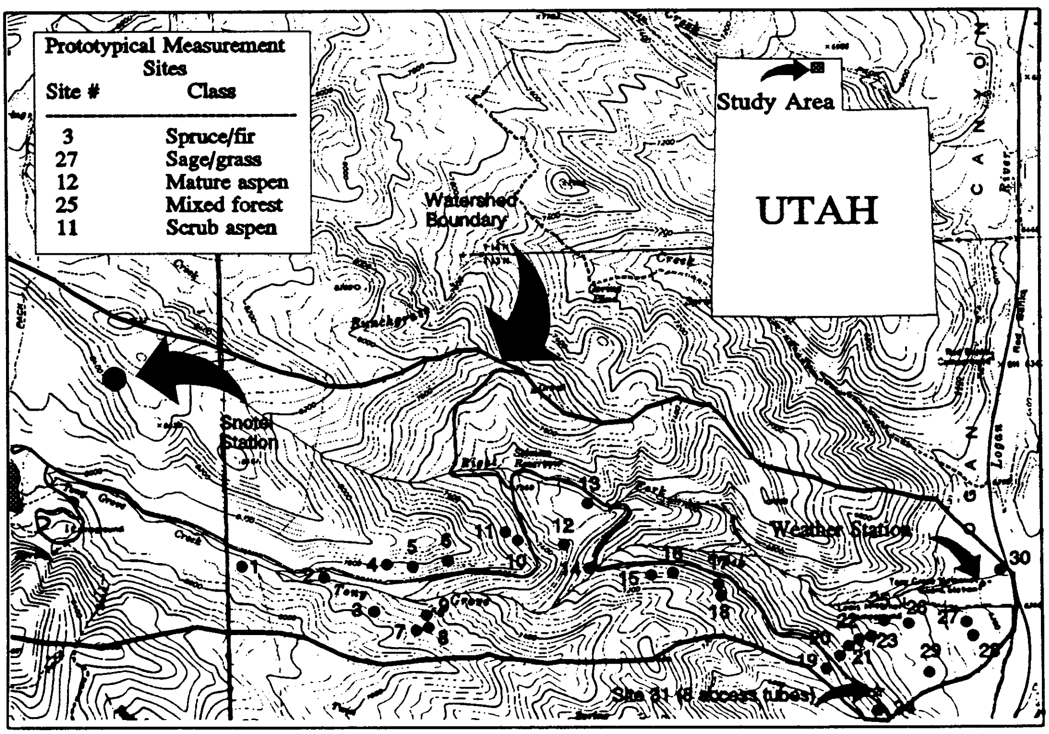

Figure 1. Location Map Showing Watershed and Individual Measurement Sites.

Self-Organizing Predictive Soil Moisture Models

As stated in the introduction, the objective of the research was to develop and test a simple procedure for obtaining good spatially and temporally distributed estimates of mountain watershed subsurface soil moisture. Ideally, the procedure would use readily available satellite multispectral data and digital elevation models (DEM) to provide an alternative to the extensive field survey requirements demanded by conventional approaches. To accomplish this goal, a generalized multivariate regression model was assumed in the form

$$SDSM_k = \sum_{i=1,c} (SMC_i^* u_{ik}) \tag{1}$$

where $SDSM_k$ represents the soil moisture predicted at time T at an arbitrary point $\underline{X}_k$ in the k-th unit of a gridded watershed. The grid scale was assumed to be dependent upon the resolution available from a merged base of satellite and DEM data, with each unit homogeneous with respect to soil moisture. The variables, denoted by SMC_i, represent known soil moisture values at time T available at i = 1, 2, . . . c prototypical *measurement* points on the watershed. Soil moisture at these few points may be obtained in several ways: from direct, on-site measurement; through the use of well known "point" physical process models; or, from combinations of the two (for example, using Kalman updating). The method used in this study is discussed in further detail below. Finally, the generalized regression coefficients u_{ik} weight the contribution of the i-th measurement site to the total soil moisture estimate at the k-th prediction site.

The major questions regarding Equation (1) are: how many prototypical measurement points are required (obviously, the fewer the better); where should the measurement points be located on the watershed; how are the weighting coefficients u_{ik} determined? It can be shown that these questions lead to the requirement of solving a weighted sum-of-squared-error optimization functional, which, in turn, supplies necessary conditions for learning the values of the parameters listed above directly from the merged satellite DEM data base (Gunderson *et al.*, 1992). This functional corresponds exactly to that minimized to obtain the fuzzy-c varieties (FCV) unsupervised classification algorithms (Bezdek *et al.*, 1981; Gunderson and Jacobsen, 1983).

Fuzzy C-Varieties Algorithm

The first step in FCV data analysis is to specify a number of classes, c, which will represent the data x, and to indicate a first guess at the centers $v_1, v_2, \ldots v_c$ for those classes. The number of classes, c, corresponds to the number of measurement sites in Equation (1). The algorithm then uses the initial guess at the centers of the classes to iteratively solve the two nonlinear equations

$$u_{ik} = \frac{1}{\sum_{j=1,c} \left(\|x_k - v_i\| / \|x_k - v_j\| \right)^2} \tag{2}$$

and

$$v_i = \frac{\sum_{k=1,n} (u_{ik})^2 x_{ik}}{\sum_{k=1,n} (u_{ik})^2} \tag{3}$$

where i and k are the number of classes and data vectors, respectively. The data vectors x_k represent the merged satellite and DEM measurements at the kth watershed unit. The term u_{ik} provides the weight or extent to which the data vectors x_k influence computations for the ith class. Alternatively, they weigh the contributions of the soil moisture measurements as given in Equation (1). These weights are constrained to satisfy the conditions

$$u_{ik} \in [0,1] \tag{4}$$

and

$$\sum_{i=1,c} u_{ik} = 1 \tag{5}$$

for all i = 1, 2, . . . c and k = 1, 2, . . . n, and are often referred to as defining the "fuzzy" membership of the data vectors in c "fuzzy" sets (Bezdek *et al.*, 1981).

The centers for the classes defined by the algorithm are given by Equation (3) and can be thought of as defining the prototypical data vectors for each class. For example, in a certain two-class case, $u_{1,k}$ for a data vector x_k occurring at the center of class 1 would have a value of 1.0 and $u_{2,k}$ a value of 0.0, while a data vector x_j falling midway between the center of classes 1 and 2, would have values of u_{1j} and u_{2j} equal to 0.5. In this manner, the algorithm defines not only the centers of the classes present in the data, but the competing influence of individual data vectors on the various classes. The algorithm also allows each data vector to influence the recalculation of the class centers. The data x can therefore be described in more meaningful terms than simply belonging to one class or another.

The prototypical measurement sites needed for Equation (1) are easily obtained from the output of the FCV algorithm by simply selecting watershed sites whose membership coefficients are near unity with respect to a desired class.

Modeling Procedures

Several approaches were examined for obtaining the known soil moisture values for Equation (1) at the prototypical measurement sites identified by use of the FCV algorithm. One obvious approach would be to make on-site measurements. This approach was not used because of the effort and expense involved in gathering on-site soil moisture data. For example, the time to complete measurements at all sites was sometimes as long as four days. At the beginning of the season, the soil moisture stayed near field capacity because transpiration and evaporation were minimal. At the end of the season, the change in soil moisture status was again minimal because most of the watershed had reached the permanent wilting point. During these periods, comparing an on-site measurement taken four days after the measurement used in Equation (1) to estimate $SDSM_k$ worked well because the temporal change in soil moisture is generally small for these seasons. The months of June and July, however, saw rapid vegetative growth and tangible amounts of daily evapotranspiration. This made evaluation of the effectiveness of the technique using only measured values impractical when two to four days elapsed between the start and finish of data gathering. Therefore, it was necessary to model the temporal change of soil moisture at each site.

The soil moisture accounting (SMA) model was developed to overcome this problem, as previously described. The SMA model is based on the Jensen-Haise equation for estimation of evapotranspiration (Jensen and Haise, 1963)

$$ET_p = (0.64*C + 1.98)\, R_s/580 \qquad (6)$$

where C is the average air temperature in degrees C and R_s is the solar radiation in Langleys. The root density and the available soil moisture are the key elements determining the actual amount of soil moisture lost through transpiration (Wight and Hanks, 1981; Wight *et al.*, 1986; Wight, 1987). Potential evaporation is calculated based on the meteorological factors for a given day, and actual evaporation is a function of available soil moisture in the upper layers of soil and also any intercepted precipitation stored in the forest canopy. The model functions with a user-specified number of soil layers; three to four layers were used to model soil moisture change for the study site. The number of layers used was determined by the depth and make-up of the soil profile and ranged in thickness from 6 to 25 cm. Recognizing the importance of topographic position on some meteorological inputs, the model adjusts temperature for both elevation and aspect.

By applying the SMA model at each point on the watershed, evaluation of the spatial distribution technique was accomplished for various dates during the season. At each validation site, soil moisture measurements for a given day were compared with soil moisture estimates from Equation (1) using SMC_i values for that same date.

The SMA model was also utilized to estimate the temporal change in soil moisture levels at the prototypical measurement sites. When measurements at a prototypical site were available for a given date, those measurements were used in Equation (1). When no measurement was available for that date, the SMA model estimate was used to account for the temporal change in soil moisture between the date of the measurements used in Equation (1) and the date of the measurements at the validation sites. The model was also used to obtain temporally equivalent estimates for each class for use in Equation (1).

Several methods of improving SMA model estimates were investigated. Kalman filtering was examined as a tool to improve the model approximations by utilizing information on the error covariance matrices of the measurements and the model process to correct model estimates of the state variable; in this case, the soil moisture at a given layer (Leu, 1985; Gunderson *et al.*, 1987). This method was not utilized because of the difficulty of determining the noise covariance matrix.

Another approach to improving model predictions involved the use of the measured data to simply update the model results. SMA would estimate the soil moisture at a given point and then check to see if a measurement occurred on that date. In that event, the model would simply reset the soil moisture for that date to the measured value and then continue to run.

The method finally chosen was a modification of the updating method. The SMA model predicts soil moisture for the next day, checks to see if a measurement exists for that day, and then compares the predicted value with the measurement. If the difference between the predicted and measured values falls within a user-specified threshold limit, the model continues to run using the model prediction. When the difference between the measurement and the prediction exceeds that threshold, the model resets the value of the state variables to the measurements and then continues on. In this manner, the user retains some control over the process and can also ascertain how well the simulated soil moisture estimates compare with measurements by examining the number of measured points used to update or reset soil moisture values during a run.

Data Requirements

The study site was extracted from the Landsat Thematic Mapper scene, and the resulting database containing seven measurements of electromagnetic band response for every 30 x 30 meter pixel was merged with a corresponding digital elevation database containing information on elevation, slope, and aspect.

Soil moisture data were gathered at the points described earlier in this section. A neutron probe was utilized to measure soil moisture data which were collected on approximately a bi-weekly basis during the summer of 1989 and from April to October of 1990. Field and laboratory measurements were made to determine pertinent physical soil characteristics such as bulk density, field capacity, and the soil moisture level at which permanent wilting occurred in vegetation.

DISCUSSION AND RESULTS

The merged Landsat Thematic Mapper-DEM data was first analyzed using the FCV algorithm to determine the number of classes, c; i.e., the number of prototypical measurement sites needed for use in Equation (1). Satellite data from July 1, 1986, was found to result in a classification which closely agreed with apparent classes identified during field examinations conducted during the 1990 measurement period. A comparison of the classification results and the field survey is shown in Table 1. Based on these results, a best number of c=5 classes (measurement sites) was determined. It was observed that only the elevation variable from the DEM data appeared to have significant influence on class structure, the remaining DEM variables being highly correlated with vegetative surficial ground features. As might be expected, the effect of the elevation variable was essentially to discriminate between observable elevation-dependent vegetative classes. It is important to stress that the known dependency of soil moisture distribution on topographic position was taken into account in the predictive modeling approach, *albeit* implicitly through the learning of model parameters from the merged Landsat-DEM data base.

TABLE 1. Contingency Table Comparing Class Indicated by Classification Algorithm and Field Survey Results (three out of 30 sites were misclassified).

Field Class	FCV Classification Result 1	2	3	4	5
1	3				
2		5	1	1	1
3			4		
4				3	
5					12

Class 1 Spruce/Fir Forest
Class 2 Sage/Grass Rangeland
Class 3 Mature Aspen Forest
Class 4 Mixed Conifer/Aspen Forest
Class 5 Scrub Aspen Forest (heavy understory)

After settling on the number of classes, the next step was to identify the corresponding measurement sites for each class. These are referred to as prototypical measurement sites. As mentioned earlier, this was easily accomplished by examining the so-called membership coefficients u_{ik} for sites corresponding to data vectors x_k, with membership values in class i having unity, or near unity, values. Membership values for all of the instrumented sites, prototypical measurement and validation sites, are shown in Table 2. Note that the membership values are, in some cases, higher for the validation sites than for the prototypical measurement sites. This can be explained by the differing methods of locating the prototypical measurement sites as opposed to the validation site. As stated, the measurement sites were located by extracting high membership value sites for each class and then locating those sites in the field. The validation sites, however, were installed in the field with the only criteria being random location. An attempt was made to obtain representative samples of each class type. Class types were determined at that time only on a basis of field observation. Later, the locations of the validation sites were examined to determine the actual class (from the classification of the satellite-DEM data base) and the membership values.

As previously mentioned, the accuracy of classification has been shown in the contingency table (Table 1). If every location had been classified correctly, all the values would have fallen on the diagonal of the contingency table. The three sites that were misclassified all had a common element. Each of these sites was a relatively small meadow or open area in a larger area of either aspen or spruce forest. Since the resolution of the Landsat Thematic Mapper is 30 meters, these sites were on the order of magnitude of one pixel. This is less than the margin of accuracy for either georeferencing or precise field location.

TABLE 2. Membership Values from FCV Classification for All Instrumented Sites in the Tony Grove Creek Watershed.

Site No.	u1	u2	u3	u4	u5
1	0.02	0.82	0.04	0.10	0.03
2	0.02	0.71	0.06	0.16	0.07
3	0.95	0.01	0.02	0.01	0.01
4	0.00	0.00	0.01	0.01	0.98
5	0.01	0.03	0.07	0.10	0.79
7	0.14	0.03	0.61	0.12	0.09
8	0.02	0.02	0.66	0.13	0.16
9	0.01	0.01	0.05	0.05	0.89
11c	0.00	0.01	0.02	0.02	0.95
12c	0.01	0.00	0.96	0.02	0.01
13	0.03	0.70	0.06	0.17	0.04
14	0.01	0.01	0.03	0.03	0.91
15	0.90	0.01	0.05	0.02	0.02
16a	0.93	0.01	0.03	0.02	0.01
17	0.15	0.12	0.38	0.27	0.09
19	0.01	0.01	0.11	0.06	0.80
20	0.02	0.02	0.23	0.12	0.61
21	0.01	0.02	0.07	0.06	0.83
22	0.02	0.02	0.08	0.07	0.82
24	0.01	0.01	0.07	0.07	0.84
25d	0.01	0.03	0.10	0.78	0.08
26	0.01	0.03	0.06	0.83	0.07
27b	0.01	0.93	0.02	0.04	0.01
28	0.00	0.97	0.01	0.02	0.01
29	0.03	0.05	0.47	0.25	0.20

KEY:

a - prototypical site for Class 1 (u1) ≈ spruce/fir forest.

b - prototypical site for Class 2 (u2) ≈ sage/grass rangeland.

c - prototypical site for Class 3 (u3) ≈ old growth aspen.

d - prototypical site for Class 4 (u4) ≈ mixed conifer and aspen forest.

e - prototypical site for Class 5 (u5) ≈ scrub aspen and understory.

Note: Some of the membership values do not sum to 1.0. This can be attributed to round-off error.

In order to adequately assess the accuracy of spatial distribution using fuzzy-c classification, an extrapolated value of point soil moisture was calculated using membership values for each measurement taken in 1990. The results are shown in Figure 2. Data shown in Figure 2 represent all measurements plotted against corresponding extrapolated soil moisture values estimated from Equation (1). The r^2 value of 0.86 from regression analysis represents all of the values except the measurements at the prototypical sites (11, 12, 16, 25, and 27).

As a means of examining the causes of the scatter seen in Figure 2, the data were plotted by individual site. This showed that the data tend to fall in a series of lines parallel to the diagonal. If data points fell exactly on the diagonal, the measured values would show complete agreement with the estimates. From Figures 3 and 4, it is apparent that a consistent bias exists for each site which is revealed by the offset of individual sites from the diagonal. In Figure 3, the data shown are for aspen sites, while Figure 4 shows results for spruce sites.

Several possible explanations were investigated to determine the cause of the bias shown in Figures 3 and 4. The data were first separated by elevation zone and plotted, but no consistent bias was discernible. By means of a sensitivity analysis, the SMA model was found to be most sensitive to changes in the input parameters of the field capacity and wilting point of the soil, and to variations in a vegetation coefficient and root density. The first two are physical characteristics of the soil. The vegetation coefficient is the ratio of evapotranspiration from a lysimeter to the potential evapotranspiration from Equation (6) with water nonlimiting. The vegetation coefficient and the root density were developed for each vegetation type and are utilized in the calculation of the evapotranspiration. It was expected that classification of the satellite data would contain some information relative to the two latter parameters. The field surveys confirmed that the classes determined through the classification were closely related to the different types of vegetative cover existent in the watershed. Little information, however, was directly inferred from the satellite data relative to the spatial variation in physical soil characteristics. Therefore, the spatial distribution of soil characteristics could be responsible for the bias occurring in Figures 3 and 4.

In order to investigate the possibility of bias resulting from the spatial distribution of soil characteristics, a site was selected at random (Site 16). Different simulations were run for values of physical soil parameters from Rawls *et al.* (1982). The simulations were run using the model parameters already determined for the site along with soil parameters for soil types loamy sand, sandy loam, loam, and silty loam. Results are shown in Figure 5. Actual measurements for Site 16 are also depicted in the figure. Using the measurements as a basis for comparison, the simulated results were plotted against the measured data. The effect is very evident in Figure 6. The same consistent bias away from measured values appears that was visible in Figures 3 and 4. Physically, the explanation for this bias is that the extrapolation of spatial estimates of soil moisture using membership values is strongly linked to the soil type at the sites used as prototypical sites. For example, using five sites with a

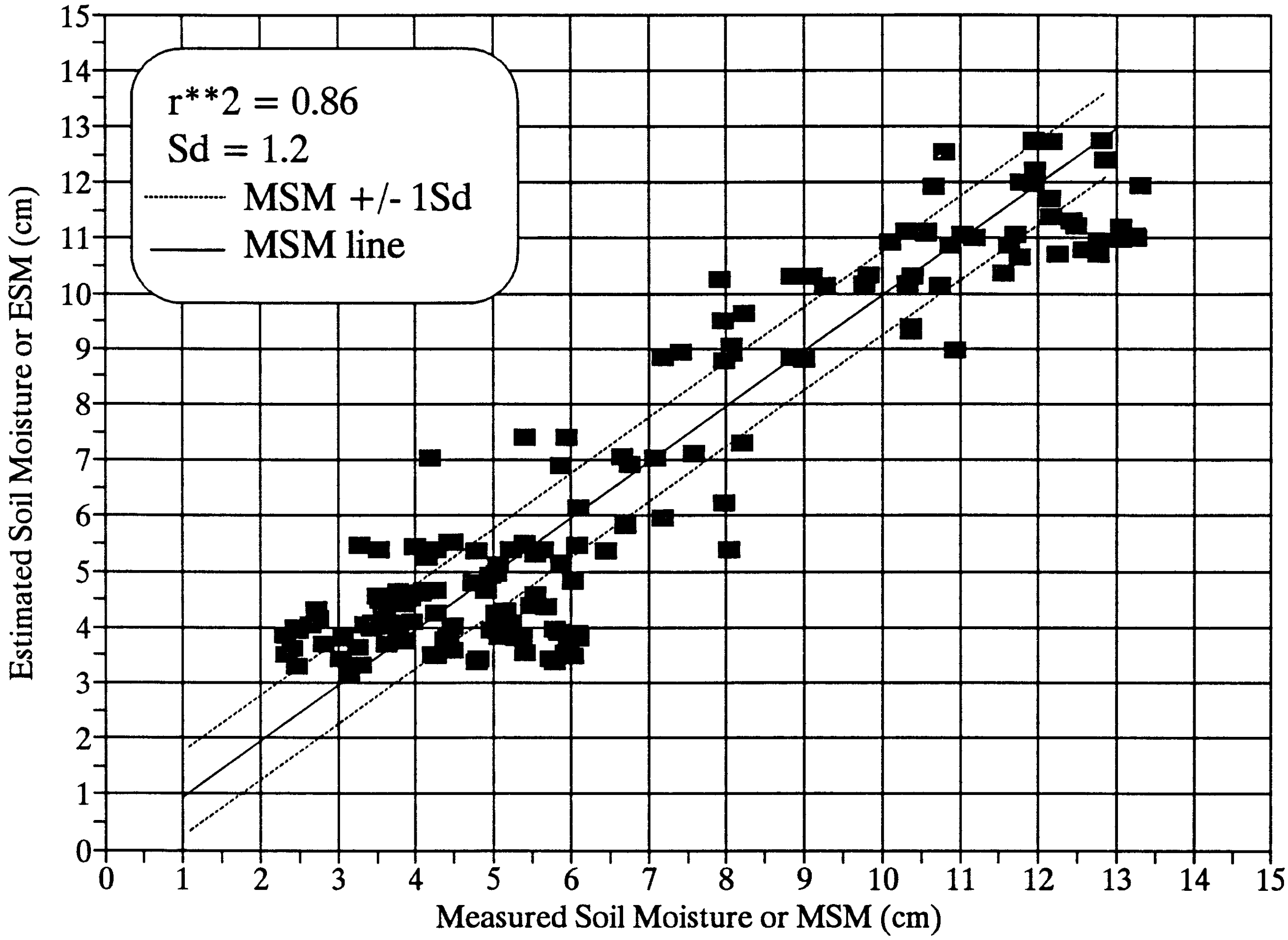

Figure 2. Results of Spatial Extrapolation Shown Against Measured Soil Moisture. (All data was collected in 1990 and regression analysis gave an r^2 of 0.86.)

soil type of sand to extrapolate over a watershed will estimate accurately at other sites with a soil type of sand, but sites with soil types of loam or clay will be much wetter in reality, suggesting the use of a soil-type dependent correction factor for improvement of the estimate.

SUMMARY AND CONCLUSIONS

The FCV classification algorithm was applied to satellite data to determine vegetation classes within the Tony Grove Creek watershed. The FCV algorithm further assigns membership values for a user-specified number of classes within the watershed for every ground element within the area of interest. Inspection of those membership values reveals the extent to which any given ground element belongs to a class. By selecting ground locations with high memberships in a given class, the number of instrumented sites needed to give an indication of the soil moisture over the entire watershed was reduced.

The potential of the FCV algorithm in the field of pattern recognition has been well documented (Bezdek *et al.*, 1981; Gunderson *et al.*, 1987). This research further validates the use of "fuzzy" classifiers in real world applications. In this case, the membership values developed from TM satellite data were sufficient to give an indication of the type and composition of vegetative cover in a mountain watershed.

The information supplied by the membership coefficients was quantified by combining soil moisture levels at the prototypical sites and then extrapolating those values over the entire watershed through the use of the membership values. This proved to be sufficient to satisfactorily model soil moisture throughout the entire watershed. The methodology has proven effective in a similar study involving snowpack distribution (Leu, 1985; Gunderson *et al.*, 1987), and, with the more complex process of soil moisture change

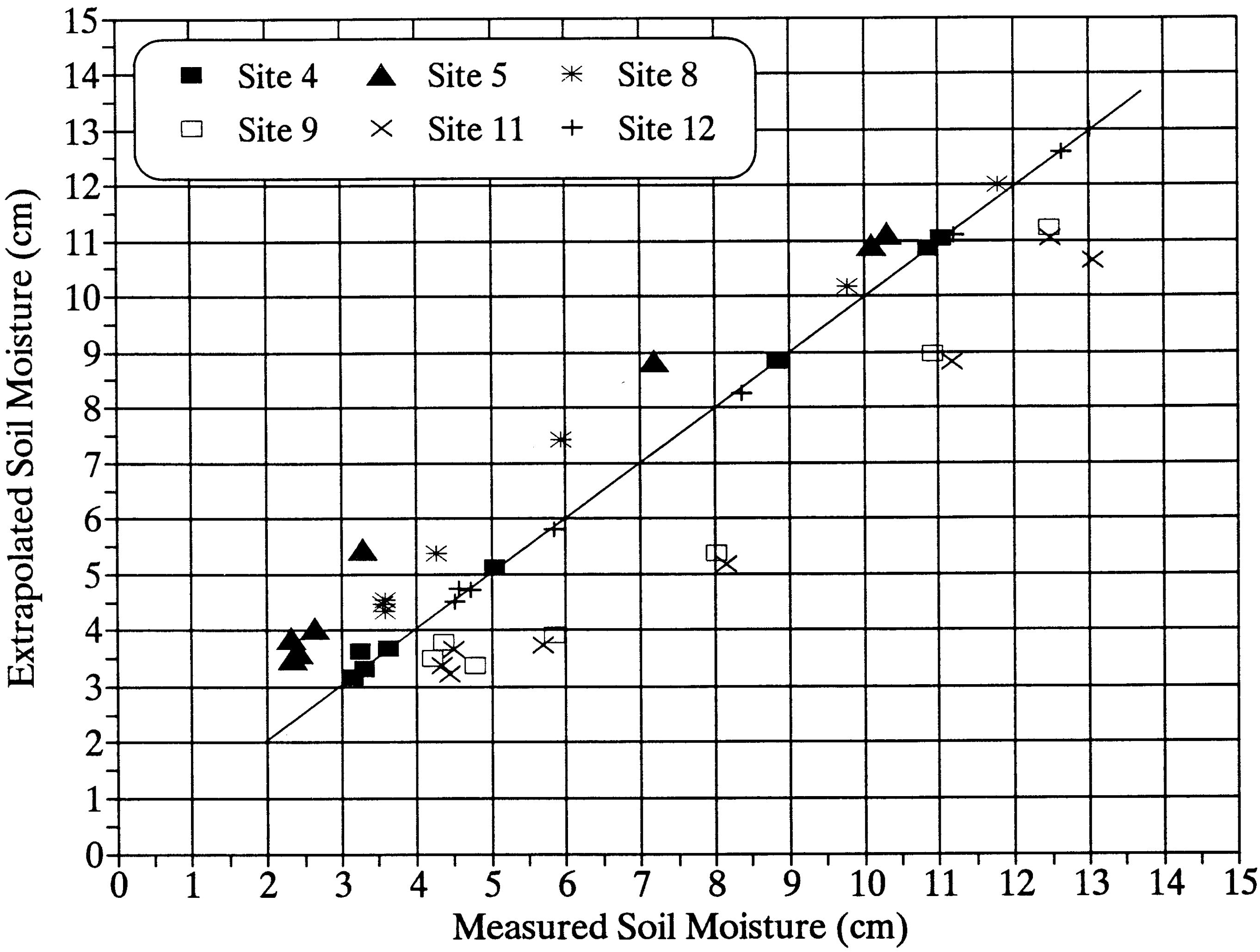

Figure 3. Comparison of Spatially Extrapolated Estimates of Soil Moisture with Measurements for Selected Aspen Sites.

during the growing season, has proven admirably effective in this research.

The estimation approach, which combined soil moisture levels at prototypical sites with membership values for the entire watershed to obtain a spatial distribution of soil moisture, was quite successful. Correlation of the extrapolated soil moisture with measured values at validation sites scattered throughout the watershed indicated an r^2 value of 0.86 for all vegetation types. The effect of different vegetative cover types on the correlation was analyzed separately, as well as the effect of elevation differences.

The variability apparent in the extrapolation results was apparently attributable to the different soil types. The "dumbbell" effect or clustering at the top and bottom of the figures showing the extrapolation results is actually a function of the three distinct periods within the growing season. The first is characterized by zero or slow change in soil moisture at the beginning of the season when all soils are at or near field capacity. The second is a relatively short period of dynamic change in soil moisture status brought about by the onset of transpiration by the vegetation, which is followed by a long period signaling the end of growth because soil moisture status has reached or is near the wilting point level.

The response of individual sites suggests a relationship between vegetative cover type and soil type, and the difference in soil type throughout the watershed is thought to have a significant contribution to the scatter in the extrapolated soil moisture values. From Figures 3 and 4, it is obvious that the extrapolated soil moisture for each site is consistently offset from the measured for the entire range of soil moisture. That this offset can be ascribed to differing soil

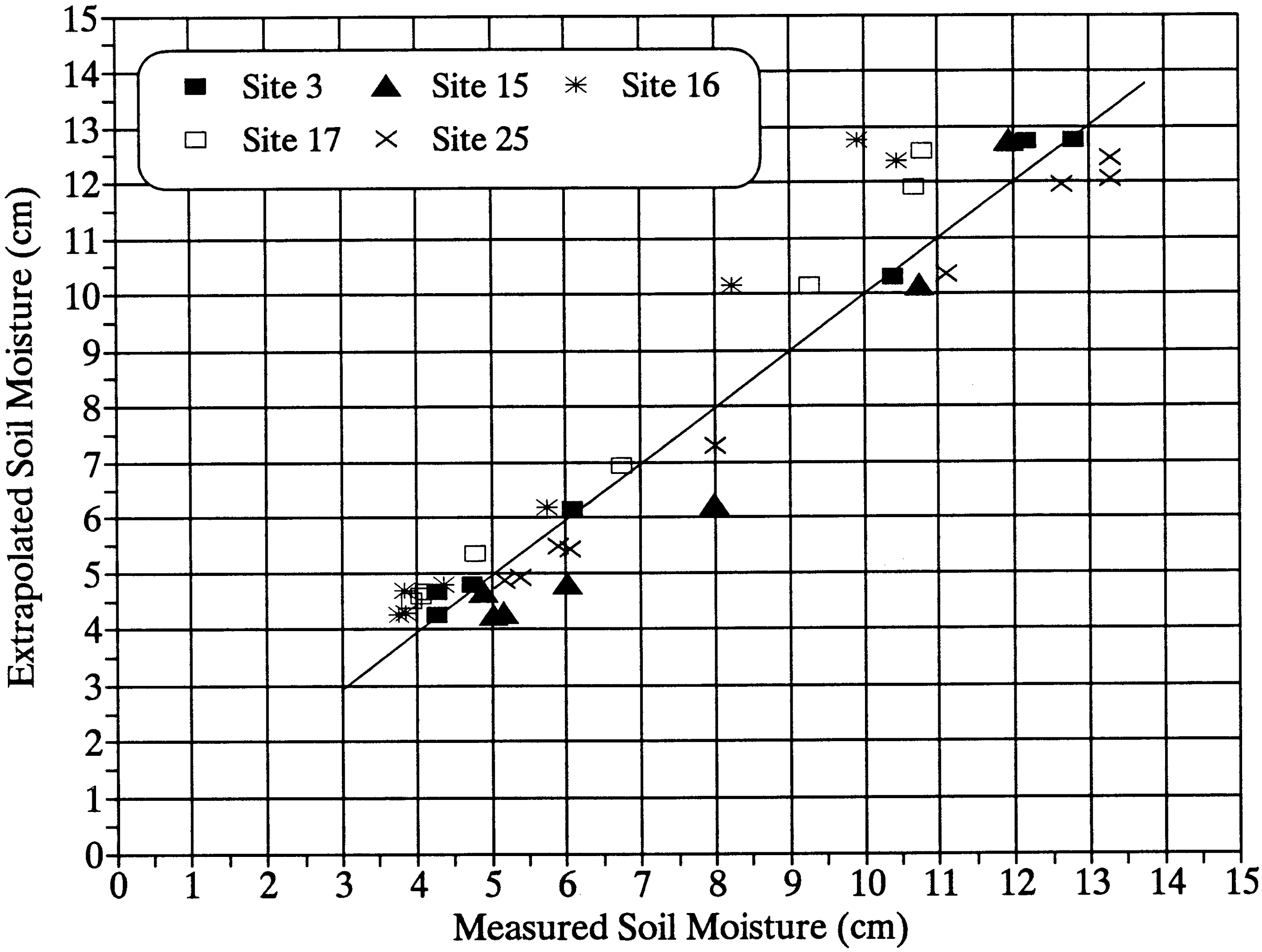

Figure 4. Comparison of Spatially Extrapolated Estimates of Soil Moisture with Measurements for Selected Spruce/Fir Sites.

types can be seen in Figures 5 and 6, and could also be deduced by a qualitative examination of the effect of different soil types on the results. The addition of a soils map (not available for this study area) as a layer input to the geographical information system (GIS), would improve the accuracy of this technique. Another possibility would be to apply a correction factor to all extrapolated estimates based on soil type. Overall, the technique using point soil moisture information with satellite data and a fuzzy-c algorithm for classification provides satisfactory estimates and insights into the difficult problem of estimating spatial distributions of subsurface soil moisture.

ACKNOWLEDGMENTS

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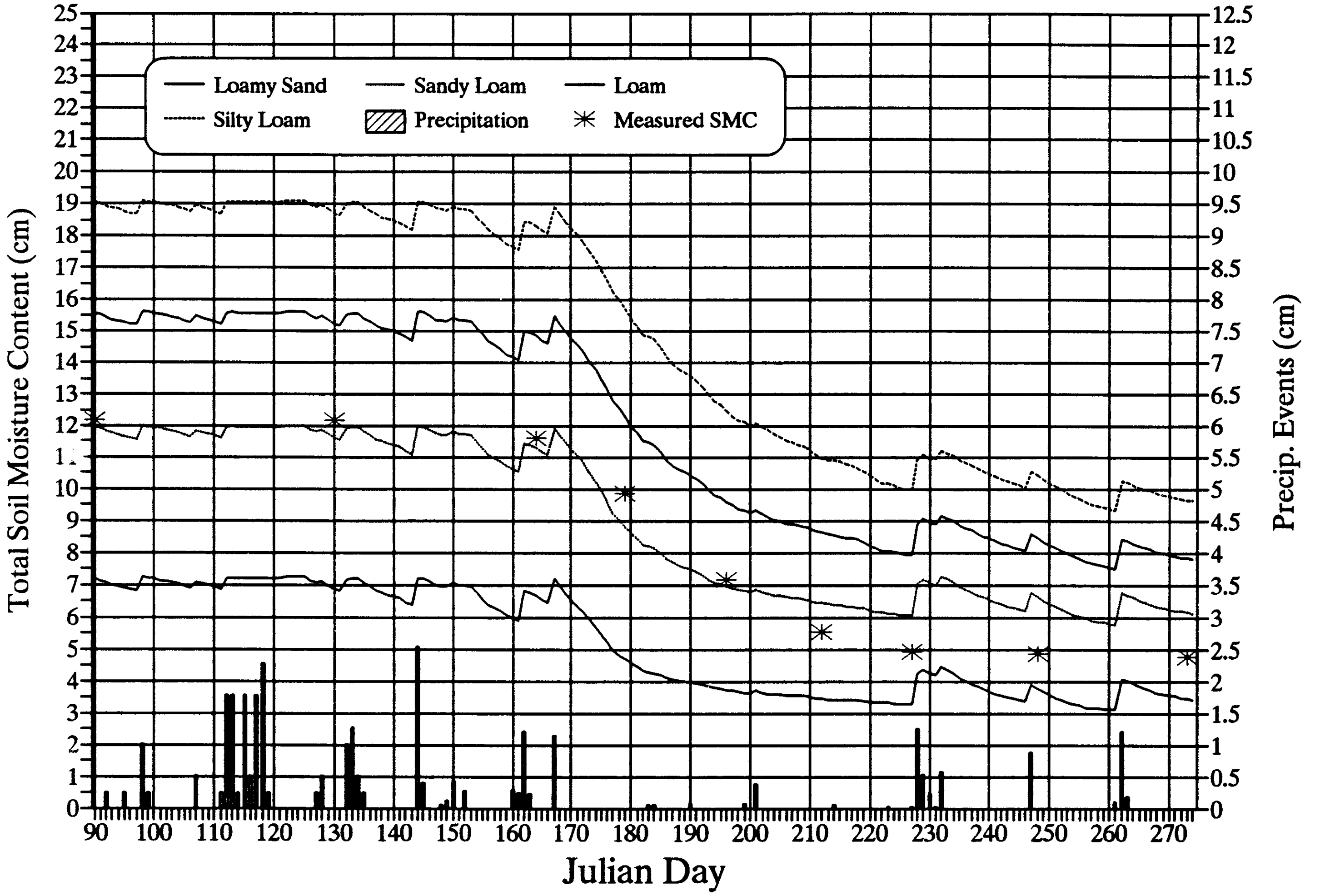

Figure 5. Result of Simulating Soil Type Changes Using a Soil Moisture Model and Input Parameters for Site 16 in the Study Area (spruce/fir vegetation).

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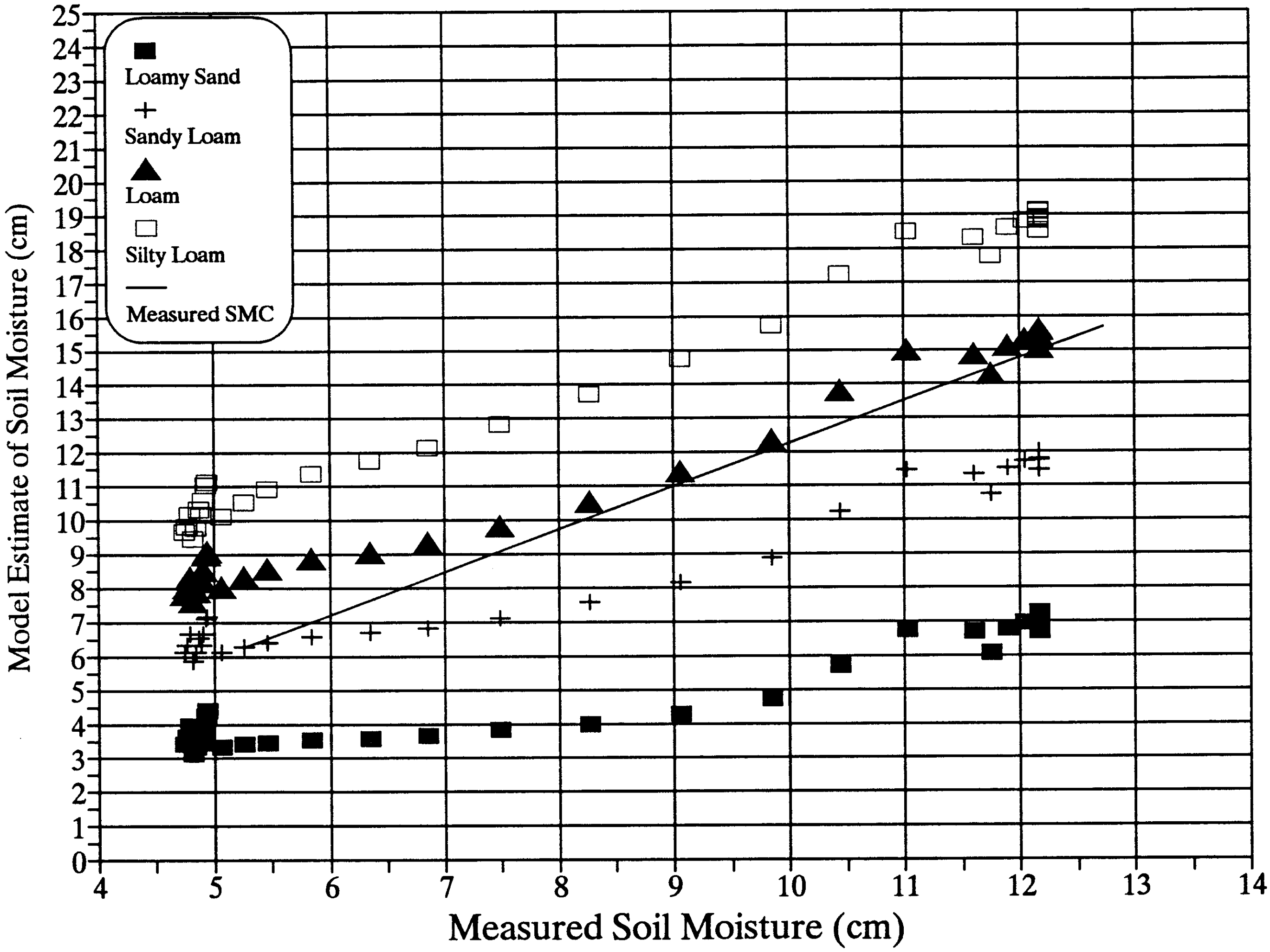

Figure 6. Comparison of Simulated Soil Moisture at Site 16 in the Study Area with Estimates for Different Soil Types Shown Versus the Actual Measurements at the Site.