Predicting soil water distribution using topographic models within four Montana farm fields
by Brian John Kozar

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Land Resources and Environmental Sciences
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Abstract:
Soil water content is a major factor controlling plant growth and crop yields in the semi-arid Northern Great Plains, and can vary substantially across a field. Farmers and land managers interested in identifying and delineating this variability need efficient methods to estimate soil water status. I hypothesized that topography influences soil water spatial distribution and could be used to delineate this distribution. The objectives of this study were to identify relationships between topography and soil water content, and determine if relationships discerned were similar across space. I used four farm fields across Northern Montana having moderate relief (15-30 m) with soils predominately formed over glacial till Soil water content was measured throughout one growing season at each site using a neutron moisture meter. Digital elevation models were used to portray the terrain. Relationships at multiple depths were examined for the beginning and end of the growing season through two, methods. Topographic region partitioning delineated the field into areas of presumed similar soil water content. Significant differences in soil water content between regions were tested using ANOVA. Secondly, the compound topographic index (CTI) was correlated with soil water content in a regression model. Study sites and topographic regions were included as covariates. Results identified differences in soil water content between regions, with the Row topographic regionpartitioning method identifying differences at all sites. However, no consistent patterns in differences between regions occurred across sites at any given depth. Reduction of across field soil water variance was also low (maximum = 21%). The strongest correlation between CTI and soil water content occurred at the end of the growing season at 20 cm (R2 = 0.40, p = 0.0001). Relationships between CTI and soil, water content varied from . .field to field. Relationships also differed between Row topographic regions at all four sites, but no differences were identified between Soil-Landscape regions. Inconsistency in model performance across sites suggests that terrain - soil water relationships differ from location to location. Difference in results may be related to differences across sites in climate, soils, and other factors. This indicates a need to integrate site-specific information regarding soils and other factors with terrain models.

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Brian John Kozar

This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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TABLE OF CONTENTS

TABLE OF CONTENTS - CONTINUED

TABLE OF CONTENTS - CONTINUED

LIST OF TABLES

LIST OF TABLES-CONTINUED

LIST OF TABLES-CONTINUED

LIST OF FIGURES

LIST OF FIGURE-CONTINUED

ABSTRACT

Soil water content is a major factor controlling plant growth and crop yields in the semi-arid Northern Great Plains, and can vary substantially across a field. Farmers and land managers interested in identifying and delineating this variability need efficient methods to estimate soil water status. I hypothesized that topography influences soil water spatial distribution and could be used to delineate this distribution. The objectives of this study were to identify relationships between topography and soil water content, and determine if relationships discerned were similar across space. I used four farm fields across Northern Montana having moderate relief (15-30 m) with soils predominately formed over glacial till. Soil water content was measured throughout one growing season at each site using a neutron moisture meter. Digital elevation models were used to portray the terrain. Relationships at multiple depths were examined for the beginning and end of the growing season through two methods. Topographic region partitioning delineated the field into areas of presumed similar soil water content. Significant differences in soil water content between regions were tested using ANOVA. Secondly, the compound topographic index (CTI) was correlated with soil water content in a regression model. Study sites and topographic regions were included as covariates. Results identified differences in soil water content between regions, with the Flow topographic region-partitioning method identifying differences at all sites. However, no consistent patterns in differences between regions occurred across sites at any given depth. Reduction of across field soil water variance was also low (maximum = 21%). The strongest correlation between CTI and soil water content occurred at the end of the growing season at 20 cm ($R^2 = 0.40$, $p = 0.0001$). Relationships between CTI and soil water content varied from field to field. Relationships also differed between Flow topographic regions at all four sites, but no differences were identified between Soil-Landscape regions. Inconsistency in model performance across sites suggests that terrain – soil water relationships differ from location to location. Difference in results may be related to differences across sites in climate, soils, and other factors. This indicates a need to integrate site-specific information regarding soils and other factors with terrain models.

CHAPTER 1

GENERAL INTRODUCTION

Background

Soil water is a major factor limiting plant growth, including crop yields in the semi-arid agricultural systems of the Northern Great Plains. Vegetation depends more on the quantity and timing of plant available soil water than on any other single environmental factor (Kramer and Boyer, 1995). Dryland agricultural management strategies are therefore strongly based on the amount of soil water in a farm field or area to be managed. Many crop yield models rely upon input of plant available soil water evaluated at the beginning of the growing season. However, environmental factors such as soil water can vary substantially in space and time (Bell et al., 1994). Managers of environmental and agricultural systems therefore find that soil water conditions are difficult to assess in an accurate or rapid manner.

To characterize the status and spatial variability of soil water across a field, land managers often employ intensive grid sampling. However, time and cost required to conduct grid sampling often compel managers to use less-intensive, sometimes haphazard methods of measuring or estimating soil water status. Management zones delineated from these methods can be vague and can misrepresent actual conditions in the field. The spatial distribution and variability of other environmental properties, such as soil and terrain attributes, may be related to spatial variation of soil water, and in many cases these are more easily measured (Trangmar et al., 1986). Identification of terrain features related to soil water variation across fields would be valuable to land managers. Quantified relationships between soil wetness and soil or terrain attributes could aid in estimating the distribution of soil water across landscapes and in delineating zones having similar soil water status.

Soil Water and Plant Available Water

Water affects plant growth by influencing physiological processes within the plant. Water acts as an essential constituent that drives physiological activity in the plant, as a solvent in which minerals, nutrients, and other solutes enter plants and move between cells and organs, and as a reactant in important plant processes such as photosynthesis (Kramer and Boyer, 1995). As water becomes limited, plant functions suffer and economic yields decrease.

Plant available water refers to soil water held between field capacity and permanent wilting point. Permanent wilting point refers to the soil water content at which plants irreversibly wilt and fail to recover. Field capacity refers to the soil water content after free drainage has essentially ceased (Or and Wraith, 2000). Soil water held below wilting point or above field capacity is not available for use by plants in most cases (Kramer and Boyer, 1995; Brady and Weil, 1999).

There are numerous ways to measure or estimate plant available soil water content. Soil water can be measured gravimetrically based on soil samples taken to the average rooting depth of a particular crop of interest (Cook and Veseth, 1991). Soil water content is often calculated as a decimal fraction of the dry weight of the soil sample. However, this method results in significant disturbance to the soil, as many samples are required to accurately characterize soil water across a field.

Soil water can also be measured, with less destruction to the soil, through the use of sensors such as neutron moisture meters, gamma ray attenuation, and time domain reflectometry (Gardner, 1986; Or and Wraith, 2000). All of these methods are useful for measuring soil water at various depths in the soil (Kramer and Boyer, 1995). However, neutron moisture meters and gamma ray attenuation require training and licensing for safe use due to radiation hazard, and calibration for different soils. The considerable expense involved with using these methods may limit their feasibility for use by land managers.

Many sampling strategies have been applied to measure soil attributes and soil water, including regular grid-based (Odeh et al., 1994; Western et al., 1999) as well as random or stratified random sampling designs (Bell et al., 1994; McKenzie and Ryan, 1999). These methods can potentially assess and spatially represent soil water across a field with high accuracy, but are often field intensive and expensive, and therefore may not be feasible for a farmer or land manager.

Spatial Variation of Soil Water and Soil Properties

Many soil and environmental properties vary substantially across a field or landscape, and studies that model or predict environmental conditions should take into account spatial heterogeneity in geology, soils, and landforms (McLaughlin et al., 1993).

Soil water content and related soil properties often exhibit extreme variability over distances of about 1 to 100 m (Yates and Warrick, 1987; Moore et al., 1993; Western et al., 1999). At small catchment and hillslope scales soil water distribution varies as a result of water routing processes, due to terrain and landscape, heterogeneity in vegetation and soil characteristics, and other factors such as microclimate (Gessler et al., 1995; Western et al., 1999).

Soil properties such as horizonation, texture, and effective porosity can affect lateral flow and accumulation of soil water by impeding vertical water flow or through their influences on soil hydraulic properties (Bell et al., 1994; Gessler et al., 1995; Or and Wraith, 2000). Terrain modifies these effects. Further, variability in soils is substantially influenced by terrain, as topography is a basic soil forming factor (Brady and Weil, 1999). Soil depth, and soil physical and chemical properties, varies with landscape position. Variation of soil properties with landscape position can thereby affect water flow patterns (Afyuni et al., 1994).

Spatial variability of soil water can be random or organized (Bloschl, 1999; Western et al., 1999). The degree of organization in spatial variability of soil water is largely related to soil properties and terrain (Western et al., 1999). For dry soils near wilting point, spatial variability is primarily random as local soil properties hold primary influence on water flow. Capillary forces exerted by the soil matrix resist displacement of water (Philip, 1957; Hillel, 1980). This effectively opposes gravitational forces inherent in terrain-driven lateral flow (Yeh and Eltahir, 1998). Hydraulic conductivity, a primary soil hydraulic property, increases exponentially as soils wet (Bouma and Anderson, 1973). Spatial patterns in soil water distribution might then be increasingly influenced by terrain-driven lateral forces and impediments to vertical water flow (Gessler et al., 1995; Grayson et al., 1997). This can lead towards high organization in the spatial pattern of soil water.

Site Specific Agriculture

Interest in precision agriculture has arisen from the realization that significant yield increases can not be efficiently obtained through additional chemical applications, and the desire to simultaneously maintain or increase yields while reducing chemical inputs into the system due to economic and environmental concerns (Bell et al., 1995; Brown, 1995). This relatively new practice incorporates the use of geographic information systems (GIS), remote sensing, and global positioning systems (GPS) to more efficiently manage farm fields on a site-specific basis. Global positioning systems provide the location for data being recorded in the field. Geographic information systems provide a method for linking, displaying, and analyzing GPS-generated and remotely-sensed data for decision support applications (Burrough and McDonnell, 1998). These systems are often used directly on farm machinery, and the farmer may conduct specific analyses or utilize consultants.

Defining and managing soil and landscape spatial variability is crucial for precision agriculture. Managers aim to characterize the spatial distribution of soil and other environmental properties as precisely as possible so they can vary their management techniques across space, maximizing management effectiveness (Bell et al., 1995). To this end a farmer may be interested in partitioning fields into management zones. Delineation of management zones is often achieved by characterizing spatial variability of one or more soil properties or crop yield. Within these zones variability of the soil property of interest is low relative to its variability across the field. Management techniques within zones are similar, yet unique with respect to the rest of the field (Goddard et al., 1999).

Within this context, integrated GIS/modeling programs must be capable of identifying the best possible management practices for a given combination of soils, topography, and any other factors relevant to the field. Concurrently, these programs must be accessible for use by a manager who might have limited expertise using such programs (Frida, 1993; Parks 1993). A computer model that requires extensive training might be prohibitive to a majority of managers, and therefore of little practical use. Models to be used for site-specific agriculture should therefore be designed for application by users beyond the researcher developing them (Parks, 1993). Within such systems, a manager could identify and delineate management zones based on having similar soil water properties. Crop yields could be maintained or enhanced while inputs such as fertilizer, pesticides, and herbicides could be optimized across the field. Consequences of such a system would include potentially favorable effects on the environment and on economic return (Power and Schepers, 1989).

Soil Survey and Terrain Analysis

Explanatory variables used to model soil water variability must be easier to obtain than soil water measurements, if these variables are to simplify the task of increasing efficiency and productivity (McKenzie and Ryan, 1999). Increasingly, easily obtained soil survey maps are displayed in a GIS for management purposes (Keck, 1998). Soil survey map units encompass a range of individual soil properties within specified limits of variation. Map units can be used as a template for soil water sampling and as management zones for use in crop yield models (Decker, 2000). A soil water sample may be taken within each soil map unit, and, based on soil properties defined in the map unit, a value for plant available water could be calculated and assigned to the map unit. Plant available water could then be used, along with other soil and climatic factors, in making crop yield predictions in a GIS.

Conventional soil survey maps, however, do not delineate all of a field's inherent variability nor represent specific soil attribute variation (Moore et al., 1993). Inferred homogeneities within soil map units do not exist for many physical and chemical attributes that affect environmental modeling and soil-specific management (Moore et al., 1993). Point samples often do not fit within the range of values assigned to a given soil series or map unit (Nettleton et al., 1991). Thus actual plant available water may vary significantly within the map unit to which only one value for plant available water has been assigned. This can lead to variation of actual crop yield within the map unit, yet not predicted in a crop yield model.

Environmental factors that might influence within-unit soil water variability include topography and geologic processes (Verhagen et al., 1995). In mountainous or hilly terrain, soil water distribution is controlled largely by vertical and horizontal water divergence and convergence (Odeh et al., 1994; Moore et al., 1993b). Two areas where soil water storage might be high due to lateral subsurface flow are hillslope hollows and low-gradient slopes. Alternatively, it could be expected that hillslope ridges might have lower soil water storage due to lack of contribution from lateral flow. This might vary with different soils (Burt and Butcher, 1985). Soil-terrain modeling incorporates soils and terrain to identify portions of the landscape where water might move predominantly in the lateral, as opposed to vertical, direction.

Digital Elevation Models

MacMillan et al. (2000) suggest it is possible to transfer manual rule-based approaches for interpreting and classifying landscapes into computer based procedures that use artificial intelligence. In doing so, the capture and application of tacit knowledge of experts in the fields of soil and landform modeling could be automated and repeatable across space (i.e. different sites) and time.

Digital elevation models (DEMs) depict a landscape by representing the spatial distribution of elevation above some arbitrary datum, usually as a grid within a GIS framework (Moore et al., 1991). Elevation contour maps or elevation data points collected with a GPS are two sources of input elevation data. As part of the classification procedure DEMs can calculate quantitative terrain attributes for each grid cell that characterize the surface shape of the landscape. The attributes can then be used for statistical correlation with other environmental properties at these nodes.

Quantitative attributes that are derived from a DEM can be divided into primary and secondary, or compound, attributes. Primary indices are calculated directly from a DEM, and four that have been correlated extensively with soil water content include local slope, aspect, plan curvature (a measure of the rate of flow convergence and divergence), and profile curvature (water concentrates where slopes flatten out) (Burt and Butcher, 1985; Moore et al., 1993b; Odeh et al., 1994; Gessler et al., 1995). A fifth primary topographic attribute considered by many researchers to be of fundamental importance in modeling soil water content is specific catchment area (Moore et al., 1993c; Western et al., 1999). This attribute is an approximate measure of runoff per unit width above a given point in a landscape, therefore estimating contributing flow to that point.

Compound attributes are generated through the combination of two or more primary attributes. The intent is to characterize and model more precisely specific processes occurring in the landscape (Gallant and Wilson, 1996). Various forms of wetness indices, the stream power index, and sediment transport capacity indices are examples of process-based secondary attributes. The compound topographic index (CTI), or steady-state wetness index, incorporates many pedological-transfer functions across landscapes that influence soil spatial variability. Therefore it can be used to capture spatial variability and distribution of select soil properties and attributes (Burt and Butcher, 1985; Moore et al., 1993c; Odeh et al., 1994; Barling et al., 1994). The spatial distribution of soil water has been extensively modeled using CTI (Burt and Butcher, 1985; Jones, 1986; Moore et al., 1988, 1993b).

Topographic Region Partitioning

An alternative approach to terrain analysis involves topographic region partitioning. This approach is based on separating a landscape into distinct sections or regions based on position or shape, i.e. ridge, shoulder, backslope, toeslope, etc., often within a GIS.

The region-partitioning approach incorporates a deterministic, expert knowledge based procedure to model the spatial distribution of soil water. Landscapes can be partitioned into any number of classes, through the separation or combination of any kind and number of terrain features (Pennock et al., 1987; Zhu et al., 1997; Nolan et al., 2000). The partitioning is based, in part, on presumed knowledge of processes occurring across a landscape and the effects of these processes on soil water distribution. As contrasted with stochastic statistical analysis, the use of expert knowledge to define landform elements permits definition of a standard set of spatial entities that can be expected to exhibit predictable behaviors (with respect to water) across a wide range of landscapes (MacMillan et al., 2000).

The methods and scales at which topography has been used for region-partitioning have been varied. Leavesley and Stannard (1990) assumed that watersheds could be divided into sub-areas, called hydrologic response units (HRU), based on homogeneity in hydrologic response. This approach emphasized that HRUs should be defined through matching the similarity of many topographic and environmental (e.g. soil, vegetation) variables.

Wood et al. (1988, 1990) introduced the idea of the representative element area (REA) to address within-unit variability. The basis of the REA concept is identification of upper and lower bounds of spatial variability of environmental variables that yield a specific homogenous hydrologic response. This is also called the critical area. At the critical area scale, the effects at the point scale are attenuated or completely submerged (Grayson et al., 1992).

Use of topographic and soil survey information for region partitioning has been conducted at relatively small, farm field scales with varying degrees of success. In one case, attributes computed from a DEM and a fuzzy rule base were integrated to identify

15 morphologically defined landform facets (MacMillan et al., 2000). The 15 facets were grouped into fewer classes to stratify soil properties. Using topographically derived regions, McBratney et al. (1991) claimed to improve representation of geostatistically mapped soil attributes. Odeh (1994) Illustrated that optimal sampling patterns could be designed to reduce representative error of samples. Nolan et al. (2000), however, suggested that the success of topographic region partitioning varied from site to site and year to year, predominantly as a function of the influence other environmental variables have over the variable being stratified.

Other studies maintain that multivariate statistics such as discriminant analysis and fuzzy-k means clustering of quantitative terrain attribute data can-be used to partition regions (Webster and Burrough, 1974; Bell et al., 1994; Thomas et al., 1998; Sinowski and Auerswald, 1999). The terrain data are grouped into classes so that "similar" data are in the same class (Manly, 2000). De Bruin and Stein (1997) maintain that this method enhances soil-landscape modeling because it allows representation of fuzziness inherent to soil landscape units.

Expert knowledge is incorporated into multivariate analysis in one of two ways, depending on the method used. In discriminant analysis, a user-defined number of classes are "seeded" with specific values of terrain and environmental variables used in the partitioning process. These values are pre-determined by the user to be representative of their respective classes. Subsequent assignment of dataset individuals is based on statistical distance of each individual to these values (Manly, 2000). For fuzzy k-means cluster analysis, the user defines the optimum number of classes to be determined for a landscape. Classification is based on statistical distances calculated between individuals in the dataset (MacMillan et al., 2000; Manly, 2000).

Models and Classification

Models that incorporate soils and terrain to characterize soil water variability can be classified into two groups: probability, or stochastic, and deterministic models. Stochastic models do not necessarily rely on understanding of processes involved with soil water variability. These models instead typically assume that small-scale water flow and accumulation can be described as random functions with known statistical properties (McLaughlin et al., 1993). These statistics are then used to calculate the probability that a given soil water value will occur. A comparison between estimates of soil water status developed from regression equations and validation samples in the field is a relatively simple stochastic method that has been attempted with variable success (Moore et al., 1993; Barling et al., 1994; Western et al., 1999).

In contrast, deterministic models incorporate mass water conservation and flux laws into the predictive process. Predicted values are thus a function of space and time. In this sense, deterministic models require an understanding, or expert knowledge, of the underlying environmental and systematic processes involved in soil water distribution and variability. Buckingham-Darcy's Law for unsaturated flow in porous media is an example of this type of model. There are two general classes of deterministic models. Quantitative models use mathematic, often differential and/or numerical, equations to characterize the underlying process. Qualitative models often use expert knowledge to produce results in the form of abstract class designations rather than numerical results (Keck, 1998).

A model at best only represents reality by capturing some aspect, or essence, of the reality it attempts to represent (Fdida and Pujolle, 1987). Natural processes that occur in an environmental system can be highly complex and involve many factors. Most models are based on a set of simplifying assumptions that allow some environmental factor to serve as a surrogate for multiple other factors, thus reducing complexity (Keck, 1998). However, outputs from such a model can only be as accurate as these assumptions are appropriate (Keck, 1998). The simplifying assumptions must capture appropriate elements of reality in a manner that is not distorted or biased. A soil-terrain model for predicting soil water distribution will not be useful to farmers if spatial estimates are incorrect.

Scope and Purpose

The work presented in this thesis contributes to a larger effort to incorporate site-specific management practices into agriculture. Research conducted for this thesis was based on the hypothesis that the integration of soil survey and terrain analysis in a GIS format could be used to delineate distribution of soil water content across landscapes. An inherent assumption was that topography is integral to modeling soil water distribution and variability across agricultural fields such as these studied, which had moderate topographic relief. The goal of the project was to increase understanding of the practice of using terrain to model soil water distribution and spatio-temporal variability, and to determine if terrain analysis might be useful to producers for identification of management zones based on soil water content. These management zones could be used to aid the farmer in optimally allocating chemical application rates, while maintaining or increasing yield and thereby reducing likelihood of groundwater pollution. Additionally, management zones could be used as a template for benchmark sampling of soil water, which is more feasible than traditional grid sampling schemes.

Objectives

Two aspects of the overall project are described in this thesis. Chapter 2 addresses two objectives: 1) to characterize and describe the spatial distribution and variability of soil water on four Montana farm fields of moderate (15-30m) relief; and 2) to evaluate the feasibility of region partitioning, through terrain analysis and soil survey, to delineate management zones based on soil water content in these four fields. This aspect of the project incorporates a qualitative deterministic modeling approach to delineate the regions. Chapter 3 addresses a single objective: to determine the correlation between soil water content and topographically-derived quantitative indices calculated at 5m grid scales. The empirical, stochastic approach used in Chapter 3 assumes that terrain attributes function as surrogates for the processes underlying soil water distribution.

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CHAPTER 2

TOPOGRAPHIC REGION PARTITIONING WITHIN FARM FIELDS AND ANALYSIS OF SOIL WATER CONTENT WITHIN AND BETWEEN REGIONS

Introduction

Soil water is integral to many processes that occur within and across landscapes, including plant growth and crop yields. Land managers, however, often find it difficult to assess the distribution and variability of soil water content in an efficient and reliable manner. Topography can influence the distribution of soil water by influencing surface and subsurface flow (Burt and Butcher, 1986; Moore et al., 1991; Grayson et al., 1997). Terrain analysis may therefore be a useful tool for delineating soil water spatial distribution and variability across landscapes.

Approaches that use terrain analysis to infer soil water attributes assume that terrain modifies soil and parent materials and can therefore serve as a surrogate by integrating many landscape processes that influence soil water patterns (Gessler et al., 1995). Region partitioning is based on separating a landscape into distinct sections or regions based on landscape position (upper, mid, and lower) or shape (convexity and concavity). If successful, variation in an environmental variable of interest, such as soil water content, is smaller within any particular region than between regions or across the landscape (Ovalles and Collins, 1986).

For modeling soil water distribution, three or four class groupings seem to offer an optimal combination of simplicity, spatial consistence, and meaningful differences in terrain and soil properties (Pennock et al., 1987; Burrough et al., 1992; MacMillan et al., 2000). Region partitioning might be useful to managers who would like to apply spatially variable management strategies based on soil water status. An assumed relationship between soil water and terrain, and the need to define effective agricultural management zones, provide motivation for the use of a terrain-based region-partitioning approach.

The purpose of this study was to evaluate the potential to delineate soil water management zones as an aid to farmers and land managers. Such zones might be used to optimize application rates and as templates for benchmark soil sampling. This study encompassed two main objectives: 1) to measure soil water content at multiple locations on four Montana farm fields several times during the growing season; and 2) to test the utility of three terrain and soil-based region-partitioning methods to delineate the measured soil water distribution and variability.

Materials and Methods

Study Sites

The study was conducted at four locations, each comprising a 25 to 60 ha portion of farm fields located across the "Hi-Line" agricultural region of north central Montana.

Liberty County Site. The study area consisted of about 25 ha within a farm field having gently rolling terrain of moderate (20m) relief and located approximately 21 km north of Chester, MT (T34N, R7E, Section 17; 48°42'30" 110°51'30") (Fig. 1). The predominant aspect trended to the south, with a moderate draw running in a south-southwesterly direction (Fig. 2a). The area has a cool, semi-arid climate, with mean annual precipitation of 31 to 43 cm (Caprio et al., 1994). However, the research site commonly receives lower amounts of annual precipitation, possibly due to its location in a rain shadow to the east south east of the Sweetgrass Hills (Janice Mattson, 2000). The field was dryland farmed by the Mattson family with an alternate wheat/fallow rotation.

The underlying geologic materials at the liberty site are primarily glacial till derived from the Bear Paw formation (Veseth and Montagne, 1980). Soils are mapped as a complex of Joplin loams (a fine-loamy, mixed, frigid Aridic Argiustoll) formed on till, and Hillon loams (fine-loamy, mixed, calcareous, frigid Aridic Ustorthent) (National Soil Survey Staff, 1998a; 1998b).

Hill County Site. The study area was a 15 ha portion of a farm field located in Hill County, approximately 16 km west of Havre, MT (T32N, R14E, Section 17; 48°31'30" 109°57') (Fig. 1). This field is characterized by a knoll of moderate relief (~15m) running west-east across the southern portion, and a knoll of lower relief (~5m) running west-east across the northern portion of the site. The remainder of the field is relatively flat (Fig. 2b). The area has a cool, semi-arid climate with mean annual precipitation of 31 to 43 cm and (Caprio et al., 1994). The field was dryland farmed by the Kaercher family with an alternate wheat/fallow rotation.

Underlying geologic materials are glacial till derived from the Bear Paw and Judith River formations (Veseth and Montagne, 1980). This site consists of three mapped soils. Soils in the southern portion (Map unit 701D), along the knoll, are a complex of Yetull loamy sands (mixed, frigid Aridic Ustipsamments) formed in sandy alluvium and/or eolian deposits, and Busby fine sandy loams (coarse-loamy, mixed, frigid Haplocalcidic Haplustepts). Just to the north is a complex (331B) of Phillips loams (fine, frigid Aridic Haplustalfs) and Elloam clay loams (fine, frigid Aridic Natrustalfs), both formed in till on plains. In the northern portion of the field, soils (421C) are the Joplin loams (fine-loamy, mixed, frigid Aridic Argiustoll) formed on till, and the Hillon loams (fine-loamy, mixed, calcareous, frigid Aridic Ustorthent) (National Soil Survey Staff, 1998c; 1999; 1998d; 1996; 1998a; 1998b).

Phillips County Sites. The remaining two study sites were neighboring strips of the same field that are dryland farmed in alternate years by the Anderson and Mavencamp families using an alternate wheat/fallow rotation. "Phillips 1" consisted of 25 ha, and the second site, "Phillips 2", consisted of 12 ha of the field, approximately 22.5 km east of Malta, MT (T31N, R32E, Section 20; 48°25'30" 107°35'30") (Fig. 1). This site has moderate relief (~30m) with uneven rolling topography and occasional severe undulations (Fig. 3). The climate is cool, semi-arid with mean annual precipitation of about 31 to 43 cm (Caprio et al., 1994).

The underlying geologic materials are primarily glacial till from the Clagget formation (Veseth and Montagne, 1980). Soils are mapped as a complex of Scobey clay loams (fine, smectitic, frigid Aridic Argiustoll), and Kevin clay loams (fine-loamy, mixed, frigid Aridic Argiustoll), formed on till plains, hills, and moraines (National Soil Survey Staff, 1998e; 1998f).

Figure 1. Location of the four sites used in this study. Two adjacent fields in Phillips County near Malta were utilized.

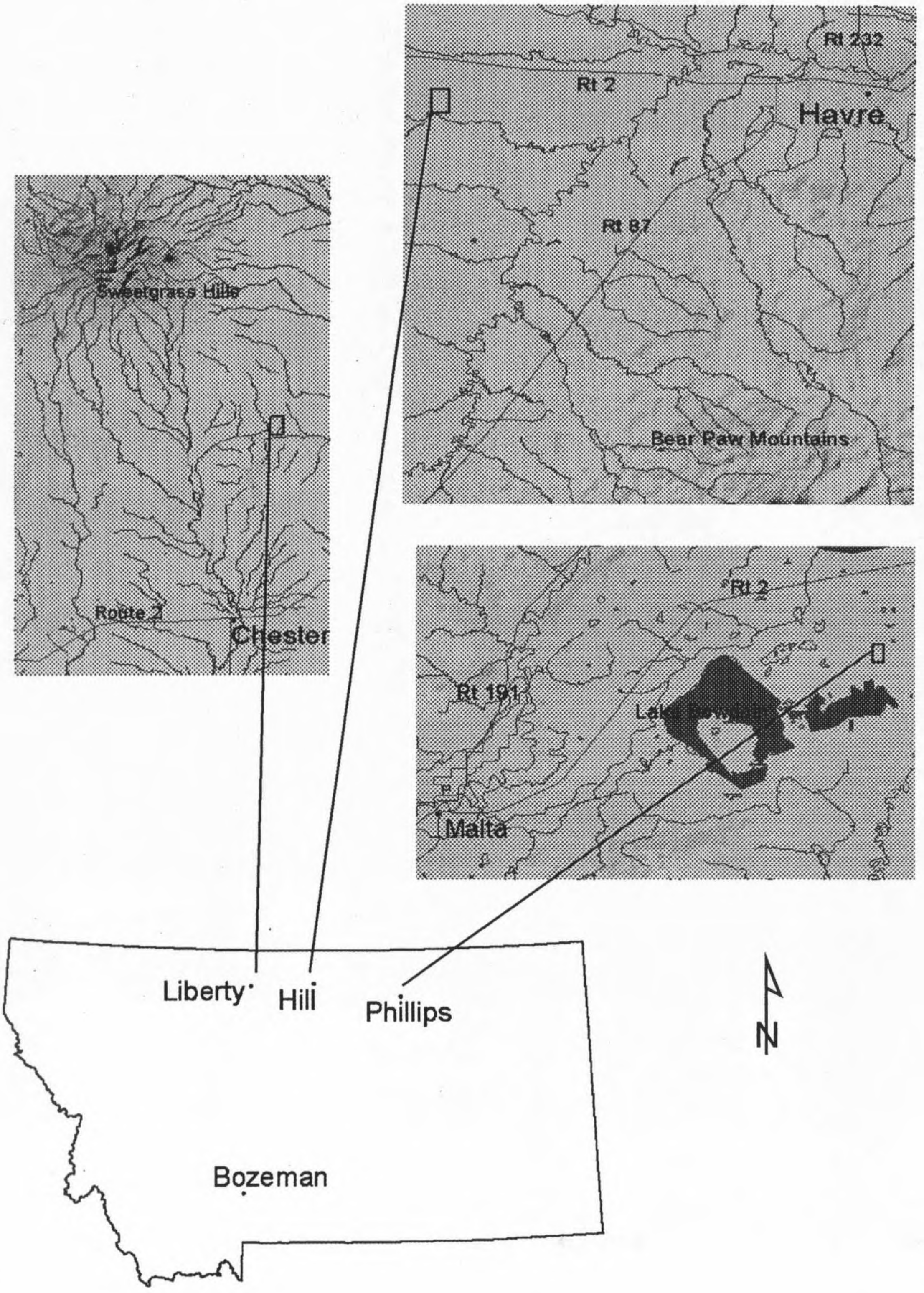


Figure 2. Interpolated 10m elevation grid surfaces for the Liberty and Hill field sites.

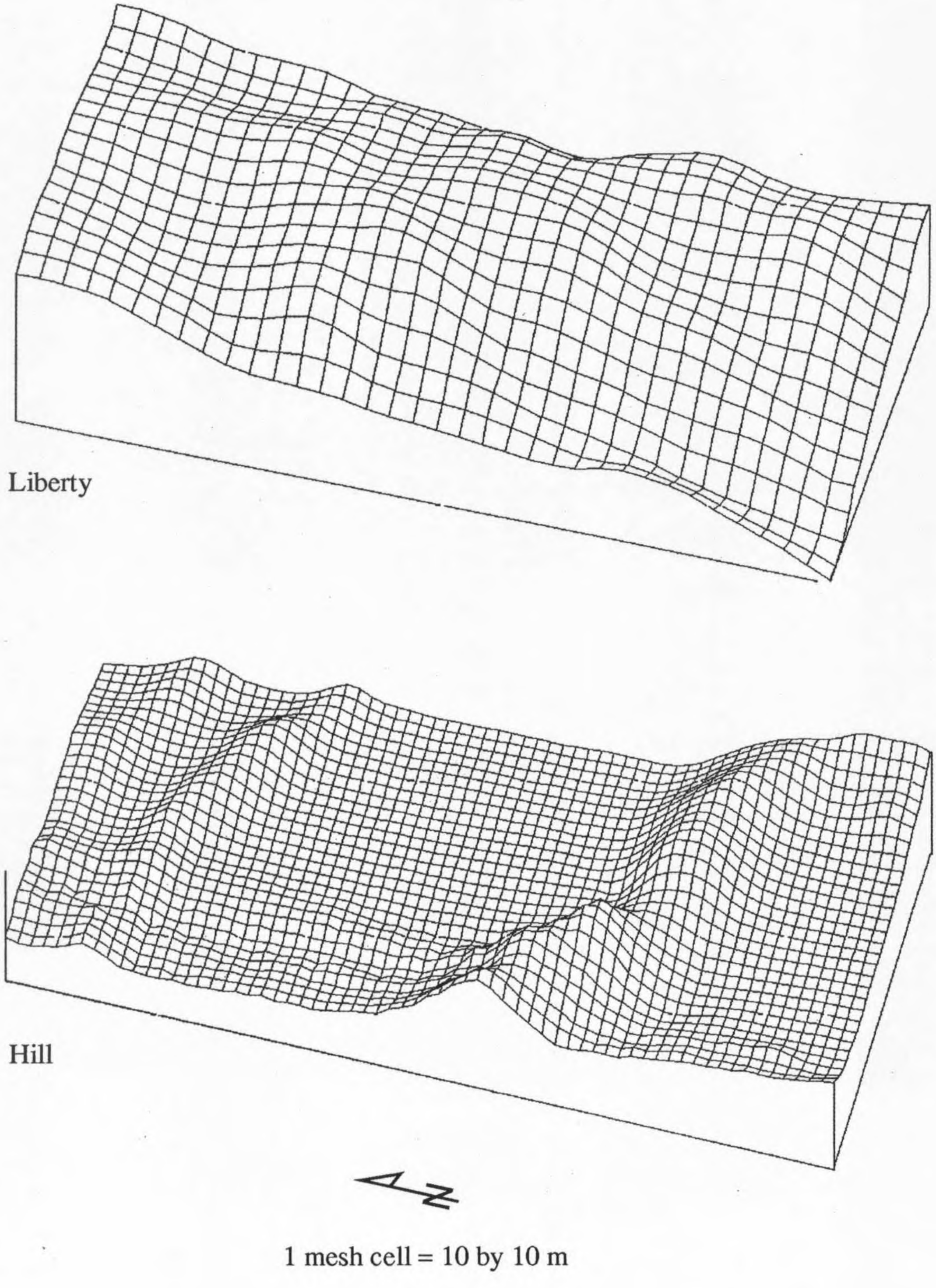
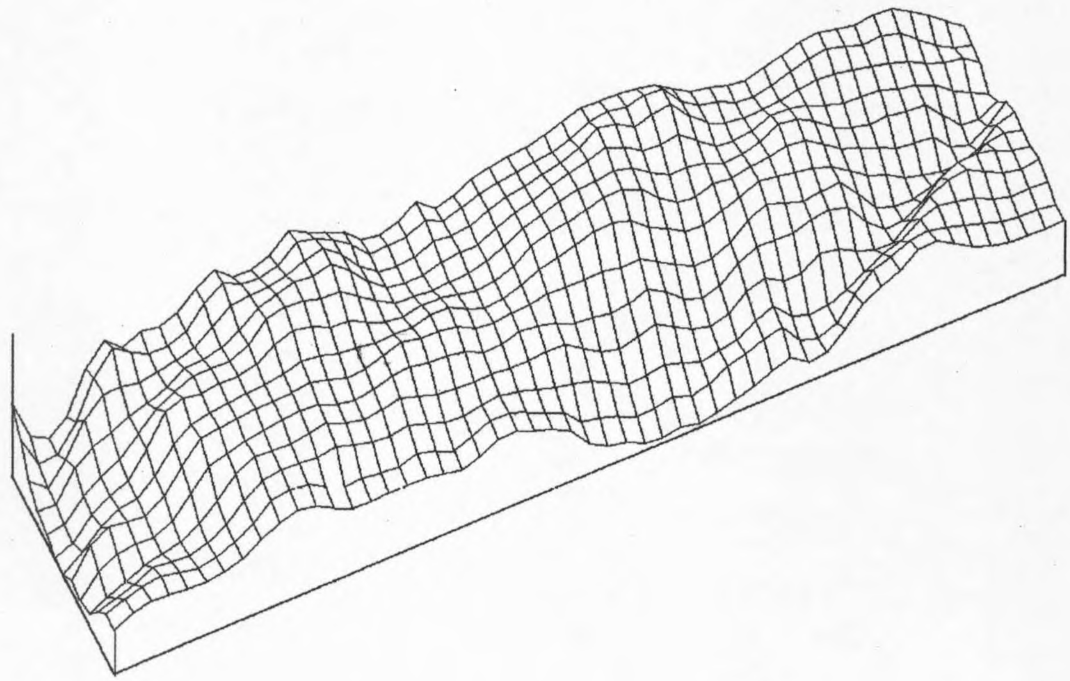
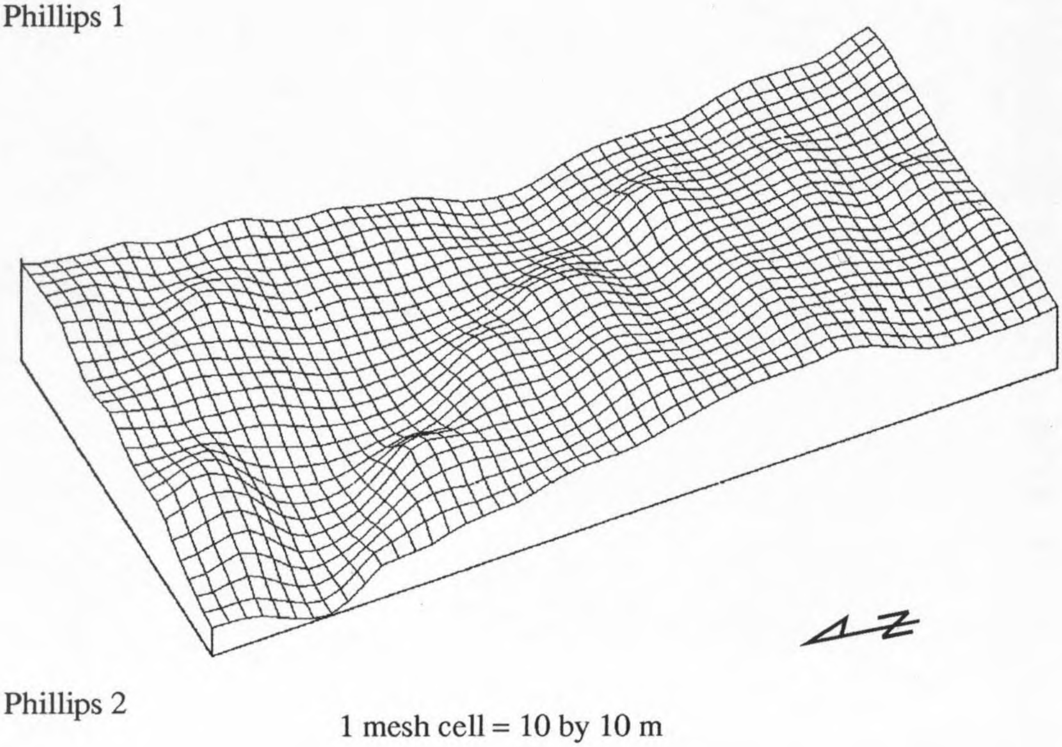


Figure 3. Interpolated 10m elevation grid surfaces for Phillips field sites.



Phillips 1



Phillips 2

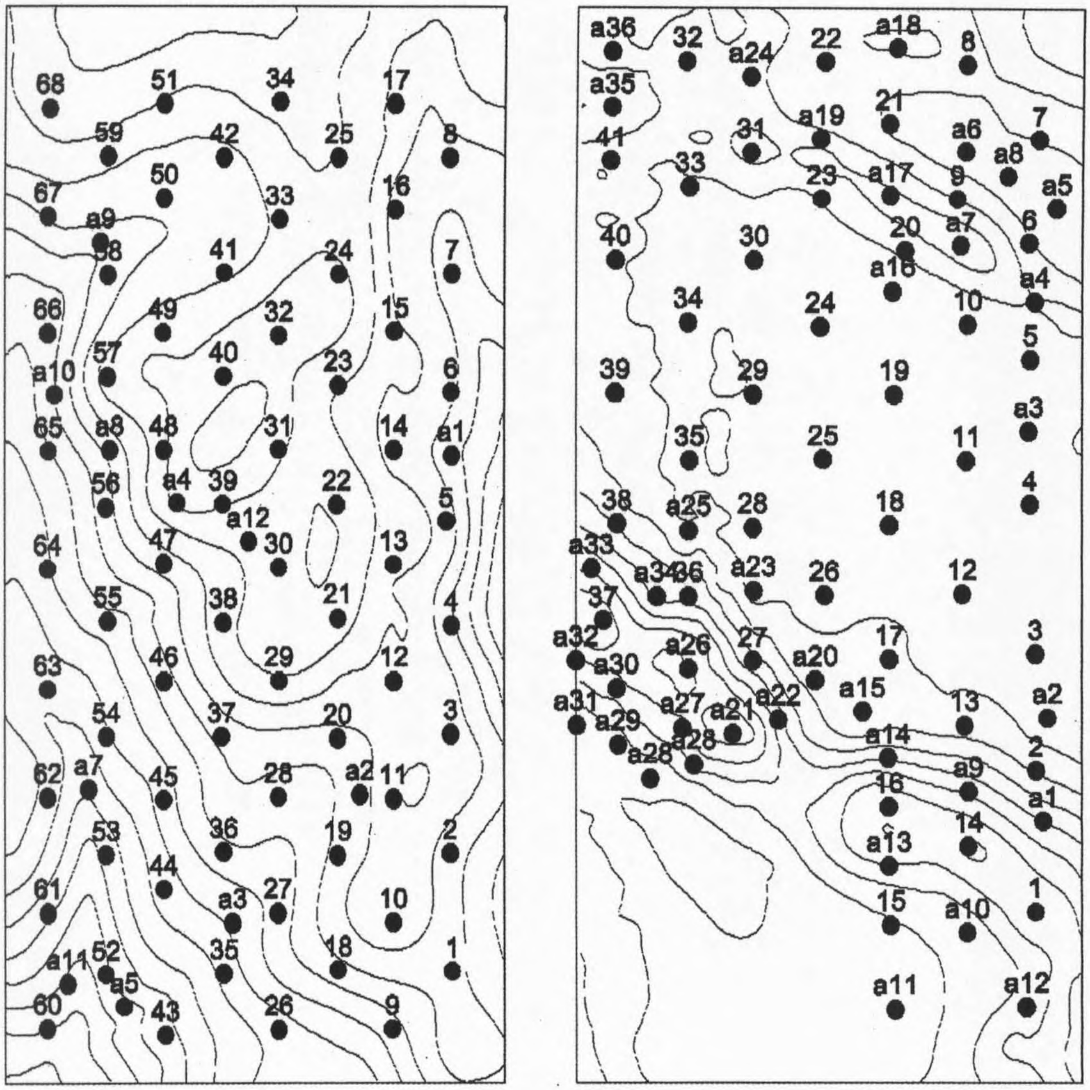
1 mesh cell = 10 by 10 m

GPS Survey and Soil Water Sample Grids

Field elevations were collected over each study site in the fall of 2000 (Liberty and Phillips) and in the fall of 2001 (Hill). A Novatel model 3151R GPS receiver (24-channel, single-frequency, L1 carrier phase) was mounted on an all-terrain vehicle and measured elevation at roughly 10-m intervals along a series of parallel transects. A second Novatel receiver was located at a base station in the same field. The raw elevation measurements were corrected in the laboratory with the commercial post-processing software GravNav (Waypoint Consulting, Inc., Calgary, Alberta, Canada) to a positional accuracy of within ± 4-cm in both the horizontal and vertical planes, relative to the location of the base station. An Ashtech AgNavigator consisting of a 486 computer, light-bar, and navigation-grade GPS receiver (12 channel, L1 C/A code) was used to provide guidance along the parallel transects within ±1-m of positional accuracy.

A permanent, augmented sampling grid of 78 to 80 points was established in each field for the purpose of measuring soil water contents (Fig. 4, 5). 50 to 65 equally spaced sample points were established in an offset grid-like pattern. The GPS system was used to develop the grid and to mark the points in each field. An additional 15 to 30 points were added to augment the grid, in order to better represent the range of soils and terrain features (e.g. areas of convergence and divergence) across the study site. The combination of grid points and augment points in any field was a product of the size of the field and visual estimation of topographic variability within the field. To insure adequate coverage, the larger plots included more points in the offset grid.

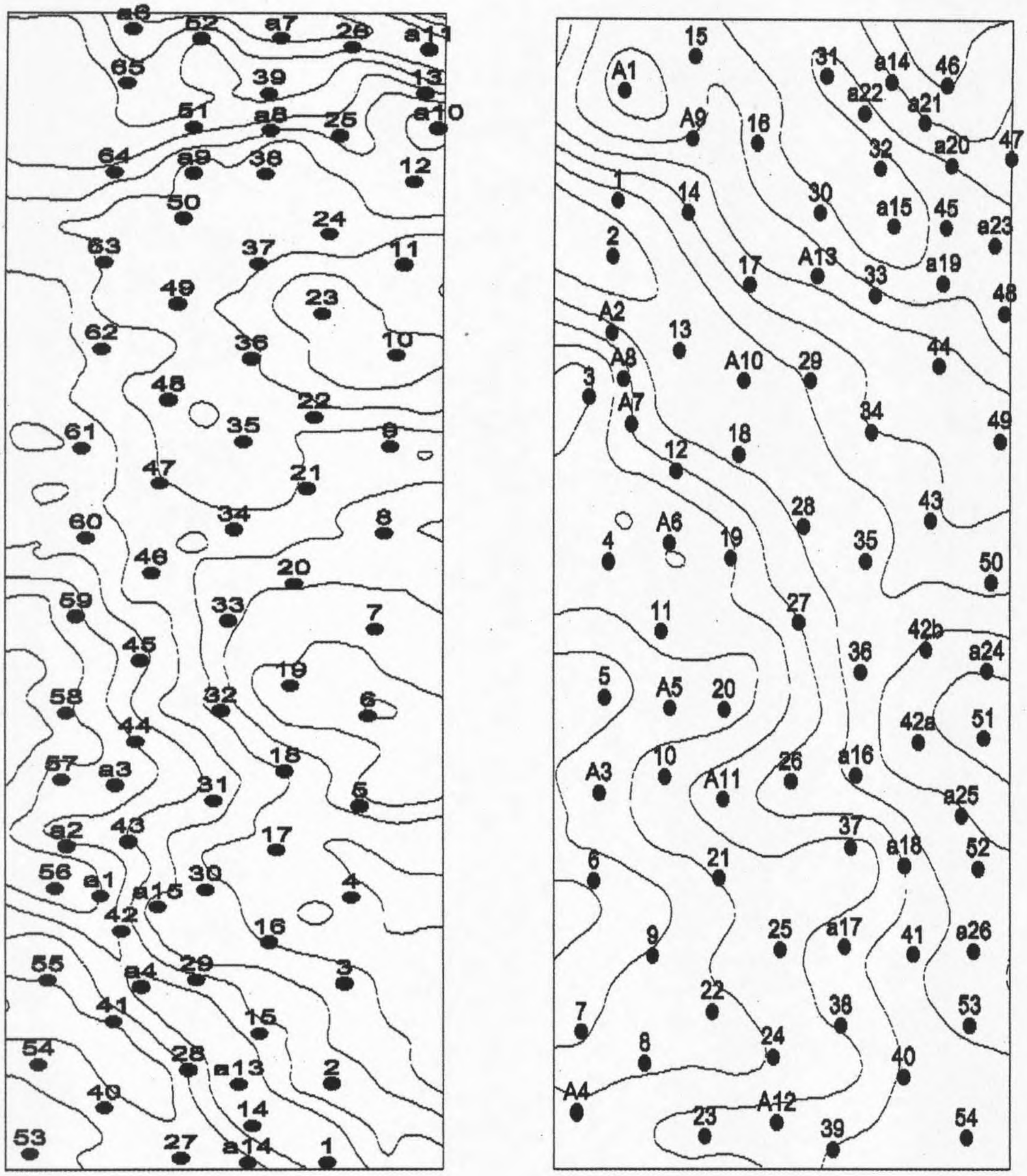
Figure 4. Permanent soil water content sampling grid for the Liberty and Hill sites.



Liberty Hill

Fields not to scale
"a" indicates augment point

Figure 5. Permanent soil water content sampling grid for the Phillips sites.



Phillips 1

Phillips 2

Fields not to scale
"a" indicates augment point

At each sample point a thin-wall PVC access tube was installed to 80 cm depth to measure soil water content with a neutron moisture meter (503DR, CPN Co., Martinez, CA) (Gardner, 1986). Following access tube installation the locations and elevations of each point were resurveyed using the GPS.

Soil Sampling and Field Characterization

Soils information used in this project was obtained through the National Cooperative Soil Survey and select field samples. All fields were mapped as complexes of soil series by the National Resource Conservation Service staff. Soil pits were excavated to investigate spatial distribution of soil series across the landscape. For every field, at least one soil pit was excavated on the upland, mid-slope, and lowland landscape positions, as well as in areas of convergence and divergence. Soil profiles were described for the sampled locations within fields (Appendix B), including some soil characteristics considered to be related or correlated to soil water storage, flow, and spatial distribution (Or and Wraith, 2000). The soils information was used in interpreting results of the region-partitioning approaches described below.

Generation of Topographic Regions

Two of the methods for partitioning landscape regions in order to model soil water distribution were landscape models that classify terrain attributes using a rule-based approach. The third method used multivariate statistical cluster analysis to numerically classify terrain attributes. The GPS elevation data for each field were converted to a regular, equally-spaced 5 m digital elevation model (DEM) grid using the interpolation software package ANUDEM (Hutchinson, 1989). ANUDEM takes as input irregularly spaced elevation point data and creates grid based DEMs using a series of smoothing operators.

Rule-Based Landscape Region-Partitioning. The interpolated 5 m elevation data were imported into Arcview Spatial Analyst v3.2 (Environmental Systems Research Institute, Inc., Redlands, CA) as an ASCII file, converted to an Arcview grid, then imported into LandMapR (MacMillan et al., 2000) to generate landscape classes. LandMapR computed quantitative terrain attributes such as slope, profile curvature, and plan curvature, for every cell in a DEM, and converted them to any of 20 basic fuzzy landform attributes. These attributes are "fuzzy" because, among other reasons, they describe the terrain in terms of relative shape (convex_down, rel_steep, etc.) and location (near_top, near_bottom, etc.). The landform attributes were used in various combinations to define 15 basic landform element classes, e.g. convergent backslope, toe-slope, etc.

The converted landform element class data was extracted from LandMapR, imported into Arcview Spatial Analyst v3.2, and converted to a 5 m grid. Using the reclassify function, the 15 landform elements were grouped into fewer classes (3-4) to reduce complexity and spatial fragmentation, using two different approaches.

One approach, termed the Flow Method, was based on empirical concepts of surface and subsurface water flow across a landscape. This approach created four classes: divergent (water shedding), convergent (water receiving), planar or flat (water neutral), and depressions (water retaining) as outlined in MacMillan et al., 2000. The second grouping method, Soil-Landscape, was based on topography and relative position in the landscape as reflections of soil spatial patterns. Three generalized classes were recognized: upper, mid, and lower as outlined in Appendix E. Soil formation as a function of one attribute of landscape, and resultant variability in soils across a landscape, were represented in this approach.

Multivariate Statistical Region-Partitioning. The 5 m interpolated data from ANUDEM were entered into the Terrain Analysis Program for the Environmental Sciences (TAPES) (Gallant and Wilson, 1996) software program to calculate terrain attributes for each 25 m^2 cell, for the four study sites. Four primary attributes correlated with soil water content in other studies (Burt and Butcher, 1985; Moore et al., 1993b; Odeh et al., 1994) were generated: slope, elevation, profile (down-slope convergence and divergence) curvature, and plan (across-slope) curvature. The finite differences (FD option) approach, rather than the approximate (D8) approach, was used to calculate slopes for this project.

The terrain attributes calculated by TAPES, along with associated coordinate data, were imported into Minitab statistical software (Minitab Inc., State College, PA). Fuzzy-k means cluster analysis was performed using the four terrain attributes. The program delineated three (upper, mid, and lower) landscape position classes for each of the four study sites. The complete dataset with class designations was imported into Arcview Spatial Analyst v3.2 where it was converted to a grid based on class designations.

In Arcview, neutron moisture meter sample point coordinates were overlaid on their respective Flow, Soil-Landscape, and cluster analysis class grids. A get-grid function was performed to determine cells in which the sample points were located. Class information for each cell containing a sample point was assigned to the sample points.

Soil Water Content

Soil water content measurements were used to evaluate efficacy of region partitioning to designate soil water management zones. Neutron moisture meters were used to measure water content at 20 cm depth intervals to 80 cm. Calibration relationships for the neutron meters were developed at each study site. Measurements were obtained five times during the growing season at each site. Some sample points were not monitored on specific dates due to equipment malfunction. The earliest measurement occurred immediately following seeding of the fields. Therefore, the influence of the crop on soil water would be minimal or nonexistent at that time. The last measurement of the growing season was collected at harvest, and more strongly reflected crop impacts on soil water status.

For all field sample points at all depths at each measurement date equivalent depth of soil water (cm) was calculated as the product of measured volume water content (cm^3/cm^3) and the corresponding measurement depth interval (cm). Thus, measurements at 20 cm were converted to equivalent depth of soil water in the top 30 cm of soil. Measurements at 40 cm, 60 cm, and 80 cm depths were converted to equivalent depth of soil water at the 30 - 50 cm, 50 - 70 cm, and 70 – 90 cm soil depth intervals, respectively. Total soil water integrated over the top 70 cm of soil were also calculated. Soil water was not summed over the top 90 cm because several neutron access tubes were not installed to sufficient depth as a result of rocks or other obstructions. All access tubes allowed measurement to the 60 cm depth.

Statistical Analysis

Excel (Microsoft Corporation, Redmond, WA 98052) spreadsheet software was used to calculate summary statistics for soil water. Tables 14 - 17 in Appendix A provide designated region classes for soil water point measurements in each field. These were linked with measured soil water contents to create composite data files for analysis of variance (ANOVA) and for calculation of relative variance in soil water contents. Analyses at depths of 20 cm (i.e. 0 – 30 cm depth interval), 60 cm (50 – 70 cm interval), and top 70 cm were performed. Analysis at 80 cm was not performed due to lack of data.

To test for differences in mean soil water content between the delineated regions, ANOVA (Minitab) was conducted for each site and for all collection dates. Semivariograms were used to evaluate autocorrelation in each water content dataset. A normal probability plot of residuals was created to test for normality in the data. The F-test with a significance P-value of 0.05 was used to find differences between at least two of the region mean soil water values. To determine which regions differed significantly, the Tukey-Kramer multiple comparison procedure was used (Devore and Peck, 2001), with a simultaneous confidence interval of 90% (family error rate of 10%). This corresponded to an individual confidence level of 97.8% (individual error rate of 2.2%).

Relative variance of composite data files was evaluated for all collection dates. This characterized map precision by expressing the percentage of variability within regions that was less than variability across the entire study field, and is calculated from the pooled variance, S_p^2, expressed as

$$S_p^2 = \frac{\sum(x_{1j}-\bar{x}_1)^2 + \sum(x_{2j}-\bar{x}_2)^2 + \ldots\ldots\sum(x_{ij}-\bar{x}_i)^2}{n_1 + n_2 + \ldots\ldots\ldots - n_t}$$

where $\sum(x_{ij}-\bar{x}_i)^2$ is the sum of squares for the *i*th region, n_i is the number of water content observations in the *i*th region, and n_t is the total number of regions (Beckett and Burrough, 1971, Long et al., 1995). Relative variance R_s^2 is then expressed as

$$R_s^2 = \frac{(S_t^2 - S_p^2)}{S_t^2}$$

where S_p^2 is the pooled variance and S_t^2 is total across-study-site variance.

Results

Soil Water Content and Precipitation

Soil water content mean values for each site for the first and last measurement dates of the growing season at three representative depths: 20 cm (0 – 30 cm depth interval), 60 cm (50 – 70 cm depth interval), and top 70 cm (0 – 70 cm depth interval), illustrated similarity in soil water content from site to site (Table 1). Of particular interest was the coefficient of variation (CV), which gives a relative measure of variability in soil water content by expressing standard deviation as a proportion of the mean. Variability in soil water content increases with CV (range 0 – 1.0). CV values of around 0.5 suggest moderate variance in a data set (Rozgonyi, 1995; Weisstein, 1999).

Soil water content CV values on the first measurement date at each depth at all sites were consistently low (CV values 0.08 - 0.15), except for the Hill County site (CV values 0.23 - 0.31). This indicates a substantial lack of variance in soil water content at the beginning of the growing season. For all study sites at all depths, CVs were greater on the last measurement date than on the first, suggesting an increase in soil water content variance as the growing season progressed. End of season CV at Liberty and Phillips 1 remained rather low (0.22 - 0.27), however. End of season CV at Phillips 2 varied with depth, and suggested moderate soil water variance(CV = 0.48) at 20 cm, but lower variance (CV = 0.22) at 60 cm depth. CVs at Hill on the last measurement date (0.38 - 0.46) indicated moderate soil water variance.

High variance in soil water content was not indicated at any depth at any of the study sites based on CV values (Rozgonyi, 1995; Weisstein, 1999). A consistent trend of decreasing CV values with depth was noted for the last measurement date at the Hill (0.46 to 0.38) and Phillips 2 (0.48 - 0.29) locations. CV values for Liberty (0.25 - 0.23) and Phillips 1 (0.27 - 0.26) on the last measurement date were uniform with depth

Table 1. Summary statistics for measured soil water contents on first and last measurement dates, at three depths, for the four study sites.

	------ 20 cm ------		------ 60 cm ------		--- Top 70 cm ---	
			Liberty			
	May 18	Aug 7	May18	Aug 7	May 18	Aug 7
n	79	77	79	78	79	77
Min	5.14	1.65	3.64	1.41	13.65	5.08
Max	8.55	5.34	7.85	4.56	22.40	13.72
Mean	7.11	3.09	5.19	2.69	17.38	8.34
S.D.	0.77	0.76	0.61	0.61	1.57	1.65
C.V.	0.11	0.25	0.12	0.23	0.09	0.20
			Hill			
	May 19	Aug 2	May 19	Aug 2	May 19	Aug 2
n	78	77	78	77	78	77
Min	2.98	0.35	2.20	0.77	8.82	1.64
Max	11.56	11.27	7.46	6.08	24.52	23.28
Mean	6.56	4.05	4.59	3.14	16.05	9.84
S.D.	2.01	1.88	1.12	1.20	3.63	4.00
C.V.	0.31	0.46	0.24	0.38	0.23	0.41
			Philips 1			
	May 19	Aug 9	May 19	Aug 9	May 19	Aug 9
n	78	77	77	75	77	75
Min	5.75	1.66	4.19	1.57	15.28	5.60
Max	9.91	6.17	6.73	4.90	23.28	14.16
Mean	7.76	3.35	5.37	2.91	18.52	8.99
S.D.	0.73	0.89	0.58	0.75	1.39	1.54
C.V.	0.09	0.27	0.11	0.26	0.08	0.17
			Philips 2			
	May 18	Aug 1	May 18	Aug 1	May 18	Aug 1
n	81	81	81	81	81	81
Min	4.06	1.71	2.86	1.27	10.55	3.85
Max	7.87	7.38	6.29	5.64	20.02	16.44
Mean	6.39	5.02	4.59	3.17	15.70	11.31
S.D.	0.89	1.32	0.70	0.92	1.78	2.56
C.V.	0.14	0.48	0.15	0.29	0.11	0.23

Little precipitation occurred during the 2000 field season, and annual precipitation was below normal for both Liberty (43% of long-term average) and Phillips 1 (71%) (Fig. 6, Table 2). Precipitation at Liberty occurred primarily during a single event that delivered less than 0.5 cm. Phillips 1 received most of its precipitation prior to July, and total seasonal rainfall was significantly greater than at Liberty (10.54 vs. 0.76 cm).

Precipitation during 2001 was also below normal at Hill (61% of long-term average) and Phillips 2 (68%) (Fig. 6, Table 2). Two separate growing season precipitation events of nearly 2.5 cm occurred at Phillips 2, one on June 4-6, and the second on August 1.

Figure 6. Daily growing season precipitation for the four study sites. Liberty and Phillips1 represent 2000, while Hill and Phillips 2 represent 2001. Note different scales on precipitation axes.

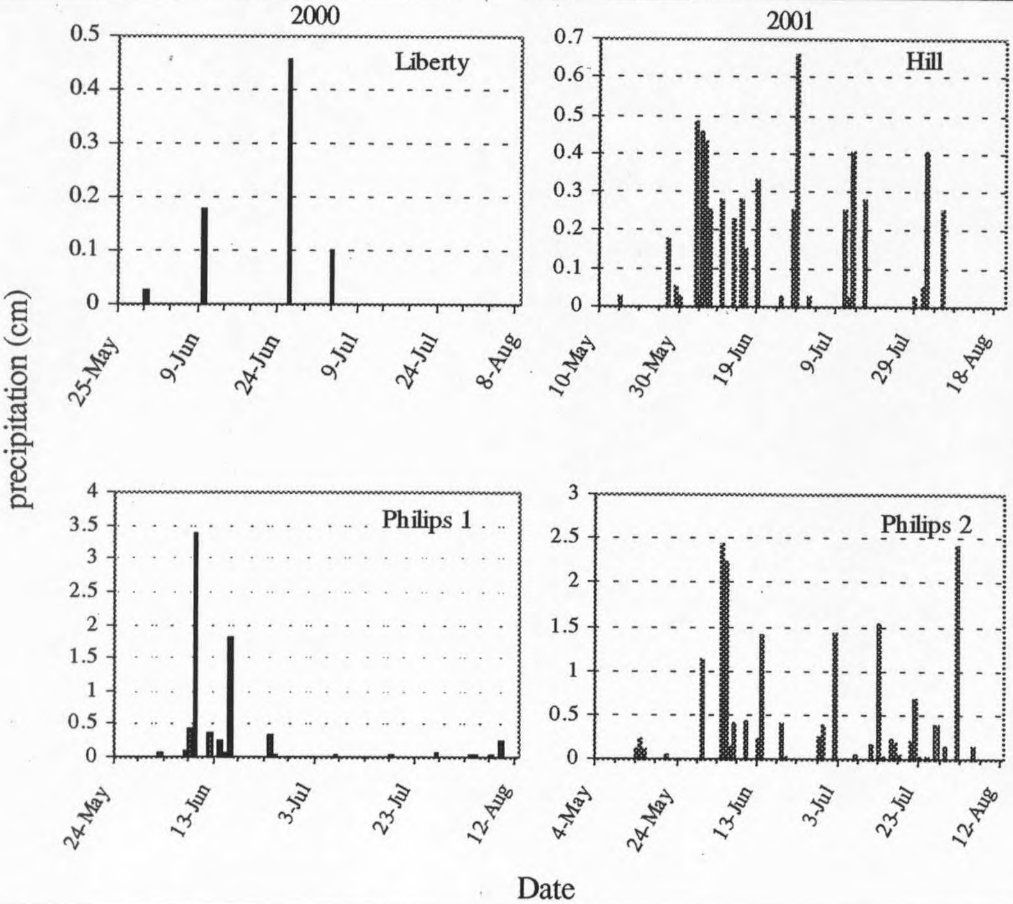


Table 2. Monthly growing season and annual precipitation amounts for the three field locations. Yearly and mean precipitation data were taken from closest weather stations at Chester, Havre, and Malta, MT for the Liberty, Hill, and Philips sites, respectively. Precipitation measured at the study sites are also included for comparative purposes. "---" indicates precipitation data not available for that time period.

		Precipitation (cm)				
Location	Year	May	June	July	August	Annual
Liberty	2000	1.98	1.91	1.29	0.46	11.79
	2000 (site)	---	0.64	0.10	---	---
	Mean	4.34	6.10	3.84	3.05	27.10
Hill	2001	1.55	3.68	7.54	0.46	17.63
	2001 (site)	1.20	3.86	4.02	---	---
	Mean	4.11	5.21	3.94	3.02	28.83
Philips	2000	2.77	6.3	4.29	0.10	22.59
	2000 (site)	---	6.71	0.16	0.24	---
	2001	2.16	7.34	5.28	2.16	21.77
	2001 (site)	1.82	8.33	5.08	2.47	---
	Mean	5.68	6.45	4.67	3.05	31.90

Soils

Appendix B contains partial descriptions of soil pits excavated. Soil series within complexes were assigned to specific regions based on the general landscape position of each excavated soil pit to assist in interpretation of region partitioning results.

In general, at Liberty, Phillips 1, and Phillips 2, convex and upper areas in the landscape exhibited thinner mollic epipedons, shallower depth to carbonates, and higher clay contents at shallow depths than concave and lower areas in the landscape. At Hill, sandy loam to sand textures and absence of a mollic epipedon characterized the upper landscape positions. Clays to clay loam soils with well-defined mollic epipedons and depth to carbonates approaching 25 cm were found in lower, level areas in the landscape.

Region Partitioning

Figure 7 illustrates how each region-partitioning method divided the field at the Liberty site. The other three sites are illustrated in Figs 19-21 in Appendix C. Patterns of region delineation for each of the three methods were similar across the four sites. However, the Cluster Method had the largest contiguous regions. Conversely, the Flow Method produced more numerous, smaller regions. Since the Flow Method partitioned the landscape based on water receiving and water shedding characteristics, differences in elevation did not necessarily result in different regions.

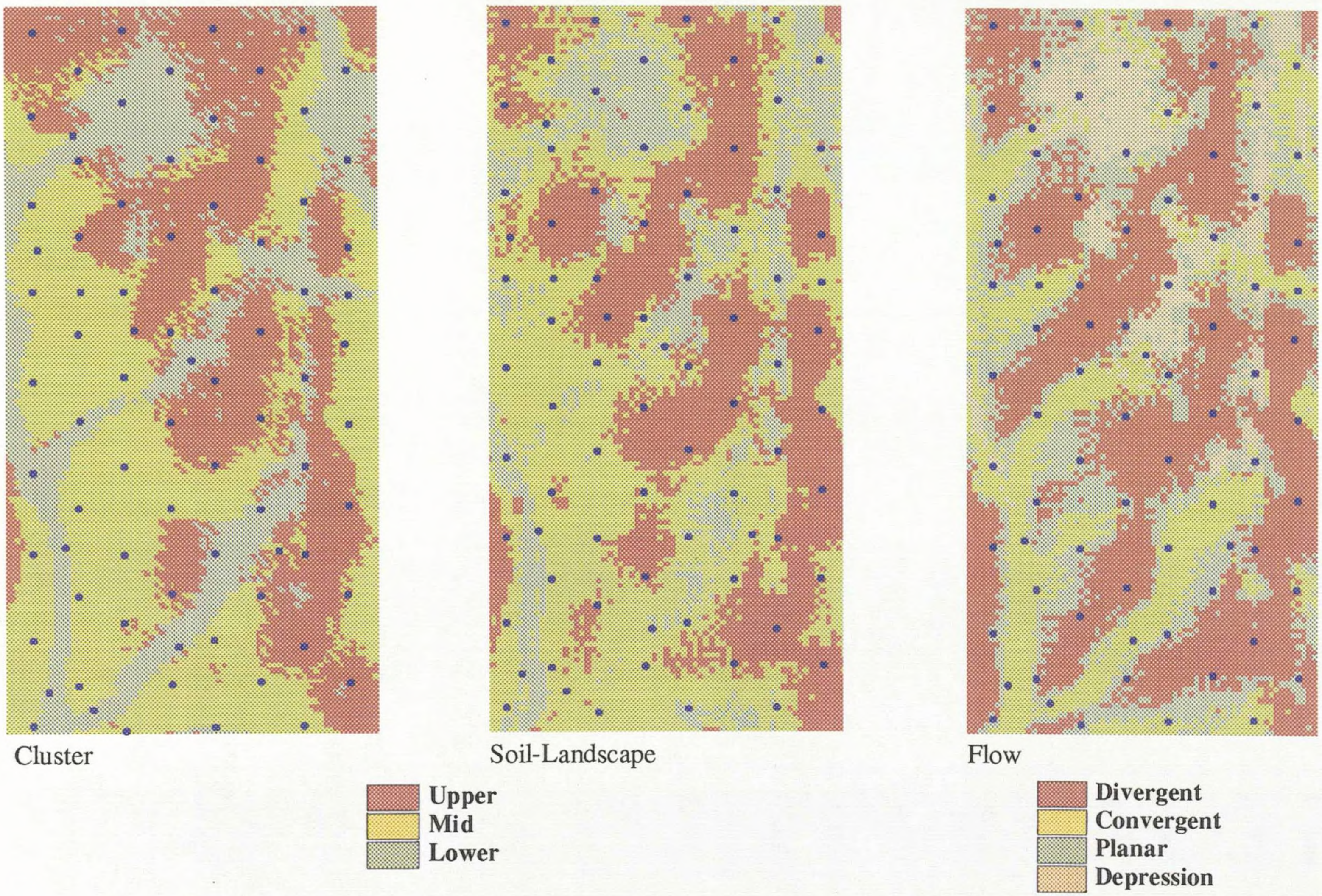
Soil-Landscape was most similar to the Cluster Method in size of regions delineated, but regions lacked the spatial continuity of those based on the Cluster Method. The Soil-Landscape Method was most different from the other methods in terms of the large area that was classified as mid landscape position. This large area resulted in inclusion of 40% to 45% of soil water sample points within the mid landscape position across all sites. This is contrasted with a maximum 36% of soil water sample points included in upper or lower Soil-Landscape regions across all sites.

Region Soil Water Dynamics

Liberty Site. At Liberty, differences in mean soil water content between regions varied with depth for the Flow and Soil-Landscape Methods, but remained relatively similar for the Cluster method. To a depth of 30 cm (20 cm), there were no significant differences in mean soil water content between regions for any method throughout the growing season (Table 3; Fig. 8, 9). No differences between Cluster region means were evident at the 50 – 70 cm (60 cm) or top 70 cm depths either.

At 60 cm depth, Flow method depression regions and the Soil-Landscape method lower regions had the highest mean soil water content throughout the growing season.

Figure 7. Results of three partitioning schemes for the Liberty site. The three partitioning methods are listed at the bottom left of the respective panels.



Depression and lower mean soil water contents were significantly different from divergent and upper regions, respectively, on May 18 and August 7 (Table 3).

For the top 70 cm, mean soil water content was highest in Flow Method depressions throughout the growing season, but significant differences were evident only on August 7 (Table 3). Soil-Landscape regions had similar soil water contents from May 18 to July 12. Between July 12 and August 7 loss in mean soil water content was greater in upper regions than lower regions, resulting in a significant difference on August 7 between the lower and upper regions in this attribute.

Table 3. ANOVA summary for region beginning and ending growing season soil water content means at Liberty. Within rows, asterisk in p-value column highlights significance at 0.05 level, and region mean values followed by the same letter are different at the 5% significance level.

			Region means			
				Flow		
Depth	Date	P-value	Divergent	Convergent	Planar	Depression
20 cm	May 18	0.564	7.07	6.91	6.85	7.20
	Aug 7	0.542	3.02	3.22	2.90	3.26
60 cm	May 18	0.022*	5.05a	5.16	5.16b	5.67ab
	Aug 7	0.002*	2.46a	2.69b	2.81	3.23ab
top 70 cm	May 18	0.124	17.22	17.1	17.27	18.38
	Aug 7	0.011*	7.86a	8.45	8.35b	9.79ab
				Soil-Landscape		
			Lower	Mid	Upper	
20 cm	May 18	0.904	7.06	6.96	7.03	
	Aug 7	0.274	3.37	2.99	3.04	
60 cm	May 18	0.053*	5.48a	5.19	5.03a	
	Aug 7	0.057*	2.97a	2.72	2.52a	
top 70 cm	May 18	0.326	17.85	17.37	17.13	
	Aug 7	0.053*	9.23a	8.25	7.99a	
				Cluster		
			Lower	Mid	Upper	
20 cm	May 18	0.668	7.07	6.93	7.09	
	Aug 7	0.42	3.30	3.01	3.05	
60 cm	May 18	0.097	5.43	5.06	5.19	
	Aug 7	0.063	2.99a	2.59a	2.64	
top 70 cm	May 18	0.382	17.78	17.15	17.42	
	Aug 7	0.067	9.16a	8.08a	8.15	

Figure 8. Mean soil water content expressed as equivalent depth of water for three measurement depths, for sample locations allocated within two different partitioning methods, at the Liberty site.

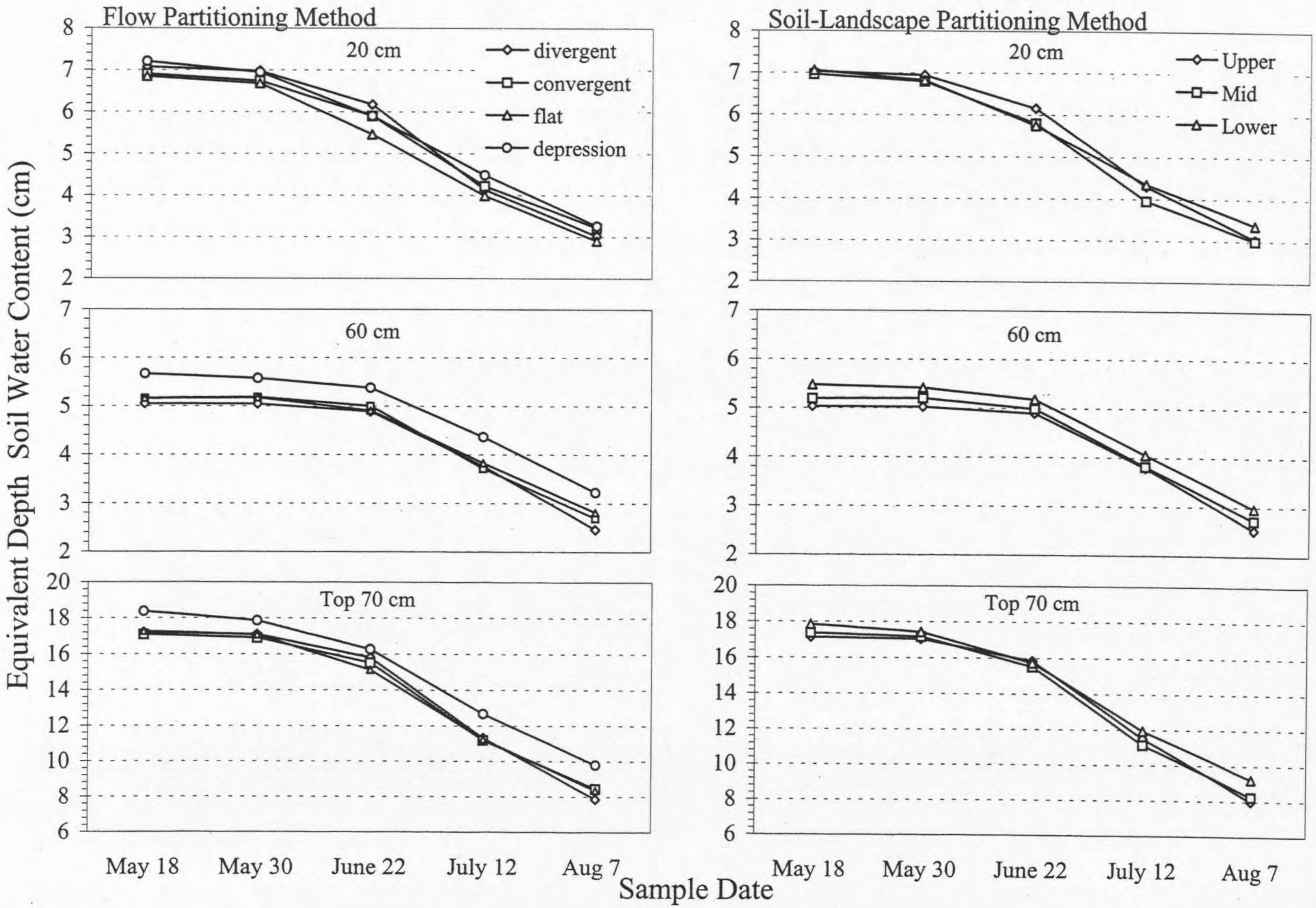
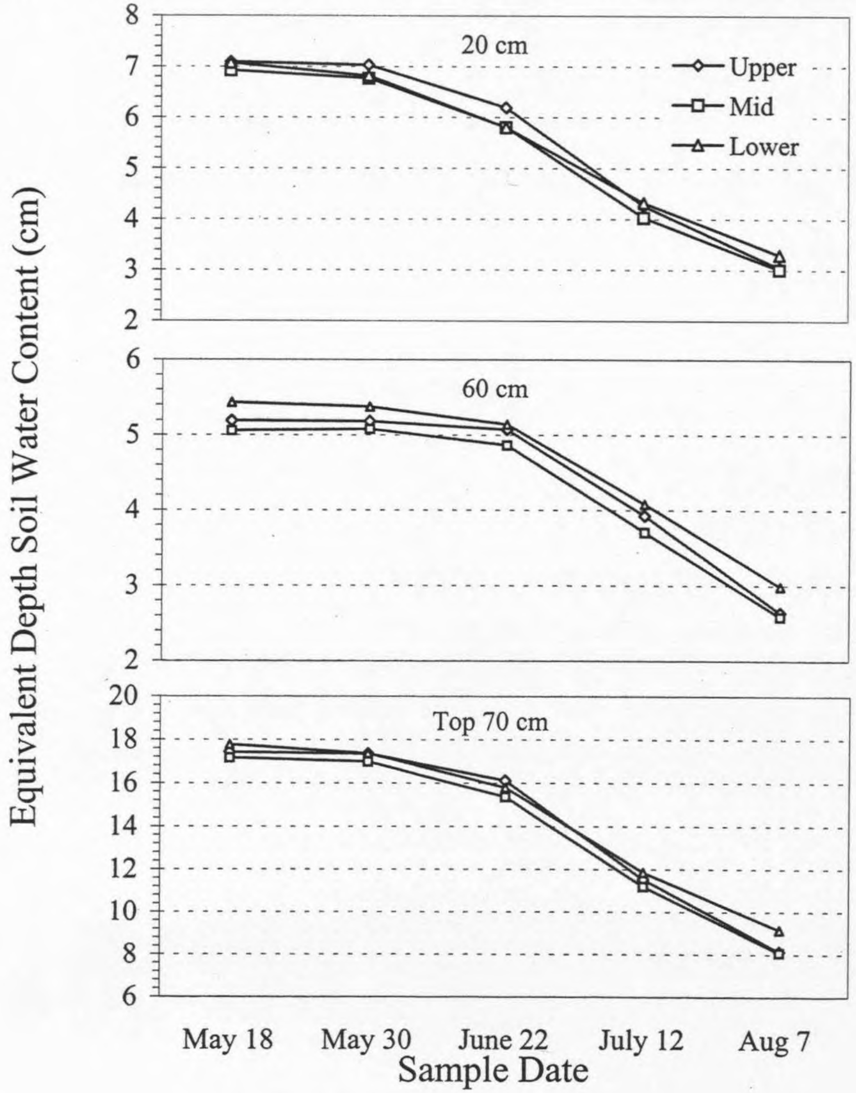


Figure 9. Mean soil water content expressed as equivalent depth of water for three measurement depths, for sample locations allocated within regions delineated at the Liberty site using the Cluster partitioning method.



Hill Site. Observed patterns in region mean soil water content were similar between the three partitioning methods at all depths at Hill (Fig. 10, 11). Increased soil water contents between July 20 and August 2 resulting from precipitation during July (Fig. 6) were evident for all regions at all depths. At the end of the growing season (August 2) at all depths, significant differences in mean soil water content were exhibited between regions in all partitioning methods (Table 4).

For the Flow partitioning method planar regions had the highest and divergent regions the lowest mean soil water contents at all depths (Fig. 10). Except for the beginning of the growing season (May 19) at 20 cm, planar and divergent region mean soil water contents were significantly different at all depths and dates (Table 4).

Soil-Landscape lower regions predominantly had the highest mean soil water content throughout the growing season at all depths for Hill (Fig.10). However, lower region mean soil water content differed significantly from other regions (mid and upper) only at the end of the growing season (August 2) (Table 4).

For the Cluster Method, lower regions predominantly had the highest soil water contents throughout the growing season at all depths. Except at 60 cm, Lower significantly differed from mid and upper on May 19 and August 2. At 60 cm depth, lower differed only from mid on August 2 (Table 4).

Figure 10. Mean soil water content expressed as equivalent depth of water for three measurement depths, for sample locations allocated within two different partitioning methods, at the Hill site.

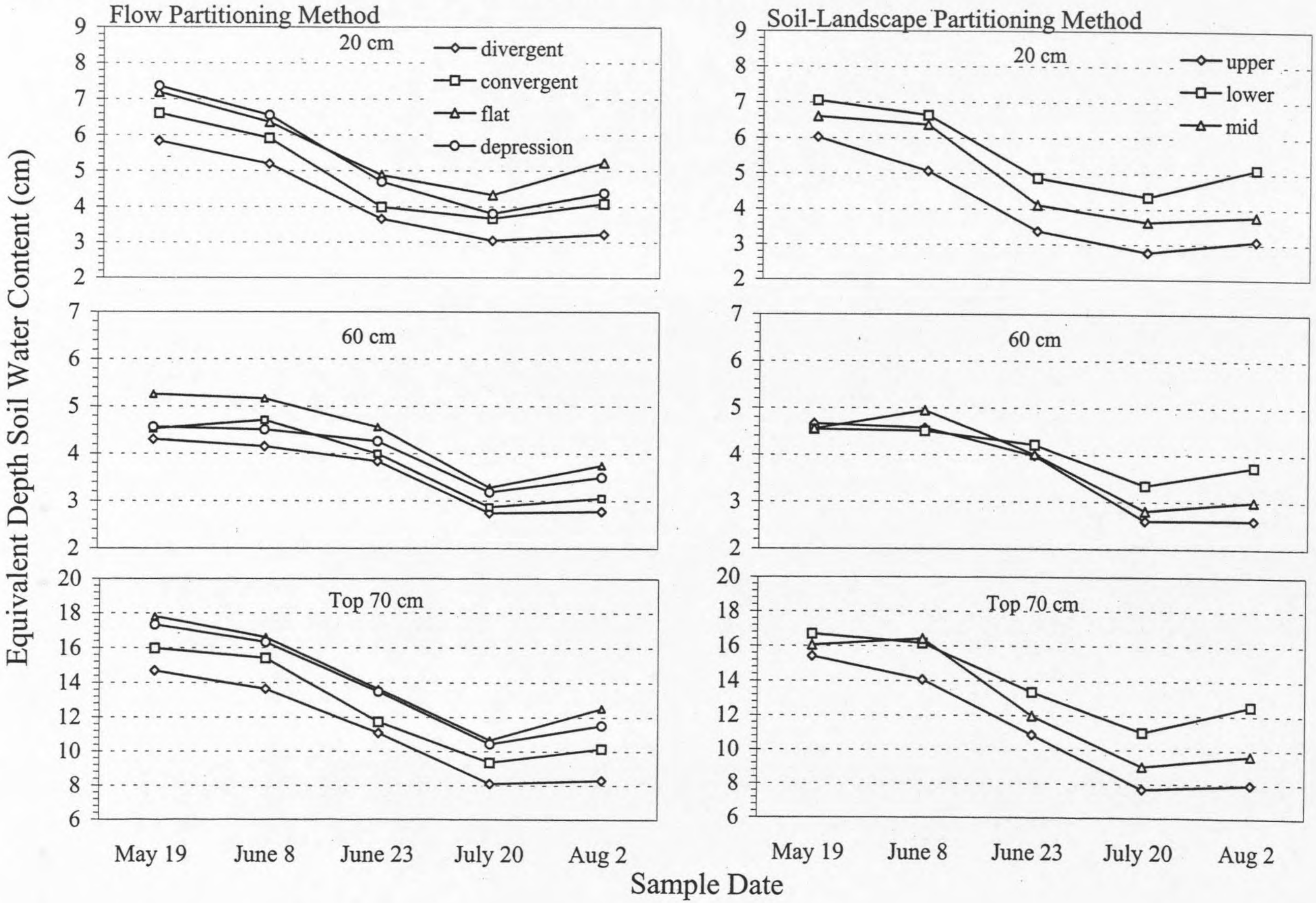


Figure 11. Mean soil water content expressed as equivalent depth of water for three measurement depths, for sample locations allocated within regions delineated at the Hill site using the Cluster partitioning method.