Spatiotemporal variation in soil moisture and hydraulic properties and their impacts on rainfall - runoff and infiltration processes

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SPATIOTEMPORAL VARIATION IN SOIL MOISTURE AND HYDRAULIC PROPERTIES AND THEIR IMPACTS ON RAINFALL-RUNOFF AND INFILTRATION PROCESSES

by

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ABSTRACT

Spatiotemporal Variation in Soil Moisture and Hydraulic Properties and Their Impacts on Rainfall-Runoff and Infiltration Processes

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In arid and semi-arid regions such as in the southwestern United States, soil moisture is an essential component of desert ecosystems. Gaining better knowledge of moisture dynamics through appropriate numerical modeling will help us understand physical mechanisms that influence soil hydrologic processes in these regions. Moreover, numerical modeling of these processes is often emphasized because most desert watersheds are ungauged, and thus field observations are either not readily available or difficult to simulate. In this dissertation, three modeling studies were conducted to investigate the temporal and spatial soil moisture variation and hydraulic properties, and their effect on rainfall-runoff and infiltration processes.

The goal of the first study was to simulate the long-term (18,000 yrs) multi-phase
(liquid and vapor) water fluxes and associated chloride fluxes in the northern Mojave Desert by applying different reconstructed boundary conditions in the simulation. The results showed that the observed near-surface chloride peak reflected the combined boundary conditions of precipitation, root-water uptake, and soil evaporation. The results showed that climate shift alone (with normal precipitation patterns) was not the major driving force that initiated the observed near-surface chloride accumulation. Rather, the results showed that root water uptake and extreme storm events, embedded within the normal precipitation patterns, were the major driving forces that controlled the paleo-water fluxes and chloride profile distributions. Also, the results showed that chloride accumulations were highest at the zone of maximum root zone distribution of Mojave Desert shrubs, not the depth of the roots. Thus, observed chloride accumulations deeper than the active root zones still cannot been fully explained.

The second study was to assess three different methods used to generate spatially distributed hydraulic properties, by simulating surface runoff on a semi-arid rangeland at the Walnut Gulch Experimental Watershed, outside of Tombstone, AZ. By collecting 66 soil samples (2 samples at each of 33 sites) and using pedotransfer functions, soil hydraulic properties were derived. Then three methods were used to generate the parameter fields of a two-dimensional diffusion wave model to simulate a total of eight storm events with measured runoff. The results showed that co-kriging was the best approach to represent the spatial variability of soil hydraulic properties. The results also showed that the need to calibrate plant interception models based on historical records of shrub versus grassland coverage.

The goal of the third study was to understand the influence of desert pavement on
infiltration and surface runoff, and to calibrate relevant Green-Ampt infiltration parameters. To achieve the goal, twelve rainfall simulator tests were conducted in the Mojave National Preserve, CA and the in-situ infiltration and surface runoff were measured. The results showed no statistical difference between the infiltration characteristics between plots with and without desert pavement (i.e., clast) surfaces. The results indicated that variability of soil texture exerted a larger effect on infiltration than the effects introduced by the surface clasts only. However, an optimization method was necessary to calibrate the Green-Ampt parameters. In these cases, the optimized parameters underestimated and overestimated hydraulic conductivity values, compared to pedotransfer functions and tension infiltrometer tests, respectively.

The modeling results in this dissertation showed how numerical simulations can be used to assess soil moisture dynamics and model parameter variations in arid and semi-arid regions. The studies quantitatively modeled several hydrologic processes in the northern Mojave Desert such as vertical water fluxes, and helped determine effective hydraulic conductivities on alluvial fans with desert pavement. These results provide fundamental knowledge of infiltration and deep percolation in this desert region of the United States, and show how features of these sites were well preserved during the physically-based modeling processes. We showed also that the modeling approaches can more effective than empirical correlations for predicting water flux as environmental (i.e., climate) conditions change. But it is noted that appropriate boundary conditions and model parameters were found to be most important aspects of producing reliable modeling results.
# TABLE OF CONTENTS

| ABSTRACT ................................................................. iii |
| LIST OF TABLES ......................................................... viii |
| LIST OF FIGURES ......................................................... ix |
| ACKNOWLEDGEMENTS .................................................... x |

## CHAPTER 1 INTRODUCTION ................................................. 1
   1.1 Introduction ......................................................... 1
   1.2 References ......................................................... 5

## CHAPTER 2 EFFECTS OF PALEOCLIMATE AND TIME-VARYING CANOPY STRUCTURES ON PALEO-WATER FLUXES .......................... 7
   2.1 Introduction ......................................................... 7
   2.2 Methods .............................................................. 9
      2.2.1 Physical model description ..................................... 9
      2.2.2 Numerical model description ................................... 10
      2.2.3 Boundary conditions ........................................... 13
         2.2.3.1 Paleoclimate reconstruction ............................... 13
         2.2.3.1.1 Construction of precipitation record .................. 14
         2.2.3.1.2 Construction of evapotranspiration record ............ 17
      2.2.3.2 Paleovegetation reconstruction ........................... 19
      2.2.4 Case Analysis .................................................. 20
   2.3 Model Results ..................................................... 22
      2.3.1 Matric potential and water content profiles .................. 22
      2.3.2 Chloride distributions .......................................... 25
   2.4 Discussion ......................................................... 28
   2.5 Conclusion ......................................................... 31
   2.6 Acknowledgements ............................................... 32
   2.7 References ......................................................... 32

## CHAPTER 3 MODELING THE EFFECT OF SPATIAL VARIABILITY OF SOIL HYDRAULIC PROPERTIES ON THE RAINFALL-RUNOFF PROCESS IN A RANGELAND WATERSHED USING A DIFFUSION WAVE MODEL .............. 53
   3.1 Introduction ......................................................... 53
   3.2 Two dimensional diffusion wave model .......................... 55
   3.3 Field sampling and data post processing .......................... 57
      3.3.1 Site description .................................................. 57
LIST OF TABLES

Table 2.1 Hydraulic properties of representative soil .......................................................... 41
Table 2.2 Calculation of LAI for different growth forms .................................................... 42
Table 2.3 Root density distributions used in model ............................................................. 43
Table 2.4 Characteristics of simulation cases ....................................................................... 44
Table 2.5 Percentage of chloride remaining in the model domain at representing time period (%) ................................................................................................................. 45
Table 3.1 Statistical characteristics of hydraulic ................................................................. 76
Table 3.2 Parameters for semivariogram models ................................................................. 77
Table 3.3 Characteristics of storm events used in the modeling ......................................... 78
Table 3.4 Nash-Sutcliffe coefficients .................................................................................... 79
Table 4.1 Runoff characteristics on all twelve rainfall simulator (RFS) plots ...............104
Table 4.2 Water mass balance calculations ......................................................................... 105
Table 4.3 Soil texture and bulk density of soil collected at runoff plots after completion of the runoff tests ................................................................................................. 106
Table 4.4 Comparison of unoptimized and optimized parameters ................................... 107
LIST OF FIGURES

Figure 2.1 Reconstructed PET and P ................................................................. 46
Figure 2.2 Reconstructed vegetation coverage .............................................. 47
Figure 2.3 Comparison of root distributions .................................................. 48
Figure 2.4 Water potential and volumetric water content (Group 1) .............. 49
Figure 2.4 (continued) Water potential and volumetric water content (Group 2) 50
Figure 2.5 Chloride concentrations (Group 1) ............................................... 51
Figure 2.5 (continued) Chloride concentrations (Group 2) .................................. 52
Figure 3.1 Geographic locations of Lucky Hills Watershed 104 and sample locations 80
Figure 3.2 Spatial patterns of the Green-Ampt parameters based on the whole population 81
Figure 3.3 Simulated runoff depth versus the measured runoff depth ............. 82
Figure 3.4 Simulated results for eight storm events ......................................... 83
Figure 3.4 (continued) Simulated results for eight storm events ................. 84
Figure 3.5 Comparisons between measured slope and slope generated by DEM at 66 sample locations .......................................................... 85
Figure 4.1 (a) Rainfall simulator; (b) Runoff collecting trough ....................... 108
Figure 4.2 Accumulated infiltration and associated ponding times .................. 109
Figure 4.3 Accumulated infiltration curves calculated from the measured, the PTF derived, and the optimized Green-Ampt parameters ......................... 110
Figure 4.3 (continued) Accumulated infiltration curves calculated from the measured, the PTF derived, and the optimized Green-Ampt parameters .......... 111
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CHAPTER 1

INTRODUCTION

1.1 Introduction

Soil moisture dynamics are of concern in the arid southwestern United States. Beside the efforts that have been paid to understanding flood events and water contamination in these regions, gaining knowledge about soil moisture dynamics will, in particular, contribute to our understanding of vulnerable desert ecosystems and environmental issues impacted by urban growth and human activities. More specifically, rapidly growing populations, ongoing disposal site research (Yucca Mountain project) for radioactive waste (e.g., Ye et al., 2007; Tyler et al., 1996) and especially the recent drying trends in western US (Barnett and Pierce, 2008) make the understanding of temporal and spatial soil moisture distributions more important. One of the significant challenges for assessing hydrologic processes in these regions is the lack of either field observations or data, mainly due to the limited water resources and the relatively slower rates of subsurface water movement. To solve this problem, numerical modeling has become an indispensable tool because of its flexibility to simulate different hydrologic processes. To study hydrologic responses to future climate changes, numerical modeling is a key tool for providing sufficient information to decision makers.
Setting aside issues of model structure, the other two major components that determine model accuracy are model parameters and boundary conditions. It is believed that successful comparisons of results between hydrologic models and physical processes largely depend on the reliability of these input data. Therefore, in addition to developing new models or to improving existing model structures, more efforts have been placed on efficiently obtaining model parameters and high quality boundary conditions, such as meteorological data and plant coverage data. For example, Wösten et al. (2001) introduced the pedotransfer functions, so that researchers could estimate soil hydraulic properties based on basic soil data information. In addition, to investigate parameter (model) uncertainties introduced by spatial heterogeneity, statistical approaches have been used for decades to analyze the confidence level of the model outputs (e.g., Smith and Goodrich, 1998; Balakrishnan et al., 2005). On the other hand, if recorded boundary conditions (e.g., precipitation and evaporation) are not available, boundary conditions have to be either created or simulated and then incorporated into the model, depending on the goals and objectives of the research. For instance, Young et al. (2007) used an artificial rainfall simulator to control precipitation rates and then assessed the hydraulic characteristics of the soil in an arid basin in Nevada. Mata-Gonzalez et al. (2005) evaluated a few approaches that estimated evapotranspiration in arid ecosystems; but their study points out the inappropriate aspects of several approaches. Though these methods have been shown to generate boundary conditions, the time frame was limited. If the modeling period covers major climate shifts, results from global (e.g., Bartlein et al., 1998) or regional (e.g., Tompson et al, 1999; Yin et al., 2008) paleoclimate studies need to be used as boundary conditions. In general, reliable model simulations depend
mainly on how the physical processes are introduced into the model. Obtaining accurate model parameters and boundary conditions thus become paramount.

The issue of scaling is a very important aspect of hydrologic modeling (Kabat et al., 1997). In addition to the spatial scale, temporal scale is also a substantial factor that needs to be determined before modeling. If the research focuses on different scales, then model structures, parameter derivations, and boundary conditions requirements also differ. In general, the climate model is associated with spatially large-scale, increasing also the temporal scale (e.g., Yu et al., 2006). For small-scale models, however, the temporal scale sometimes needs to decrease to seconds to efficiently solve the governing partial difference equations (e.g., Chen and Young, 2008). Therefore, establishing appropriate temporal and spatial scales depend on the needs of the study.

To fully understand soil moisture dynamics in the arid southwestern United States, studies in this dissertation simulate both large-scale and small-scale soil moisture distributions. The distributions in some studies are indirectly reflected by soil hydraulic properties and by surface runoff and infiltration. By successfully simulating observed hydrologic processes such as infiltration and surface runoff, the robustness of the proposed models can be evaluated. Moreover, future sensitivity and uncertainty analyses can be conducted because the behavior of the numerical models have been assessed.

In each study, in addition to the modeling itself, associated data collection and processing, and field experiments were also introduced. These are basic tasks required for successful numerical models, as are building the relationships between model structure and physical processes. This dissertation is thus comprised of three individual, but internally-related, research themes. The first theme is the simulation of long-term,
multiphase water flux and chloride movement in a thick vadose zone in the northern Mojave Desert. Boundary conditions such as paleoclimate and paleo-vegetation changes were reconstructed mainly based on other studies. The purpose of this study was to understand the magnitude of water fluxes in the northern Mojave Desert during different climate conditions, which will benefit relevant studies such as arid region recharge. The second theme was the simulation of surface runoff using a diffusion wave model. The purpose of this study was to evaluate three sampling strategies used to represent the spatial variability of soil hydraulic properties. Impacts of this spatial variability on surface runoff generation were also studied. The third theme was to investigate the effect of desert pavements on infiltration, using a well-controlled rainfall simulator. The purposes were to obtain in-situ Green-Ampt infiltration parameters on desert pavements and to observe how the desert pavement affected the infiltration rates during a 1-hour high intensity storm. In this latter case, an optimization method was used to calibrate the Green-Ampt infiltration parameters using field measurements. Comparisons were then made between the calibrated parameters, the parameters derived from pedotransfer functions, and the field measurements.

This dissertation study is a collaborative work with author's two co-advisors and Dr. Li Chen of the Desert Research Institute, in particular the last two studies. Chapters of this dissertation can be regarded as three independent research papers. Drs. Young, Yu, and Chen are co-authors of these research papers. However, Mr. Yin is largely responsible for the research in this dissertation.
1.2 References


Thompson, R. S., Anderson, K. H., and Bartlein, P. J. (1999), Quantitative paleoclimatic reconstructions from late Pleistocene plant macrofossils of the Yucca mountain region, USGS open-file report 99-338.


CHAPTER 2

EFFECTS OF PALEOCLIMATE AND TIME-VARYING CANOPY STRUCTURES ON PALEO-WATER FLUXES

2.1 Introduction

In arid regions where evapotranspiration (ET) rates are high and precipitation rates are low, water resources are often limited. How water is partitioned between surface runoff, recharge, evaporation, and transpiration depends on linkages between climate, vegetation, soil properties, and water balances. Among these, climate is the key driving force affecting the desert ecosystem. If the linkages between past climatic and ecohydrological responses can be understood, it might be possible to predict how desert ecosystems will respond to potential future climate changes.

Studies of global climate change (Bartlein et al., 1998; Kutzbach et al., 1998), regional climate change (Smith et al., 1997), and the associated changes in soil properties (McDonald et al., 1996; McDonald et al., 2003; Young et al., 2004) and vegetation structure (Van Devender and Spaulding, 1979; Spaulding, 1985; Spaulding, 1990) have shown that surface conditions vary through time and are effected by changes in environmental conditions. These sometimes subtle relationships can be included in long-term simulations, where past atmospheric changes are used as boundary conditions to evaluate variations in soil water status and water partitioning.
However, long-term (decadal) soil water data are mostly unavailable. So, investigators have used different solute accumulation rates, specifically chloride, to derive long-term averaged water fluxes (Allison and Hughes, 1978; Allison et al., 1994; Murphy et al., 1996; Tyler et al., 1996) in thick vadose zones. The chloride mass balance (CMB) technique (Allison and Hughes, 1978; Scanlon, 1991; Cook et al., 1992; Ginn and Murphy, 1997; Scanlon et al., 2003) is one method that can be used to evaluate average paleorecharge rates (e.g., water that percolates below the root zone). As indicated by Cook et al. (1992), “variations in solute and isotopic concentration within a soil profile can arise from a variety of causes, other than recharge or climatic variability.” An increase in chloride concentration could be caused either by decreased precipitation or by increased root growth. For this reason, merely detecting changes in chloride concentration cannot provide sufficient information to explain differences in water fluxes.

Forward simulations of water and solute movement can be rather complex depending on the simulation time and variability of boundary conditions. In some cases, variable boundary conditions and the complexity of climate change were omitted to simplify the problem (e.g., Ginn and Murphy, 1997; Walvoord and Phillips, 2002; Scanlon et al., 2003). However, errors in estimated fluxes could occur if time-invariant boundary conditions and climate are assumed, because dynamically-changing boundary conditions could significantly affect water balance conditions. In addition, long-term averaged precipitation neglects possible episodic flushing, which is very important to the redistribution of soil moisture in arid regions (Sandvig and Phillips, 2006). These different processes may result in different soil water profiles, even given similar boundary conditions. Though uniform boundary conditions may be valid for shorter-time
frames (i.e., decades), they could have larger impacts on soil water fluxes as time periods lengthen, especially when those time periods span major climatic and plant-community structural switches.

The purpose of this study is to conduct forward numerical modeling to evaluate the effects of past climate changes on soil water and solute (chloride) concentration, while considering environmental factors including the evolution of canopy structure and plant rooting patterns in a Mojave Desert ecosystem. The modeling period in this study is from 18,000 years ago (18 ka) to present. This period was chosen because of the large environmental changes that occurred after the last glacial period (i.e., late Pleistocene and early Holocene Periods). The environmental factors listed above were reconstructed based on the knowledge of paleoclimatology. This chapter will discuss the roles played by these factors in a climate-plant-soil water system, and will include possible explanations for the existence of chloride profiles in arid soil profiles.

2.2 Methods

2.2.1 Physical model description

The soil material used in this research is located at the Amargosa Desert Research Site (ADRS), located in the Mojave Desert near Beatty, Nevada, about 20 km east of Death Valley National Park, California, USA. Five significant soil layers within the upper 5 m have been visually identified using texture, cohesiveness, and color. Physical properties of these five soil layers were described by Andraski (1996). Following the assumptions of Scanlon et al. (2003), the hydraulic properties of the top 100-cm soil for this study were considered to be representative of the soil material (described below).
Groundwater at ADRS is present at depths ranging from 85 to 110 m below land surface (Fischer, 1992). The bottom of the model domain was set as 15 m, significantly above the known groundwater level. This shallower model domain was also chosen because most of the Cl information is preserved in this depth range. For example, Stonestrom (2003) examined Cl concentration profiles at nine locations with different upper-boundary conditions in the Amargosa Desert and showed that most of the variations in concentration were restricted to the top 15 m of the soil.

2.2.2 Numerical model description

This study requires a numerical approach that considers liquid water flow, thermal and isothermal vapor transport, chloride transport, root water uptake by plants, and evaporation from the soil surface. These processes account for some of the complexities of the near-surface water balance of arid and semi-arid landscapes. The numerical package (HYDRUS-1D, Šimunek et al., 2005) used to simulate these processes accounts for these processes in one-dimensional variably-saturated media. HYDRUS-1D approximates the solution to the governing equation for water flow:

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x} \left[ K \left( \frac{\partial h}{\partial x} + 1 \right) \right] - S
\]

(2.1)

where \( \theta \) is the volumetric water content, \( t \) is time, \( h \) is the water pressure head, \( x \) is a spatial coordinate, and \( K \) is the unsaturated hydraulic conductivity, which is a function of the saturated hydraulic conductivity \( (K_s) \) and water content. The parameter, \( S \), in equation (2.1) represents a sink term, which accounts for the uptake of soil water by vegetation (Feddes et al., 1978):

\[
S(h) = \alpha(h)S_p
\]

(2.2)
where $S(h)$ is the water uptake rate, $\alpha$ is a water stress response function, and $S_p$ is the potential water uptake rate. The value $S(h)$ is partitioned into each layer according to the depth-specific root density. The van Genuchten (1980) and Mualem (1976) representations for unsaturated hydraulic properties used in this study are given by:

\[
\theta(h) = \begin{cases} 
\theta_r + \frac{\theta_s - \theta_r}{[1 + (\alpha h)^n]^m} & h < 0 \\
\theta_s & h \geq 0
\end{cases}
\]

(2.3)

\[
K(h) = K_s \frac{\theta_s^m}{[1 - (1 - S_e^{1/m})^m]^2}
\]

(2.4)

\[
m = 1 - \frac{1}{n} \quad n > 1
\]

(2.5)

where $\theta_r$ is residual soil water content, $\theta_s$ is saturated soil water content, and $\alpha$ and $n$ are parameters for the water retention curve. To aggregate the vegetation effects of each plant type, a weighted linear combination was used to calculate a "lumped root density," as shown by:

\[
R = \sum_{i=1}^{N} r_i c_i
\]

(2.6)

where $N$ is an index for the growth form (i.e., plant type), $r$ is the root density of each growth form, and $c$ is the percent ground cover for each growth form. We discretized the 15-m soil column into 175 adjoining elements. Element thickness ranges from 2.5 cm (at ground surface) to 50 cm (at bottom of domain). Equation (2.6) is applied to each element, allowing for transpiration losses in each element as well.

The governing equation in HYDRUS-1D for solute transport is given by:

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x} \left( \theta D_x \frac{\partial c}{\partial x} \right) - \frac{\partial q c}{\partial x}
\]

(2.7)
where $D^w$ is the dispersion coefficient, $c$ is the solute concentration, and $q$ is the volumetric flux density. The dispersion coefficient can be represented by:

$$\theta D^w = D_L |q| + \theta D_w \tau_w$$

(2.8)

where $D_L$ is the longitudinal dispersivity, $D_w$ is the diffusion coefficient in free water, and $\tau_w$ is a tortuosity factor in the liquid phase. According to Millington and Quirk (1968), the tortuosity factor $\tau_w$ can be described as:

$$\tau_w = \frac{\gamma}{\theta^3}$$

(2.9)

We note that a few assumptions are intrinsic when applying this model: 1) chloride in the soil is in steady state with no “sources” (i.e., no mineral dissolution or formation), or “sinks” (i.e., no interaction with soil or uptake by vegetation); and 2) the effect of salt concentration gradient on the driving force of water movement can be disregarded because the modeled site does not have clay-rich soil (Hillel, 1998). Table 2.1 shows that the soil profile contains only 6% clay.

The governing equation in HYDRUS-1D for thermal and isothermal vapor flow was provided by Scanlon et al. (2003):

$$q_v = q_{vh} + q_{vT} = -K_{vh} \frac{\partial h}{\partial z} - K_{vT} \frac{\partial T}{\partial z} = -\frac{D}{\rho_w} \frac{Mg}{RT} \frac{H_r}{\rho_w} \frac{\partial h}{\partial z} - \frac{D}{\rho_w} \eta \frac{\partial \rho_{vs}}{\partial T} \frac{\partial T}{\partial z}$$

(2.10)

where $q_{vh}$ is isothermal vapor flux, $q_{vT}$ is thermal vapor flux, $K_{vh}$ is isothermal vapor conductivity, $K_{vT}$ is thermal vapor conductivity, $D$ is vapor diffusivity in soil, $\rho_w$ is water density, $\rho_{vs}$ is saturated vapor density, $M$ is molecular weight of water, $g$ is gravitational acceleration, $R$ is gas constant, $H_r$ is relatively humidity, $\eta$ is an enhancement factor, and
$T$ is temperature. Given the tortuosity, volumetric air content, saturated water content, and mass fraction of clay in soil, parameters $D$ and $\eta$ can be solved (Scanlon et al., 2003).

The governing equation for heat transport can be represented by a convection-dispersion-type equation:

$$\frac{\partial C_p(\theta)T}{\partial t} = \frac{\partial}{\partial x} \left[ \lambda(\theta) \frac{\partial T}{\partial x} \right] - C_w \frac{\partial qT}{\partial x} - C_w ST \tag{2.11}$$

where $\lambda(\theta)$ is the apparent thermal conductivity of the soil, and $C_p(\theta)$ and $C_w$ are the volumetric heat capacities of the porous medium and the liquid phase, respectively. de Vries (1963) expressed the volumetric heat capacity as the sum of individual components of the bulk soil. The apparent thermal conductivity $\lambda(\theta)$ can be expressed as:

$$\lambda(\theta) = \lambda_0(\theta) + \beta_t C_w |q| \tag{2.12}$$

where $\lambda_0(\theta)$ is the thermal conductivity of the porous medium, $\beta_t$ is the thermal dispersivity and $q$ is the velocity. The Chung and Horton (1987) model was used to calculate $\lambda_0(\theta)$. Parameters in equations (2.11), (2.12) and in Chung and Horton (1987)’s model are given in HYDRUS-1D. In this study, we used the default parameters for loam.

2.2.3 Boundary conditions

2.2.3.1 Paleoclimate reconstruction

Climate change can significantly impact the percent coverage and types of vegetation that are likely to flourish through long time periods. For example, Walvoord et al. (2002) indicated that, when paleoclimate shifted to a warmer and drier climate, the mesic vegetation was replaced by xeric vegetation. Recently, various paleoclimate reconstructions were done for the Sierra Nevada and the deserts of the southwestern United States (Spaulding et al., 1985; Kutzbach et al., 1996; Smith et al., 1997; Bartlein
et al., 1998; Kutzbach et al., 1998; Sharpe, 2004). These results support the understanding that a significant climate switch occurred in most regions in the southwestern United States after the Last Glacial Maximum (LGM), when decreases in effective environmental moisture were observed in paleoclimate proxies. Some studies (e.g., Tyler et al., 1996) concluded that this shift to drier climate conditions allowed chloride to accumulate in the soil profile. In the southwestern United States, a “wetter” LGM could be explained by either higher precipitation rates (McDonald et al., 1996), or a combination of either similar or lower precipitation rates and lower evapotranspiration rates due to the lower mean temperatures (Brakenridge, 1978; Galloway, 1983). More recent evidence (e.g., Menking et al., 2004) supports the former hypothesis. Spaulding (1985) suggested that the precipitation in the LGM in the Mojave Desert was about 1.4 times larger than the current value. McDonald et al. (1996) indicated that the annual precipitation in the LGM would have to increase by as much as 100% to simulate the observed soil carbonate. A study conducted at the Nevada Test Site (Thompson et al., 1999) derived precipitation values of 2.5X and 2.6X (X: modern precipitation multiplied by this number) in the LGM. We referenced this study because its location is in our area of interest.

2.2.3.1.1 Construction of precipitation record

A temporal resolution on the order of thousands of years is common in paleoclimate proxies; however, numerical models typically require higher temporal resolution, especially given the potential impact of short-term, episodic rainfall on recharge (e.g., Sandvig and Phillips, 2006). If annual precipitation rates were evenly distributed in the model over an entire year, given the time step of one day, soil water
recharge would be zero, because the extremely low (averaged) daily precipitation rates will be much smaller than daily evapotranspiration rates. Therefore, we require time steps that can account for those specific time periods when the precipitation rate is higher than the evapotranspiration rate. This allows water to (perhaps temporarily) percolate to depths below the root zone, and potentially recharge deep soil material.

To account for the extreme temporal heterogeneity in precipitation patterns found in the southwestern U.S., the Community Climate Model (Version 1, CCM1) (Kutzbach et al. 1996; Bartlein et al., 1998) was used to generate paleoclimate data from 18 ka to present in 3,000-yr sequences. CCM1 quantitatively interprets past climatic changes and takes into account intra-annual variations. These time periods (carbon-14 dating) were designated as: 18 – 15 ka, full-glacial environment; 15 – 12 ka, late-glacial environment; 12 – 9 ka, early-Holocene environment; 9 – 6 ka, mid-Holocene environment; and 6 ka – present, late Holocene environment. The paleoclimate proxies in the CCM1 model include the stratigraphic pollen records, plant macrofossil assemblages from packrat middens, and lake-level records. The climate generated from 18-15 ka shows an annual temperature 5.7 °C lower than the present value and an annual precipitation 13% higher than the present value.

Using paleoclimate reconstruction from Thompson et al. (1999), we replaced CCM1 precipitation values from 18-15 ka and 15-12 ka to 2.5X and 2.6X, respectively. The simulation time interval is daily in this reconstruction. However, the simulated precipitation is the same every day within each month for successive years (i.e., no within-month variation from year-to-year). Thus, to make the CCM1 simulations more representative of climate in the northern Mojave Desert, a few steps were taken.
1. All climate data were averaged over four CCM1 model grids (bounded between 120° and 112.5°W longitude and 37.77° and 33.77°N latitude) surrounding the northern Mojave Desert.

2. The number of days in each month was multiplied with the daily precipitation, producing the monthly precipitation. It is noted that the daily precipitation presented here is only a reflection of intraannual precipitation variability rather than showing specific rainfall amount on certain days.

3. The monthly precipitation record for each 3,000-yr period was derived from recorded (i.e., modern) precipitation (Stonestrom et al., 2003) when using the CCM1 precipitation transition trends. In other words, the modern precipitation pattern simulated by CCM1 was scaled down to be equivalent to the recorded modern precipitation pattern in the northern Mojave Desert, and then the transition trends were used to reconstruct the paleoclimate which is more suitable to the research area.

4. The monthly precipitation data were randomly distributed to each raining day within the month using the recorded average (1972-2005) monthly precipitation days from the meteorological station Beatty 8N in Beatty, Nevada, and the appropriate multipliers as suggested by Thompson et al. (1999). The averaged monthly precipitation days range from 1 day in June and 5 days in January.

Using steps 2 to 4 for each month, the CCM1 daily precipitation data was used to create a precipitation series with variations within each month.

To account for the impact of different precipitation intensities, a second precipitation series was created for Case 4 (described below) by forcing daily precipitation into a six-hour period: 0:00 - 6:00, 6:00 - 12:00, 12:00 - 18:00, or 18:00 -
24:00. Potential ET (PET), however, was not evenly distributed in this six-hour series. Rather, 10% PET was assigned to occur from each 0:00 - 6:00 and 18:00 - 24:00, and 80% PET was assigned to the rest of the day. So the time step in HYDRUS-1D becomes hourly rather than daily to account for variations in daily precipitation. Figure 2.1 shows the reconstructed monthly precipitation and PET patterns for the simulation period.

To examine the potential impacts of a “wet year” on water flow and Cl balance, one wet year was randomly embedded into each 100-yr period in each 3,000-yr climate sequence for Case 5 (described below), thus simulating a 100-year return period. Each wet year, with a total of 48.63 cm precipitation, was based on data recorded at the Beatty 8N station during an 87-yr (1918-2005) yearly precipitation record. The frequency analysis in this study was described by Chow et al. (1998). Precipitation was then randomly distributed across the 52 raining days within the wet year. These raining days are the same as those recorded in 1998, which is the wettest year among the 87-yr record and has a yearly precipitation value of 32.05 cm.

2.2.3.1.2 Construction of evapotranspiration record

To acquire \( S_p \) as listed in equation (2.2), the potential evapotranspiration (PET) was first determined. We chose the approach given by Hargreaves et al. (2003) and Wu (1997):

\[
ET_0 = 0.0135(T + 17.78)R_s \left[ \frac{238.8}{595.5 - 0.55T} \right] \tag{2.13}
\]

where \( ET_0 \) is the reference ET (equivalent to PET), \( T \) is the daily mean temperature (Celsius) and \( R_s \) is the incident solar radiation in units of MJ/m\(^2\)/day. This simpler approach was necessary because the parameters needed in the commonly-used (and more complicated) Penman equation are not available, even in General Circulation Models.
Output from the CCM1 model includes the daily $T$ and $R_s$ values, and considers the controls of paleoclimate variations across North America (Bartlein et al., 1998). The parameters $T$ and $R_s$ do not vary within each month.

Potential ET rates were partitioned into potential soil evaporation (PE) and potential plant transpiration (PT) using an approach described by Kemp et al. (1997). This approach is as follows:

$$PT = PET \times (1 - e^{-kLAI})$$  \hspace{1cm} (2.14)$$

$$PE = PET \times e^{-kLAI}$$  \hspace{1cm} (2.15)$$

where $k$ is radiation extinction by the canopy and is related to the value of LAI (leaf area index). The parameter $k$ ranges from 0.5 to 0.75 when LAI is between 0.2 and 2.0 (Nichols, 1992), and was linearly interpolated based on the value of LAI. Table 2.2 shows the calculation of LAI. By using equations (2.14) and (2.15) and Table 2.2, partitioned PT is positively correlated to the LAI and the vegetation ground coverage.

Similar to equation (2.6), PE is a weighted linear combination of PE for each growth form, based on reconstructed ground cover in each simulation period.

To calculate the vapor transport driven by the thermal gradient, temperature at 15-m depth was set at 22.7°C for 3-0 ka, as derived based on the temperature of groundwater 26.5°C at 110-m depth (Walvoord et al., 2004) and a geothermal gradient of 40°C/km (Scanlon et al., 2003). Hence, the transient trends of yearly averaged atmospheric temperatures were used to derive the bottom temperature for each 3,000-yr period based on the temperature at 15-m depth for 3-0 ka period.
2.2.3.2 Paleovegetation reconstruction

Based on the existing plant community in the northern Mojave Desert, vegetation growth forms can be classified into five different categories: evergreen, deciduous, grasses, annuals and succulents. A total of five guilds were used in the model depending on the time period, as shown in Figure 2.2 (note that succulents were not present in modern times in the Mojave Desert (Spaulding, 1990), and thus are not included in the last guild). Rooting depth ranges from 0 cm to 100 cm. Though some research indicates that xeric shrubs may extend their roots to 5-m depth (Schenk and Jackson, 2002a, Seyfried et al., 2005), root density generally decreases exponentially with depth because of limited water resources, such that more than 90% of the root mass can be found in soils at 0 – 100 cm depth in desert regions (Jackson et al., 1996). Moreover, desert plant species usually have most of their fine roots – roots that are involved in transpiration – shallower than 1-m depth (Wilcox, 2004, Peek et al. 2005). Sandvig and Phillips (2006) also reported that most of roots in their study were found in the upper 40 cm of excavation pits.

Observed root distributions of similar categories were published by Kemp et al. (1997) when classifying creosote bush (Larrea tridentata) as an evergreen and subshrubs as deciduous (Table 2.3). Jackson et al. (1996) described root distributions of 11 different biomes using a model based on an asymptotic equation (Gale and Grigal, 1987). Jackson et al.’s (1996) general model was used to describe the root distribution of succulent (which do not exist between 3 ka and 0 ka) in this study (Table 2.3). Furthermore, to account for phenology of root-water uptake and vegetation coverage, root distribution was allowed to vary according to season, with three seasons accounting for winter, late
spring, and summer/fall periods. We assumed the same annual transitions of vegetation coverage and root growth throughout the 18-ka modeling period, and a constant root distribution as long as the growth forms were the same. We also assumed that annuals and grasses would be classified as separate growth forms with identical ground coverage but distinct root distributions in the numerical model. Figure 2.2 shows the reconstructed percent vegetation coverage.

2.2.4 Case analysis

Scanlon (1991) and Tyler et al. (1996) reported one or more nonuniform Cl "bulges" at their sites. They (and others) attributed the unevenly distributed Cl concentration to the changing ratio of P to PET with time due to climate change. Major climate shifts during the late Pleistocene – early Holocene periods are likely one of the important factors that initiated Cl accumulation in the soil profile as the near-surface water balance changed (Scanlon, 1991; Phillips, 1994; Tyler et al., 1996; Scanlon, 2003). Because the climate shift and vegetation responses occurred essentially contemporaneously, it is difficult to identify whether one factor dominates another, or whether each factor has some influence on water and solute fluxes. We attempted to examine the role of changing climate and vegetation through a series of case studies in which some processes were held constant and others were allowed to vary according to known amounts. Table 2.4 is a breakdown of characteristics of each case. Because these cases were conducted sequentially, several boundary conditions or model parameters were determined through the completion of earlier runs. This allowed for direct comparisons between simulated soil water potential, volumetric water content, thermal regime, and Cl profiles in different cases.
The cases vary as follows:

*Case 1* – Base case in which model boundary conditions are similar to those measured currently at ADRS in the northern Mojave Desert.

*Case 2* – Use a reconstructed paleoclimate sequence.

*Case 3* – Use root water uptake processes, including reconstructed vegetation parameters and paleoclimate.

*Case 4* – Compress daily precipitation to occur within a 6-hr period, rather than a 24-hr period (described in Section 2.3.1.1).

*Case 5* – Embed design-basis storm events (i.e., 100-yr return period) into each century in each 3,000-yr climate sequence (described in Section 2.3.1).

*Case 6* – Modify the root characteristics to include highest root density at 200-cm depth and an active root zone at 300-cm depth, rather than 100-cm in previous cases.

Note that the depth of the plant roots (Figure 2.3) is restricted to the upper 100 cm of soil for Cases 3–5, and extended to 300-cm depth for Case 6 to better understand the influence of the maximum root density on the Cl profile.

We also assumed the following:

1. Average Cl concentration in the precipitation (0.0016 mg/ml) was assumed to be constant over the entire simulation period (Scanlon et al., 2003).

2. The initial Cl concentration in the soil was set to zero, due to the high water fluxes before 18 ka. This wettest glacial climate is supported by most paleoclimate proxies (Tyler et al., 1996).

3. Initial water pressure head was arbitrarily set to -0.098 MPa (equivalent to -10 m water pressure head) to represent a relatively wet environment during the LGM.
4. For solute transport, longitudinal dispersivity was set to 100 cm based on the soil profile scale (Domenico and Schwartz, 1998), and the diffusion coefficient of Cl in water was set to 1.3 cm$^2$ d$^{-1}$ (Cook et al., 1992).

5. Value of the soil matric potential, below which root water uptake ceases, was set at -4.9 MPa (equivalent to -500 m water pressure head), which is the average of the measured low water potential under an undisturbed, vegetated site in the Amargosa Desert (Andraski, 1997).

6. In Cases 1 – 2, a free drainage lower boundary condition was used to simulate a thicker soil sequence when no plants were present. In Cases 3 – 6, the lower boundary condition was set at a constant matric potential of -2.45 MPa (equivalent to -250 m water pressure head), roughly equaling the measured matric potential at the same depth in the Amargosa Desert (Scanlon, 2003).

2.3 Model results

2.3.1 Matric potential and water content profiles

Simulated matric potential and water content profiles are shown in Figure 2.4. Note that the test cases are split into two groups (Group 1 includes Cases 1 and 2 and Group 2 includes Cases 3 to 6) because the largest discrepancies are observed between these two groups. In Figure 2.4a and 2.4b (Group 1), soil water potential and water content showed very little variation in depth because of a lack of root water uptake. In Figure 2.4a (Case 1), matric potential and water content were nearly constant over 18,000 years, reflecting the steady meteorological input. Both water potential and water content profiles show very steep gradients in the top 30 cm of soil and are then constant in deeper
Once the simulation reaches steady state, yearly averaged net water flux (liquid + vapor) at the lower boundary is approximately 1.2 mm yr\(^{-1}\). In the uppermost soil, the direction of liquid flux became upward due to the effects of evaporation, even though summer thermal gradients induce downward thermal vapor transport. Figure 2.4b shows two distinct matric potential and water content profiles due to the large differences in precipitation between pluvial and dry periods. For example, matric potential in 15 and 12 ka (top graph in Figure 2.4b) shows an upward potential gradient in soil shallower than 20 cm and a downward potential gradient in soil from 40 – 60 cm. The divergence of the gradient at about 30-cm depth is a direct result of a water bulge that existed in the profile from a precipitation event that occurred near the end of the 3,000 year simulation period. This water bulge dissipated due to evaporation or percolation to deeper soil, or both, after the precipitation event. During the final 6,000 years of simulation, water flow rates and directions in the majority of the soil profile were unchanged, and the downward potential gradient approached zero, because the supply of water at the surface was not sufficient to sustain a potential gradient. In these two cases, response time of the water content to the surface climate change is short relative to the simulation period.

After the processes of root water uptake were accounted for in Group 2 (Figures 2.4c – 2.4f), the soil water potential throughout the profile decreased substantially, especially in the upper 100 cm in Cases 3 – 5, and in the upper 300 cm in Case 6. Soil water content profiles also showed the same trends. Large differences in water content were observed below the root zone between Cases 3, 4 and 5, especially during the periods of 15 and 12 ka. This observation is supported by the reduced net water flux at the bottom of the domain which previously was unaffected by variations in surface
climatic conditions. For example, at 15 ka, bottom water fluxes were -0.13 mm yr\(^{-1}\) (negative represents upward water flux), 0.07 mm yr\(^{-1}\) and 1.11 mm yr\(^{-1}\) in Cases 3, 4 and 5, respectively. However, when the climate was much drier, for example at 0 ka, water fluxes were -0.16 mm yr\(^{-1}\), 0.06 mm yr\(^{-1}\) and -0.16 mm yr\(^{-1}\), respectively. Therefore, although 100-yr return period events were introduced in Case 5, they only increased the recharge when total water supply was relatively large (e.g., 15 ka and 12 ka). During drier periods, however, the effect of 100-yr storm events was buffered by a long drying process, so the upward bottom flux was the same as observed in Case 3 (e.g., -0.16 mm yr\(^{-1}\) at 0 ka), which had no extreme events. Based on the simulation results, only Case 4 produced recharge during dry periods of 6 ka to 0 ka, reflecting the impact of increased precipitation intensity imposed on the upper boundary (i.e., precipitation occurred during 6-hr period instead of 24-hr period). Moreover, even though the climate changed between 15 ka and 0 ka, the difference in flux was 0.01 mm yr\(^{-1}\) (i.e., 0.07 versus 0.06 mm yr\(^{-1}\)).

Bottom net fluxes in Case 6 at 15 ka and 0 ka were -0.16 mm yr\(^{-1}\) and -0.23 mm yr\(^{-1}\), respectively, which were the lowest fluxes for all cases that included root water uptake. The results indicate that the increased root mass essentially stopped liquid water from percolating below the root zone, and then induced a net upward water flux as has been observed by others (Walvoord et al., 2002; Scanlon et al., 2003). The water content profile (Figure 2.4f) also supports this observation. Also, after 6,000 years of simulation (time = 12 ka), soils in the uppermost 30 cm became significantly drier, showing the effect of higher PET rates (Figure 2.1) toward the end of the last glacial period. In Case 6, where the root zone distribution was extended to 300 cm below ground surface, reduced
water contents begin at 55 cm rather than 30 cm in other cases, illustrating the importance of where plant roots are placed in the simulation.

An important phenomenon is that bottom net water fluxes in Group 2 (Figures 2.4c – 2.4f) during dry climates are actually upward, except in Case 4. Considering that a large downward matric potential gradient was artificially created by the constant soil water matric potential of -2.45 MPa (equivalent to -250 m water pressure head) at the bottom of the domain, root water extraction and upward thermally-driven vapor transport exceeded the downward liquid fluxes induced by the downward gradient, causing water to move vertically upward toward ground surface. Therefore, under such conditions, water from soil deeper than 15 m could be extracted given sufficient time.

2.3.2 Chloride distributions

Figure 2.5 shows Cl distributions for Cases 1 – 6, divided into groups similar to those described for the water potential and water content profiles. Cases 1 and 2 (Figures 2.5a and 2.5b) show nearly uniform Cl profiles at the end of the simulation period without discernible peaks. Some differences are noted between the two cases, however. For example, the Cl concentration profile in Case 1 is uniform with depth, reaching steady state relatively quickly. In Case 2 (Figure 2.5b), two distinct concentration profiles exist, illustrating the different Cl accumulation rates caused by the climatic switch. In both cases, even though root water uptake is not occurring, soil evaporation does remove enough soil water to eventually create a profile with steadily increasing Cl concentrations very close to ground surface. Figure 2.5b also shows that during the period when climate switched (12ka), Cl accumulated in the entire soil domain rather than only close to the soil surface. Also, one may notice that the stored Cl at the end of the simulation record
(i.e., time = 0 ka) is lower than observed at the end of 12,000 years of simulation (or time = 6 ka) (Figure 2.5b). This implies that Cl output rates during this time exceeded input rates. The net liquid water fluxes were equal to 0.96 cm yr⁻¹ and 1.19 cm yr⁻¹, respectively. When taking into account the upward vapor transport, however, the downward liquid fluxes were actually larger.

The importance of vegetation in this environmental system is revealed in Cases 3–6 (Figures 2.5c–2.5f). Here, the Cl concentrations at depths approaching 15 m are essentially zero, again illustrating the small liquid flux occurring below the root zone during the 18,000 years of simulation. In Case 3, the root water uptake clearly led to significant increases in Cl concentration near ground surface, with values almost 100 times higher than in Case 2, which did not include transpiration. Case 4 shows a very similar Cl distribution to those presented when daily precipitation was applied during a 24-hr period (Case 3). However, the increased precipitation intensity in Case 4 flushed Cl deeper into the profile and through the base of the domain. We noted that the average percent of Cl mass stored in the profile was only 59.2% of the total input, which is less than in all other cases (Table 2.5).

Figure 2.5e (Case 5) reflects the addition of a single “wet year” for each 100 years of simulation. Significantly lower Cl concentrations are noted near ground surface after simulation periods 15 ka and 12 ka, versus those from Cases 3, 4 and 6. Figure 2.5e also shows lower Cl concentrations in other simulation periods, though we note that these lower concentrations resulted from low initial Cl mass in the profile after 12 ka. Adding 100-yr storm events during the LGM caused larger downward Cl fluxes; however, during
modern times with lower annual precipitation, Cl was flushed deeper into the soil profile but through the bottom of the domain.

The most significant finding in Case 5 is the formation of a distinct Cl bulge at approximately 90-100 cm depth at 0 ka (Figure 2.5e). The depth of maximum Cl concentration, which corresponds to the base of the root zone (Figure 2.3), is also much deeper than simulated in Cases 3, 4 and 6. Apparently, Cl is transported further downward during the simulated wetter (100-yr storm) periods and then became concentrated deeper within the root zone. When compared to Cases 3 and 4 (Figures 2.5c and 2.5d), the results show the importance of the precipitation record on the Cl profile. For example, using the ‘normal’ precipitation record (Case 3), the Cl bulge remains close to 10-20 cm depth with concentrations of about 40 mg L\(^{-1}\). Compressing the precipitation record into 6-hr (Case 4) led to increased Cl fluxes from the bottom of the domain during all climate periods and a lower overall Cl mass remaining in the profile at the end of the simulation (Table 5). Adding periodic wet years to the record (Case 5) led to a deeper Cl bulge (Figure 2.5e) with lower concentrations than seen in Cases 3 and 4. Moreover, we note in Case 5 that significant bottom Cl fluxes occurred only during wet climates (i.e., 15 ka and 12 ka). When the climate became drier, almost no downward bottom Cl fluxes were observed.

When roots were extended deeper into soil (Case 6), the depth of the highest Cl concentration increased to 100-cm depth in 15 ka and 12 ka (Figure 2.5f). When the climate became drier (after 12 ka), the Cl peak moved upward in the profile to about 20-40 cm depth. We contrast these results to those of Case 3, where maximum root zone density and rooting depth were 20-30 cm and 100 cm, respectively, and the Cl bulge was
simulated at about 20-cm depth. Apparently, the distinct Cl bulges observed for the wetter 15-ka and 12-ka conditions in Case 6 were deep enough into the soil profile to buffer the bulge against diffusion. Moving the maximum root zone density to 200-cm depth allowed water and Cl to percolate and migrate deeper in the soil profile, away from effects of soil evaporation.

2.4 Discussion

The measured Cl peak at ADRS is 230 cm below ground surface and the peak concentration is 9 mg/ml (Scanlon et al., 2003). Some differences exist between our model predictions and field data for Cl concentration reported by Scanlon et al. (2003), but, given the long simulation time and spatial variability in root zone distribution in desert systems, the results are generally close and represent spatially-averaged hydrologic processes in the northern Mojave Desert, and not at a particular site. In another study, Sandvig and Phillips (2006) showed matric potential and Cl profiles under different species and climatic conditions. Most of their experiment sites were located in arid/semiarid regions in central New Mexico, and consisted of sandy-textured soils. Their results also showed sharp decreases in average matric potential (from three sites) from the soil surface to a depth of about 100 cm, and an average depth to the Cl peak of 250 cm. The field conditions for Sandvig and Phillips (2006) at locations 1, 2 and 3 are closest to our simulation conditions described for Case 5 (Figs. 4e and 5c), and the results are conceptually similar. Differences in water potential and Cl are attributed to several potential factors, including soil conditions, climate and the structure of the numerical model (in our study) where root water uptake is strictly associated with the root locations.
The results of the numerical experiments by Walvoord et al. (2002) and Scanlon et al. (2003) illustrated that Cl will concentrate at the depth of a fixed subroot zone, which in their cases were implemented using a single sink node kept constant at -4.9 MPa at a depth of 230 cm. However, according to Sandvig and Phillips (2006), who examined conditions in the upper 10 m of soil, large negative matric potentials exist through the whole root zone as well as large part of the subroot zone. In our study, a root zone distribution was calculated for a mixed canopy with different rooting characteristics for each plant type, and with different maximum root zone densities. We showed that, in Cases 3 and 4, the depth of elevated Cl concentrations was associated with the depth of the maximum root density. But, in Case 6, the association no longer holds during dry periods. Given that the peak did move deeper in 15 and 12 ka, we propose that the location of the Cl peak is secondarily associated with the distribution of the root zone, and primarily associated with climatic conditions. The results indicate that, in arid regions, root water uptake rapidly removes water that infiltrates the soil, and continues throughout the entire root zone.

Recharge below the root zone, potentially resulting in groundwater recharge, apparently will become more significant during episodes of plant mortality or widespread plant loss (e.g., from brush fires or disease), as was demonstrated in Case 2. However, at other times when vegetation is present and active, on average, almost all water infiltrating through the soil surface eventually will be transpired (Case 3). Although other models suggest that transpiration responds to the average soil water potential (Fahey and Young, 1984), rather than to the water potential in layers where roots exist (as simulated in HYDRUS-1D), the simulated extremely dry conditions throughout the root zone are still
likely to sustain the constant root sink. Moreover, during dry time periods, thermally-driven vapor water transport could sustain an upward net flux. Our results are consistent with Walvoord et al. (2002) and Scanlon et al. (2003), who demonstrated that vapor water transport in arid regions plays important roles on the distribution of the matric potential in the soil, but has a relatively unimportant role in the absolute values of soil water content (especially within the active root zone). Thus, inasmuch as the effective diffusion coefficient of Cl is a function of soil water content, and given that Cl is nonvolatile, the redistribution of Cl affected by the enhanced vapor flux could be ignored. In addition, Scanlon (1991) and Walvoord et al. (2002) showed that osmotic potential has a much smaller effect than matric potential on water flow in arid vadose zones.

Present-day root zone distributions for mixed canopies in arid climates generally have co-existing shallow and deep roots which are active for different seasons and lengths of time. The paradox, then, is how Cl bulges deeper than 100 cm could form and persist given current root zone distributions and plant phenologies. For example, only in Case 5 of our study, which included the most realistic environmental setting, did the depth of penetrating moisture correspond to the rooting depth for the entire guild. In Cases 3, 4 and 6, the depth of the Cl bulge was significantly above the base of the roots. These results illustrate the importance of including realistic root zone distributions and climate sequences when simulating paleo-water fluxes.

Other physical and/or biological processes may explain the deep presence of Cl. For example, soil aggradation processes that create desert pavement surfaces (McFadden et al., 1998) could lead to buried soil horizons containing higher chloride levels. Similarly, pedologic development (including the creation of macropores) may cause significant
changes of soil hydraulic properties given the time scale of thousands of years (Young et al., 2004), and a stronger coupling of soil properties and canopy characteristics as shown by Shafer et al. (2007). Another explanation could be an inaccurate dry fallout chloride rate in the simulation. Although this dry deposition is variable (Zhu et al., 2003), Dettinger (1989) suggested a 33% uncertainty in the Great Basin, which would explain the discrepancy between our simulated results and the Cl concentrations reported by others.

2.5 Conclusion

The results showed that the total amount of water entering the soil through precipitation, the precipitation intensity, and the vegetation root distribution play important roles in the water flux mechanisms in arid regions. Rather than assuming that the Cl profile is controlled only by climate and the climate switch, our results show that the depth of root water uptake has a substantial influence on the depth of the Cl bulge commonly preserved in thick vadose zones of the southwestern United States. Moreover, under the conditions of typical desert vegetative cover and normal precipitation patterns (e.g., Case 3), recharge rates below the root zone became almost zero, even in the more pluvial 15 ka - 12 ka climate. Any recharge into the deep vadose zone occurring during this period is most probably focused in topographic lows like channels and washes. Large intensity precipitation events may contribute to recharge or perhaps to groundwater recharge. Large storms such as 100-yr precipitation events (Case 5) may also contribute to recharge, but our results showed that this occurrence was restricted to the pluvial period (i.e., 15 and 12 ka) when the initial soil water content was higher. The yearly
averaged net upward water flux found in Case 5 during the present time (-0.16 mm yr\(^{-1}\)) is larger than -0.01 mm yr\(^{-1}\) that was simulated by Walvoord et al. (2004), and is smaller (and opposite in direction) than the net downward flux calculated by Andraski (1996) at 5-m depth in a vegetated soil plot at the end of September, 1990 (0.09 cm yr\(^{-1}\)).

The results of the simulations provide a better understanding of soil water flux and Cl concentration variations under the influence of long-term climate change. The results also suggest that further research on water fluxes in arid regions should focus on the development of desert plant roots and the interactions between roots and soil moisture under the conditions of climate change. These are the most significant factors that govern water fluxes in vadose zone.

2.6 Acknowledgements

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Table 2.1 Hydraulic properties of representative soil (Andraski, 1996; Scanlon et al., 2003)

<table>
<thead>
<tr>
<th>USDA texture</th>
<th>Sand %</th>
<th>Silt %</th>
<th>Clay %</th>
<th>Ks cm d⁻¹</th>
<th>θₛ cm⁻³ cm⁻³</th>
<th>θᵣ cm⁻³ cm⁻³</th>
<th>α cm⁻¹</th>
<th>n --</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loamy sand</td>
<td>80</td>
<td>14</td>
<td>6</td>
<td>43.0</td>
<td>0.29</td>
<td>0.026</td>
<td>0.026</td>
<td>1.42</td>
</tr>
</tbody>
</table>
Table 2.2 Calculation of LAI for different growth forms

<table>
<thead>
<tr>
<th>Vegetation type</th>
<th>*LAI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evergreen (L. tridentada)</td>
<td>0.65×cover</td>
</tr>
<tr>
<td>Deciduous (subshrub)</td>
<td>5.70×cover</td>
</tr>
<tr>
<td>Annual</td>
<td>1.17×cover</td>
</tr>
<tr>
<td>Grass</td>
<td>3.60×cover</td>
</tr>
</tbody>
</table>

Modified from Kemp et al. (1997)

*LAI is calculated by converting the ground coverage of each vegetation type to leaf biomass and then to leaf area. The related sources in the calculation in this table include: IBP (1974), Deuit and Caldwell (1975), Ludwig et al. (1975), and Barbour (1977), Werk et al. (1983), Willoamson et al. (1987).
Table 2.3 Root density distributions used in model

<table>
<thead>
<tr>
<th>Depth (cm)</th>
<th>Evergreen†</th>
<th>Deciduous†</th>
<th>Grass†</th>
<th>Annual†</th>
<th>Succulent‡</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-10</td>
<td>0.0</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
<td>0.22</td>
</tr>
<tr>
<td>10-20</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
<td>0.5</td>
<td>0.18</td>
</tr>
<tr>
<td>20-30</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.13</td>
</tr>
<tr>
<td>30-40</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0</td>
<td>0.11</td>
</tr>
<tr>
<td>40-60</td>
<td>0.3</td>
<td>0.2</td>
<td>0.1</td>
<td>0</td>
<td>0.14</td>
</tr>
<tr>
<td>60-80</td>
<td>0.1</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
<td>0.09</td>
</tr>
<tr>
<td>80-100</td>
<td>0.1</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
</tbody>
</table>

† - After Kemp et al. (1997)

‡ - After Jackson et al. (1996), when using equation $Y = 1 - \beta^d$. Where $Y$ is the cumulative root fraction, $d$ is depth in the soil (cm), and $\beta$ is the fitted parameter. Here we use $\beta = 0.975$ as suggested value for desert biome.
Table 2.4 Characteristics of simulation cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Base case</th>
<th>Paleoflux record</th>
<th>Root water uptake</th>
<th>Compressed daily precipitation</th>
<th>100-yr storm events</th>
<th>Deeper active root zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>• • •</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>• • • •</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>• • •</td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>• •</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>•</td>
</tr>
</tbody>
</table>
Table 2.5 Percentage of chloride remaining in the model domain at representing time period (%)

<table>
<thead>
<tr>
<th>Period Ending</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>15ka</td>
<td>0.1</td>
<td>1.0</td>
<td>99.8</td>
<td>86.8</td>
<td>56.2</td>
<td>99.9</td>
</tr>
<tr>
<td>0ka</td>
<td>0.0</td>
<td>-5.9</td>
<td>71.3</td>
<td>59.2</td>
<td>68.4</td>
<td>91.9</td>
</tr>
</tbody>
</table>
Figure 2.1 Reconstructed PET and P. Note that blocks separated by dashed lines are climate conditions for each 3,000-yr simulation period.
Figure 2.2 Reconstructed vegetation coverage. Pie charts show partitioning of ground coverage for each growth form.
Figure 2.3 Comparison of root distributions. The distribution represents the root conditions in spring at 0 ka simulation.
Figure 2.4 Water potential and volumetric water content (Group 1). The figure does not show the simulated water potential and water content at the ending points of 9 ka and 3 ka. Matric potential on ground surface in both cases is -10 MPa, which is the lowest allowed water potential in the numerical model.
Figure 2.4 (continued) Water potential and volumetric water content (Group 2). The figure does not show the simulated water potential at the ending points of 9 ka and 3ka. Note that the horizontal scales in matric potential are different between Group 1 and Group 2.
Figure 2.5 Chloride concentrations (Group 1). The figure does not show the simulated chloride concentration at the ending points of 9 ka and 3 ka.
Figure 2.5 (continued) Chloride concentrations (Group 2). The figure does not show the simulated chloride concentration at the ending points of 9 ka and 3 ka. Note that the scales are different between Group 1 and Group 2.
CHAPTER 3

MODELING THE EFFECT OF SPATIAL VARIABILITY OF SOIL HYDRAULIC
PROPERTIES ON THE RAINFALL-RUNOFF PROCESS IN A RANGELAND
WATERSHED USING A DIFFUSION WAVE MODEL

3.1. Introduction

Hydrological models are very important tools used to address the nonlinear
relationships between rainfall and surface runoff. For numerical simulations, spatial
variability of soil hydraulic properties plays a significant role in controlling the predictive
accuracy of hydrologic simulations. In a physically-based hydrologic model, introducing
more spatial variability usually better represents the research site and then increases the
confidence of the model. However, it also brings more computational efforts and requires
much more detailed information than the lumped model (Grayson et al., 1992). As
indicated by Seyfried and Wilcox (1995), the need to include spatial variability is always
scale dependent. They showed that the parameter field affecting small-scale hydrologic
processes can be represented stochastically, but determining the threshold of the scale
where the variability of the hydraulic parameters can be treated as deterministic or
stochastic is often very difficult (Seyfried and Wilcox, 1995). Because studies in small-
scale catchments show that strong spatial variability exists for soil hydraulic properties

53
(Herbst et al., 2006), studies are needed to analyze the sensitivity of variability sources, such as slope and elevation, which all have strong correlations with the soil physical and watershed properties (Herbst et al., 2006), and to more efficiently represent variability.

Many studies have generated parameter fields that represent natural field conditions at catchments (e.g., Mueller et al., 2007; Herbst et al., 2006). Rather than relying only on deterministically-derived property fields, which needs significant levels of field measurement efforts, geostatistical methods based on smaller amounts of \textit{in-situ} measurements are often more time efficient and widely used (Ünlü et al., 1990), though some tradeoff with accuracy often is needed. Geostatistical methods range from the simple average, such as arithmetic mean and geometric mean, to more complicated interpolation schemes, which are usually applied to spatially continuous variables, assuming that points with shorter distances maintain some similarities versus points further apart (Isaaks and Srivastava, 1989). For instance, Merz and Plate (1997) took field measurements and then conducted numerical simulations on a small watershed. They evaluated the impacts of three different spatial patterns (structured, random, and spatially constant) and then indicated that effects on runoff predictions were event dependent. Michaelides and Wilson (2007) also analyzed uncertainties in modeled runoff due to spatially-varying infiltration patterns using geostatistical approaches. Their results demonstrate that the optimum variogram model parameters largely affected the connectivity of runoff pathways and hence the simulated runoff.

The purpose of this study is to investigate the spatial patterns of different characteristics such as vegetation coverage and soil hydraulic properties (e.g., hydraulic conductivity and saturated water content) in a semi-arid watershed based on samples
collected in the field, and to examine how the strategy for generating the property field will affect the accuracy of runoff predictions. In addition, this study will also examine whether physically-based parameters can be generated through limited numbers of field measurements, rather than calibrating the model. This is particularly useful for ungaged watersheds. By simulating eight different storm events where field measurements of runoff were obtained, sources of error that affect runoff predictions will be identified. Moreover, we evaluate whether a distributed-parameter field or a lumped-parameter field is needed in the model. To minimize the uncertainties of the rainfall-runoff model itself, we used a physically based, two-dimensional diffusion wave model, which can solve water flow directions accurately, and applied the model to a site with a very-high-resolution DEM (1m x 1m). Given the high resolution DEM data, we assume that the sub-grid soil is homogeneous. Therefore, point-scale field measurements within that grid can be considered as the averaged value for the area occupied by this grid. Due to a lack of measurements, parameters associated with vegetation (e.g., rainfall interception and hydraulic roughness) used in the model are not included in the spatial pattern analysis.

3.2 Two dimensional diffusion wave model

A two-dimensional distributed model named Cell-based Rainfall-Infiltration-Runoff Model (CeRIRM) was used in this study (Chen and Young, 2008). CeRIRM uses the diffusion wave approximation of the St. Venant equations. Continuity equation and momentum equation are:

\[
\frac{\partial h}{\partial t} + \frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y} = p - i \tag{3.1}
\]
\[ S_o - \frac{\partial h}{\partial s} = S_f \]  
(3.2)

\[ q = \frac{1}{n} \left( \frac{h^3}{S_f^2} \right) \frac{1}{q_x} = q \cos \alpha, q_y = q \sin \alpha \]  
(3.3)

where \( t \) is time, \( x \) and \( y \) are spatial coordinates which are defined in horizontal plane, \( q_x \) and \( q_y \) are unit discharges in \( x \) and \( y \) coordinates, \( p \) is rainfall intensity, \( i \) is infiltration rate, \( H \) is the vertical flow depth, \( h \) is flow depth normal to the slope, \( h = H \cos \gamma \), \( \gamma \) is the slope angle, \( S_0 \) is the ground slope, \( S_0 = \sin \gamma \), \( S_f \) is the energy slope, \( s \) is the flow direction in the horizontal plane, and \( \alpha \) is the angle between \( x \) and \( s \). A revised Green-Ampt model (Mein and Larson, 1973; Chu, 1978) is used to calculate infiltration:

\[ i = \frac{dl}{dt} = K_s \left[ 1 + (\theta_s - \theta_f) S / I \right] \]  
(3.4)

\[ K_s \left[ 1 - (t_p - t_s) \right] - I - \frac{S(\theta_s - \theta_f)}{\cos^2 \gamma} \ln \left[ 1 + \frac{I \cos^2 \gamma}{S(\theta_s - \theta_f)} \right] \quad t > t_p \]  
(3.5)

\[ K_s t_s = I_p - S(\theta_s - \theta_f) \ln \left[ 1 + \frac{I_p}{S(\theta_s - \theta_f)} \right] \]  
(3.6)

\[ I_p = \frac{(\theta_s - \theta_f) S}{P/K - 1} \quad t_p = I_p / p \]  
(3.7)

where \( i \) is the vertical infiltration rate, \( I \) is the vertical cumulative infiltration depth, \( S \) is the soil capillary pressure at the wetting front, \( \theta_s \) and \( \theta_f \) are initial and saturated soil moisture, \( K_e \) is effective soil hydraulic conductivity, \( t_p \) is the ground ponding time, \( I_p \) is the cumulative infiltration depth at ponding time.

CeRIRM routes flow along calculated topographic gradients for every rectangular cell (equivalent to a DEM grid if square), which allows water in each cell to flow into two possible downstream neighboring cells. The two-dimensional routing is realized
through a decomposition approach which avoids an inconsistency in the representation of the two-dimensional diffusion wave. This model has been applied to other alluvial fan complexes (i.e., Young et al., 2005). Input parameters required in the model include: $\theta_s$ and $\theta_i$, $S$, $K_s$, and hydraulic roughness ($n$) in Manning’s equation. In this study, we investigate the affects of spatial variability of $\theta_s$, $S$, and $K_s$ on the modeling results of surface runoff. The simulations assume a uniform $\theta_i$ before each simulation, and two different $n$ values - one for interspace soil and one for undercanopy soil. Saturated hydraulic conductivity ($K_s$) used in the Green-Ampt model is 50% of the measured saturated hydraulic conductivity as suggested by Bouwer (1966) and in the Handbook of Groundwater Engineering (Delleur, 1999). This value is widely used in practical applications of the Green-Ampt model (e.g., Rawls et al., 1983).

3.3 Field sampling and data post processing

3.3.1 Site description

The field site is located in the Walnut Gulch Experimental Watershed near Tombstone, Arizona (31°43’N, 110°41’W). A detailed description of the watershed has been given by Nichols (2007) and updated information is provided on a website maintained by the US Dept. of Agriculture, Agric. Research Service (USDA-ARS) (http://ars.usda.gov/main/site_main.htm?modecode=53-42-45-00). One subwatershed, known as Lucky Hills 104 (LH104), is located at the northern part of the experimental watershed. The high resolution DEM was provided by USDA-ARS (Goodrich and Lainie Levick, 2006, personal communication) and was represented on a GIS platform (ArcGIS 9.2), where a watershed area of 44,079 m² was calculated. Sparsely distributed desert
species are mostly creosote bush (*Larrea tridentada*), along with some mesquite (Prosopis glandulosa), white-thorn (Acacia constricta) and various grasses. The slope of the watershed ranges from <1 % at the highest elevation of the watershed to >15 % in the rainfall rill toward the outlet of the watershed. Precipitation was measured using a digital rain gauge (#384), located in the northwestern part of the watershed (data recorded before 1999 is analog). Due to the relatively small watershed area, we assume that readings from gauge #384 represent precipitation depths on the entire watershed (i.e., uniform precipitation amounts). Streamflow is measured by a flume (#104) at the outlet of the watershed. Both rainfall and streamflow data have been continuously measured since 1953.

3.3.2 Sample collection and data post processing

Sample collection was conducted from 11/27/06 to 11/28/06. A total of 66 soil samples were collected at 33 locations at the research site. Based on the watershed delineation, one major rill and one tributary rill exist across the watershed (Fig. 1). Therefore, selected sample locations were established along six transects: one along the major rill, one across the major rill at the upstream location and four across the major rill at downstream location (Fig 1). Distance between two samples at each transect is 30 m. During the field measurements, individual sampling locations were slightly adjusted based on the accessibility of specific points, though typically measurements were within a meter of the target point. Due to influences introduced by plants such as rainfall interception (*Domingo et al., 1998*) and hydraulic roughness under canopies (*Weltz et al., 1992*), two samples were collected at each location: one found between shrubs, known as the interspace sample and one found underneath the plant canopy, known as the
undercanopy sample. At each location, when an interspace sample was identified, an
undercanopy sample was collected under a closest shrub. Major and minor axes and
height of each chosen shrub were measured. Spacing between three closest shrubs
(including the chosen shrub) was also measured, and the average was taken accordingly.
Soil samples were collected by a hand trowel in each selected location. Samples were
shipped to the Quaternary Pedology and Soil Characterization Laboratory in Reno, NV
and analyzed using the laser light scattering method (Digisizer, Micromeretics, Norcross,
GA).

The pedotransfer function (PTF) method, using the program Rosetta (Schaap et al.,
2001), was applied to calculate the van Genuchten parameters (van Genuchten, 1980)
from percentages of sand, silt and clay only. In addition to the van Genuchten parameters,
parameters specific to the Green-Ampt equation were also estimated using non-linear
regression, where Rawls et al. (1983) calculate the wetting front capillary pressure ($S$)
based on the Brooks and Corey model:

$$S = \frac{2λ + 3}{2λ + 2} \left[ \frac{ψ_b}{2} \right]$$

(3.8)

where $λ$ is the pore size distribution index and $ψ_b$ is the bubbling pressure, which were
both estimated by Lenhard (1989)'s method:

$$λ = \frac{-m}{1-m} \left[ 1 - 0.5^{1/m} \right]$$

(3.9)

$$h_d = \frac{S_s^{1/λ}}{α} \left[ S_s^{-1/m} - 1 \right]^{1/m}$$

(3.10)

where $λ$ and $h_d$ are Brooks and Corey parameters; $m$ is a parameter related to the van
Genuchten parameter $n$ by $m = 1 - 1/n$. $S_s$ is an empirical expression calculated by Lenhard
(1989): \( S_x = 0.72 - 0.35 \exp(-n^4) \). Parameter uncertainties were discussed in Mishra et al. (1989), but were not accounted for in this study. Due to the high percentage of rock fragments in the soil at the watershed, saturated hydraulic conductivity \( K_s \), derived from Rosetta) needs to be corrected accordingly. Brakensiek et al. (1986) showed a linear conversion:

\[
K_{rg} = K_s \frac{1 - R_w}{1 - R_w (1 - 3a / 2)}
\]  

(3.11)

where \( R_w \) is the rock fragment content by weight; and \( a \) is an empirical parameter, which has a suggested averaged value of 0.5 (Brakensiek et al. 1986). Moreover, considering that the wetting front capillary pressure is a parameter related to the soil matrix, \( S \) in equation (3.8) is reduced proportionally to the percentage of fine material volume in the soil sample (assume bulk density is 1.6 g/cm\(^3\) for fine material and 2.65 g/cm\(^3\) for coarse material, respectively).

3.4 Interception and hydraulic roughness

The interception theory used in this study is based on Rutter and Morton (1977) and Domingo et al. (1998). The equation representing the effective rainfall (i.e., rainfall that contributes to infiltration) between time \( t \) and \( t + dt \) is (Domingo et al. 1998):

\[
R_{e,i} = R_t + aC_v^b dt
\]  

(3.12)

where \( R_{e,i} \) is the effective rainfall, \( R_t \) is the rainfall depth between time \( t \) and \( t + dt \), \( p \) is the percentage of free throughfall; \( a \) and \( b \) are canopy drainage parameters; and \( C \) is water quantity stored on the canopy. The second term on the right hand side in equation (3.12) accounts for water drainage from the canopy between \( t \) and \( t + dt \).
To simplify the calculation, we assume that the canopy becomes fully wetted immediately after rainfall begins. Therefore, \( C \) is a time-independent parameter and can be regarded as a function of the canopy area projected to ground surface. The rewritten equation (3.12) is thus:

\[
R_{\varepsilon,t} = R_t + p + a(cA)^b \Delta t
\]  

(3.13)

where \( A \) is the total area of a single plant (cm\(^2\)) projected to ground surface, \( c \) is the storage capacity per unit projected area (mm/cm\(^2\)); and \( \Delta t \) is equivalent to the time step of rainfall input. Domingo et al. (1998) tested three semiarid shrubs and listed the corresponding parameters based on field experiments. According to visual inspection of \( L. \) tridentada shrubs at LH104, we assume \( Retama sphaerocarpa \) (L.) Boiss has a similar, very open canopy morphology, allowing us to adopt parameters in equation (3.13) as 0.7, 32.5, 3.12 and \( 1.92 \times 10^{-5} \) for \( p, a, b \) and \( c \), respectively. Therefore, in each vegetated grid (with 1 m\(^2\) projected canopy area), 75\% of rainfall reaches the soil surface in a 140-min storm event with total precipitation of 70.62 mm. Same calculations are used for each of the eight storm events tested.

The hydraulic roughness is chosen from Table 3.3 in Wektz et al. (1992), while two Manning’s roughness coefficients are used: 0.02 for native soil (gravel surface) and 0.25 for soil covered by plants (shrubland). As indicated before, variabilities in roughness within the interspace grids and undercanopy grids were not considered in this study.

3.5 Parameter field generation

Three approaches are used to generate the parameter fields: uniform, random and conditioned structural stochastic (co-kriging). Each method was repeated three times
based on samples collected from the field, which were grouped according to the sample origins: entire population versus interspace versus undercanopy. Therefore, nine simulations were conducted for each storm event (i.e., three different parameter fields based on three different data sources). Within each computational grid, a dataset of $\theta$, $S$, and $K_{sg}$ was generated using each approach. Shrub spacing measurements obtained during field sampling shows that the ground area occupied by the plant canopy is 1.4 times as large as the interspace area, or that shrub coverage of about 58% exists at the site. Based on the intrinsic assumption in the model that mixed grids do not exist (i.e., a grid is occupied by either open soil or covered soil), we assigned undercanopy area to 25,713 grids and interspace area to the remaining 18,366 grids. To apply the corresponding rainfall interception and Manning’s roughness when the parameters were derived from the entire population, the distribution of interspace and undercanopy grids across the watershed was random.

Uniform field

In this parameterization strategy, homogeneous parameter fields were created based on derived hydraulic properties using different sample populations. A single parameter set was applied to the entire watershed. Therefore, the spatial variability was neglected in this case. Table 3.1 lists the arithmetically-averaged value for $\theta$, and $S$ and geometrically-averaged values for $K_{sg}$.

Latin hypercube sampling (LHS)

Several studies indicated that saturated hydraulic conductivity should be treated as a completely random variable (Gomez-Plaza, 2000, Castillo et al., 2003). Castillo et al. (2003) showed that hydrographs derived from the homogeneous and completely random
fields have very similar performance. Thus, rather than applying a purely random strategy to generate the parameter field, a constrained sampling technique using Latin Hypercube Sampling (LHS) was used to generate the random fields. The approach takes advantage of probability distributions of parameters and ensures that the random sampling covers the entire probability distribution in question (Iuzzolino et al., 2004). More specifically, in this study, LHS was first used to generate 44,079 parameter sets, accounting for the covariances between $\theta_s$, $S$, and $K_{sg}$. Secondly, the parameter sets were randomly distributed onto the grids. Comparing this method with a purely random strategy, the only restriction in LHS is that the probability distribution for each parameter was derived from the measured data, though parameter values were unconditioned on measured values.

**Cokriging**

Because of the significant correlation between the parameters, cokriging was used as the last method to generate parameter fields. Semivariogram models were derived for each parameter using the program VARIOWIN (Pannatier, 1996). Parameter generation, conditioned on known data values, was done using GSLIB (Deutsch and Journel, 1998). Table 3.2 summarizes the semivariogram model parameters. Because of the regular grid sampling strategy, the minimum sampling distance for the interspace and undercanopy subpopulations is 30 m; therefore, the discontinuity at zero lag distance (i.e., nugget) is difficult to determine. Thus, for the interspace and undercanopy subpopulations, the nuggets were chosen to be the same as the nuggets for the entire population. Exceptions are $S$ in interspace subpopulation and $S$ & $\theta_s$ for both subpopulations. The nuggets were chosen as 60% and 45% respectively of the variogram value for the shortest lag distance (i.e., 30 m) to facilitate the fitting of the Gaussian model to dataset.
Eight storm events with observed surface runoff data were selected for comparison with model predictions. Characteristics of these storms are summarized in Table 3.3. Antecedent soil moisture for Storms 1-4 were obtained from David Goodrich and Carl Unkrich (USDA-ARS, personal communications). Antecedent soil moisture for Storms 5-8 were roughly calculated from Whitaker (1993)'s field measurements, using a simple linear regression equation (antecedent soil moisture = 0.214xelapsed time in hours $^{-0.204}$) derived from the measured soil moisture and elapsed time (in hours) from the previous rainfall event. Antecedent soil moisture was assumed to be spatially homogeneous across the watershed due to lack of in-situ measurements.

3.6 Results and discussions

Figure 3.2 shows the examples of Green-Ampt parameters generated from the entire population of soil samples (Appendix A) using LHS (upper row) and cokriging (lower row), respectively. According to the Kruskal-Wallis one way analysis of variance, it is also noted that no statistically significant differences were found between any two parameter sets generated from three populations with $P=0.989, 0.638, 0.405$, respectively. The figure shows that the cokriging approach creates fields with significant spatial patterns. In general, when parameter fields are compared with the stream (rill) network shown in Fig. 1, all three fields obtained through cokriging show alternating patterns of low and high parameter zones on the upland area (upper left of each plot). Distributions close to the watershed outlet, however, are relatively smooth. Moreover, an apparent low $K_{sg}$ zone is found at the outlet of the watershed, which is probably unduly influenced by the parameter values from only two measurement locations close to the watershed outlet.
Negative correlations between $K_{sg}$ versus $S$ (rank correlation = -0.518; $P<0.05$), and $K_{sg}$ versus $\theta_s$ (rank correlation = -0.819; $P<0.05$) are explained by the use of Rosetta to obtain $K_{sg}$ and $\theta_s$, and the process of calculating $S$, which is strongly correlated to the derived van Genuchten parameters. No significant correlations are found between the parameters and stream networks.

Given the nine different scenarios simulated for each storm (3 parameterization strategies and 3 data sources), we will discuss the results by referring to specific combinations of parameterization strategies and data sources, where numbers “1,” “2,” and “3” to represent parameterization strategies corresponding to average, LHS and cokriging. Capital letters “A,” “I,” and “U” will be used to represent parameter fields generated from all populations, interspace populations and undercanopy populations, respectively. The combination of one number and one capital letter represents one simulation scenario. For examples, scenario “1A” represents homogeneous parameter fields generated using all populations.

Most of the storms that generated runoff in the watershed occurred during the summer monsoon season, or from July through September (Whitaker, 1993). Runoff coefficients (calculated as the ratio of runoff depth to rainfall depth) exhibit a wide range, from 0.08 for storm 3 to 0.64 for storm 2, illustrating that different storms yield different watershed responses. Figure 3.3 shows simulated runoff depths versus measured runoff depths. Coefficients of determination ($r^2$) were calculated to evaluate the degree of comparability. Under parameterization schemes 1 and 3, better correlations were observed when data source A was used, with $r^2 = 0.943$ and 0.926, respectively. Predictions of runoff depths were overestimated and underestimated when data source I
and data source U were used, respectively. Under parameterization scheme 2, however, the best correlations occurred when using data source I ($r^2 = 0.952$), while the runoff depths were consistently underestimated when using data sources A and U. In terms of water balance calculations, the calculated runoff depth is an indicator that assesses the relationship between precipitation and predictions of infiltration.

Theoretically, models ignoring interception are likely to bias precipitation high and then overestimate runoff volumes. Therefore, the combination of parameterization scheme 2 and data source I incorrectly yielded a high $r^2$. This phenomenon could be explained by the fact that the overestimated precipitation due to neglecting interception was canceled by the overestimated infiltration. More specifically, parameterization scheme 2 neglected the connectivity of flow paths by randomly distributing the infiltration parameters. This connectivity is equivalent to the connectivity of low infiltration regions (Michaekides and Wilson, 2007), which is regarded to be the preferential paths of water flow. Therefore, when data source A (which includes interception) and parameterization scheme 2 is used, the model underestimated the surface runoff due to the overestimation of infiltration, but precipitation was accurately represented, so these two effects did not cancel each other.

Figure 3.4 shows the runoff hydrographs for each of the eight storms simulated. Some general trends can be observed. For example, simulated hydrographs using data source A are higher than simulated hydrographs using data source U and lower than simulated hydrographs using data source I. With 100% and 0% coverages assumed in data source U and I, and data source A somewhere in between, this trend apparently is attributed to decreased precipitation due to canopy interception. Moreover, higher
roughness values in the undercanopy grids, when accounted for in data sources A and U, delayed timings of flood peaks. Comparing with measured discharge peaks, significant delays were observed in all storms when data source U was used. This phenomenon indicates that modeling surface runoff using 100% plant coverage will unrealistically increase the flow travel time. Another general trend observed in Figure 3.4 is that the hydrographs simulated under parameterization scheme 3 are between the hydrographs under parameterization schemes 1 and 2, and differences between them are very much event dependent. To quantitatively evaluate modeling efficiency, we introduce the Nash-Sutcliffe model efficiency coefficient (Nash and Sutcliffe, 1970):

\[ e = 1 - \frac{\sum_{t} (q_{o} - q_{m}^t)^2}{\sum_{t} (q_{o} - \bar{q}_{o})^2} \]  

(3.14)

where \( q_{o} \) is observed discharge; \( q_{m} \) is modeled discharge and subscript \( t \) represents time \( t \).

The accuracy of the model depends on how the calculated \( e \) approaches to unity. This efficiency criterion is an improvement of the widely used mean squared error (MSE) and is the most popular dimensionless transformation of MSE (Węglarczyk, 1998). Table 3.4 summarizes calculated N-S coefficients of all scenarios for eight storm events. Coefficients showed significant variability between different scenarios, and the variability was also event dependent. For example, simulation results for condition 3I produced the best N-S coefficient in storm 1, but showed very low coefficient in storm 8. For all storm events, higher N-S coefficients (closer to unity) were generally found for simulations using conditions 2I (e.g., storms 1 and 2) and 3I (e.g., storms 1 and 2), and then conditions 1A (e.g., storms 5 and 8) and 3A (e.g., storms 5 and 8). The highest probability of a good simulation occurred for parameterization scheme 3 (using
cokriging), which indicates that conditioned spatial interpolation was the most effective method of parameter field generation for the storm events studied in this watershed. The results also show the significant role of the spatial variability of the estimated model parameters obtained from *Rosetta* and cokriging, which were originally derived only from soil texture. Moreover, although no significant correlations between model parameters and stream networks were found, spatial patterns do exist in LH104 and the results show that modeling efficiency will decrease if these patterns are neglected.

Although the best simulations sometimes were observed under parameterization scheme 1 (e.g., Storms 5 and 8), parameterization scheme 3 was shown to produce better-than-average simulation results and hence a higher confidence level that the predicted runoff volumes will be closer to field conditions.

A distinct separation exists between storm events in the 1970s (Storms 1-4) versus those modeled in the 1990s and 2000 (Storms 5-8). More specifically, hydrographs calculated using condition 31 were more accurate for storms occurring in the 1970s versus those occurring in 1990s and 2000, indicating that a gradual increase in interception took place since the 1970s. At the same time, hydrographs calculated using condition 3A were more accurate for storms in the 1990s and 2000. Woody plant encroachment gradually increased shrub coverage and decreased grass coverage during this time period (Goodrich et al. 2000), and therefore corresponded to the increased interception. Although other factors such as antecedent soil moisture content and rainfall patterns (e.g., rainfall duration and intensity) could also affect the simulated runoff, these factors were checked as possible explanations for differences in runoff, and no correlations existed. Thus, the gradually changed land coverage is more likely to explain
these systematic errors. These results indicate that the currently-observed vegetation pattern and interception model are more suitable to current watershed conditions, though slightly improvements still need to be made. The results also imply that reinvestigating watershed characteristics are necessary when modeling historical flood events.

Figure 3.4 also shows a very low modeling efficiency in Storm 3, where no discharge was simulated for almost all scenarios. This consistent underestimation of runoff prediction can be explained partially by the uncertainties that exist in infiltration simulations, which play a more important role in surface runoff calculations when the total surface runoff is small. For example, overestimating 1 mm of infiltration produced only 2% relative error in Storm 2, with 45.5 mm runoff depth; when considering Storm 3, with 0.85 mm runoff depth, the 1 mm overestimation in infiltration leads to a 100% relative error. In addition, the concept of contributing area by Merz and Plate (1997), which indicates that only a small part of the watershed contributes to the discharge at the outlet may also explain the poor simulation result of Storm 3, though the averaged runoff coefficient (0.287) is much higher than the coefficient used in the study by Merz and Plate (1997) (<0.02). More specifically, when the precipitation amount is small and when the intensity is low, only runoff generated close to the flume location can reach the outlet and then be measured. Runoff generated at locations far from the flume location will re-infiltrate into the soil and usually will not contribute to measured runoff. This mechanism can be captured by a distributed modeling approach, though lack of flumes at this higher resolution makes verifying this behavior difficult. Therefore, precisely capturing the small scale spatial variability close to the outlet becomes very important. In our study, errors due to missing sub-grid information such as microtopography and connectivity of
low infiltration regions may have been amplified given the small runoff depth in Storm 3.
For example, Figure 3.5 plots measured slopes (using a Brunton compass) at 66 sample
locations and the corresponding slopes calculated using the DEM. Data in Figure 3.5
show a low correlation between two slopes, indicating that significant differences exist
between local microtopography and averaged topography calculated from 1m resolution
DEM data. Local microtopography could create flow paths, which reduces the arrival
time of water at the flume. Under such conditions, infiltration occurs mostly along discrete
and localized flow paths, rather than uniformly across the whole grid; therefore, the
model may exaggerate total infiltration. When large storm events occur, however, the
relatively higher rainfall intensity exceeds the infiltration rate and so the contributing area
is closer to the area of the entire watershed. Therefore, local spatial variability close to
the flume is no longer the dominant factor that affects the simulated hydrograph, although
the absolute error actually may be larger.

3.7 Conclusions

Modeling results show that the 2D diffusion wave model plus the Green-Ampt
infiltration approach is capable of reproducing the surface runoff when proper
parameterization strategies and correct watershed characteristics were chosen. The results
also indicate that changes in vegetation coverage affected the accuracy of the simulations
for storms occurring in the 1970s versus the 1990s and 2000. The watershed
characteristics associated with plant conditions (e.g., the interception model) were shown
to be more suitable for modeling recent storm events; thus, rainfall interception has to be
considered in the model, even in conditions of sparse coverage of open canopies.
The application of a random parameterization approach using LHS could not accurately represent the spatial variability of soil hydraulic parameters, even when derived distribution functions were used. However, the conditioned geostatistical approach (cokriging) improved the modeling efficiency for most storms because the general spatial patterns that control runoff generation (e.g., infiltration) are also captured. Although the general PTF approach using Rosetta is based on a universal soil database and is unable to generate site specific parameters, this general approach is still worth the effort to improve modeling confidence level. Moreover, given that simulation of smaller storm events is prone to larger relative errors in runoff depths, detailed spatial variability at the smaller scale is needed in the future to better understand runoff mechanisms. This conclusion was described by Seyfried and Wilcox (1995), who concluded that non-deterministic spatial variability (e.g., stochastic approach) used in physically-based models does not necessarily improve simulation results when compared to models using spatially-averaged data. Our simulations on LH104, however, showed that the best parameterization scheme is event dependent. The model, based on a high resolution DEM, was shown to capture the runoff generation mechanism when large storm events occurred. But, the deterministic spatial variability at the smaller scale still needs to be considered for capturing local spatial patterns, and is very important to predicting runoff when the contributing area is small.

3.8 Acknowledgements

Funding for this project was made available by Nevada Water Resource Research Institute under the contract number 06HQGR0098, and NSF EPSCoR under grant EPS-
We are grateful to David Goodrich, Carl Unkrich, Timothy Keefer, and Lainie Levick of the Southwest Watershed Research Center, USDA-ARS for providing LH104 data and field assistance.

3.9 References


Table 3.1 Statistical characteristics of hydraulic

<table>
<thead>
<tr>
<th></th>
<th>*Mean</th>
<th>Variance</th>
<th>Min</th>
<th>Max</th>
<th>**Probability distribution</th>
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</thead>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>% sand</td>
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<td>77.4</td>
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<td>0.008</td>
<td>0.719</td>
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<tr>
<td>S (cm)</td>
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<td>Lognormal</td>
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<td></td>
<td></td>
<td></td>
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Data calculations are based on 65 samples. We deleted one suspicious interspace sample (with high sand content of 88.7%) following lab technician’s suggestion.

* Geometric mean is used to calculate $K_{sg}$ and arithmetic mean is used to calculate the rest of the parameters.

**Kolmogorov-Smirnov normality test has been applied.
Table 3.2 Parameters for semivariogram models

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<td>$S &amp; \theta_s$</td>
<td>0.024</td>
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* Range in VARIOWIN is the distance at which the variogram value is 95% of the sill.
Table 3.3 Characteristics of storm events used in the modeling

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<tr>
<th>Storm #</th>
<th>Start day</th>
<th>Start time of rainfall</th>
<th>Rainfall duration</th>
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<th>Accumulated rainfall depth</th>
<th>Accumulated runoff depth</th>
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<tr>
<td>1</td>
<td>8/1/74</td>
<td>18:18</td>
<td>565</td>
<td>0.241</td>
<td>23.11</td>
<td>4.50</td>
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<tr>
<td>2</td>
<td>7/17/75</td>
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<td>140</td>
<td>0.196</td>
<td>70.61</td>
<td>45.50</td>
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<tr>
<td>3</td>
<td>8/1/77</td>
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<td>69</td>
<td>0.153</td>
<td>10.41</td>
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<td>323</td>
<td>0.081</td>
<td>42.67</td>
<td>15.21</td>
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<tr>
<td>6</td>
<td>8/2/91</td>
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Table 3.4 Nash-Sutcliffe coefficients

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<td></td>
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<td>I</td>
<td>U</td>
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<tr>
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<td>8</td>
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Figure 3.1 Geographic locations of Lucky Hills Watershed 104 and sample locations. In each location, one interspace sample and one undercanopy sample were collected. Stream network in right figure was generated with ArcGIS.
Figure 3.2 Spatial patterns of the Green-Ampt parameters based on the whole population.

The upper row is generated using LHS and the lower row is generated using cokriging.
Figure 3.4 Simulated results for eight storm events. In legend, numbers 1, 2, and 3 represent homogenous field, field generated by LHS and field generated by Cokriging, respectively; letters "A", "I" and "U" represent samples from all population, interspace and undercanopy.
Figure 3.4 (continued) Simulated results for eight storm events. In legend, numbers 1, 2, and 3 represent homogeneous field, field generated by LHS and field generated by Cokriging, respectively; letters “A”, “I” and “U” represent samples from all population, interspace and undercanopy.
Figure 3.5 Comparisons between measured slope and slope generated by DEM at 66 sample locations. The solid line is the regression line (r²=0.268, p<0.05)
CHAPTER 4

GREEN-AMPT INFILTRATION PARAMETERS FOR DESERT PAVEMENTS
USING FIELD EXPERIMENTS AND NUMERICAL APPROACHES

4.1 Introduction

Older desert soils can be covered by a layer of desert pavement, which consists of closely packed gravel, partially embedded in a layer of a silt- and (sometimes) clay-rich Av soil horizon (Bull, 1991; Cooke et al., 1993; McFadden et al., 1998). Existing research has shown that hydrologic processes are mostly related to the pedogenic evolution of the surface, hence its relationship to surface age (e.g., Tromble et al., 1974; Wilcox et al., 1988; Abrahams and Parsons, 1991; McDonald et al., 1996; Young et al., 2004; Meadows et al., 2007). However, studies on relevant infiltration parameters for infiltration models are limited in these pavements, partially due to the lack of recorded rainfall events and contemporaneous in-situ infiltration measurements. Furthermore, during the tension infiltrometer test (a popular way to measure the in-situ hydraulic properties), surface clasts need to be removed to facilitate contact between the infiltrometer disc and soil. Studies therefore are needed to evaluate whether this treatment affects the resulting hydraulic property values by comparing infiltration readings on two adjacent plots, where one plot has clasts removed and the other adjacent plot has clasts intact, and where soil textures of these two plots are assumed to be the same.
The Green-Ampt infiltration model has been widely used in infiltration simulations since Green and Ampt (1911) suggested this theoretical approach. Mein and Larson (1973) extended the theory to steady rainfall conditions, which separates the infiltration rates using a ponding time. The Green-Ampt approach is based physically on Darcy’s law to some extent. It has been demonstrated to be suitable for a variety of field conditions (Gupta et al., 1998). The approach assumes a distinct wetting front in the soil profile and a capillary pressure head associated with this wetting front. Although Hillel (1998) indicated that the capillary pressure head is essentially empirical and also case dependent, efforts have been made to predict model parameters based on soil physical properties. For example, studies showed that Green-Ampt parameters could be derived from soil texture information (e.g., McCuen et al., 1981, Rawls et al., 1989). However, Huttem and Gifford (1988) showed that prediction methods sometimes have a low confidence level, and suggested to measure infiltration rates using appropriate methodologies.

By assuming that the theory of the Green-Ampt infiltration is valid on paved desert alluvial fans, parameters such as hydraulic conductivities can be obtained from two approaches: in-situ measurement using instruments such as the tension infiltrometer (Young et al., 2004) or regression calculations from pedotransfer functions (PTF) based on soil physical properties collected in the field (Schaap et al., 2001; Pachepsky and Rawls, 2003). Pachepsky and Rawls (2003) indicated that affecting the soil structure by disturbing the soil would alter the accuracy of the estimated parameters, and although Meadows et al. (2005) showed that soil hydraulic properties of the undisturbed soil can be obtained, methods are usually expensive and time consuming. Moreover, in terms of
the hydraulic conductivity, the value used in the Green-Ampt model is different from the traditional saturated hydraulic conductivity (Delleur, 1999). Therefore, numerical calibration based on in-situ measured infiltration rates and volumes is an alternative way to obtain the Green-Ampt parameter sets without disturbing the soil. The calibrated parameters could be more suitable for predicting infiltration when the Green-Ampt model is used.

Therefore, the objectives for this study are to: 1) investigate the effects of the desert pavement on infiltration rates and volumes, 2) calibrate the Green-Ampt infiltration parameters using a least square optimization approach; 3) and compare the estimated infiltration parameters obtained using the optimization approach to those derived from PTF and from in-situ tension infiltrometer measurements.

4.2 Materials and methods

4.2.1 Description of the field site

Field measurements of infiltration were conducted on a desert alluvial fan at the Mojave National Preserve, CA (between 115.61 and 115.39° W and 35.31 and 34.83° N) close to the Providence Mountains. The test site is characterized by a layer of desert pavement with an age of ~100 ka using local radiometric dates (McDonald et al., 2003). The site is dominated by sparsely distributed L. trendentata and A. domosa (Hamerlynck et al., 2003).

4.2.2 Field methods

All rainfall simulator and infiltration tests were conducted in interspace microsites (away from the direct influence of plants and plant mounds). Each pair consisted of a
paved plot and an adjacent unpaved plot (desert pavement was gently removed by hand). The plot was visually divided into four quadrants.

Portable rainfall simulators were used for this study to produce the controlled precipitation. The rainfall simulator (Fig. 1a) consists of a flat, 61 cm x 61 cm, Plexiglas reservoir for water, with 827 hypodermic needles on the under side (Munn and Huntington, 1976). Water drops were produced on the needles by providing a constant gravity head, wetting a 3,721-cm² area of ground directly beneath the rainfall simulator. Rainfall intensity was artificially maintained as 6.77 cm hr⁻¹ through a mariotte tube. This intensity is equivalent to the maximum rainfall intensity of a 100-year, 6-hour storm in this region (34.924N, 115.552 W, 4845 feet), per National Oceanic and Atmospheric Administration (NOAA) Atlas 14 (http://hdsc.nws.noaa.gov/hdsc/pfds/sa/sca_pfds.html). The rainfall intensity was calibrated three times before and after each test to ensure that the rainfall intensity was constant with time. At the lower slope of each plot, a trench was dug and a plastic trough was placed into the trench to collect surface runoff (Young et al., 2007). The gap between the trough and the plot was connected by a 90° bend aluminum flashing and sealed using expandable insulating foam to prevent leakage (Fig. 1b). After the initial calibration measurements, the experimental precipitation event was started on the test surface, after which five time-related measurements of the surface runoff generation were taken (when possible): (1) when initial ponding occurred anywhere on the surface test plot, (2) when initial runoff occurred anywhere on the surface test plot, (3) when runoff occurred in each quadrant of the surface test plot, (4) when a flowpath developed from the back to the front of the surface test plot, and (5) when initial runoff reached the collection trough. The post-calibration measurements of the rainfall intensity
were made after the time measurements were completed and the experiment had run for 60 min. Water samples were collected from the trough at 2-min increments, volume was measured in the field using a graduated cylinder and the increments were summed at the end of the test, providing a total volume of runoff.

Prior to the test, a 13-cm-long water content reflectometer (WCR) probe (model CS-616, Campbell Scientific, Inc., Logan, UT), was installed toward the upslope portion of the test area at an angle of 30°. Therefore, the reading of the WCR can be regarded as the average water content within 6.5-cm depth of soil. At each location (with two paired plots), two WRC (one for paved plot and one for unpaved plot) were connected to a data logger (model 10X, Campbell Scientific, Inc.) and the water content was automatically recorded every one second. Following the test, a soil sample in each plot was collected by pressing a soil ring (with the volume of 63 cm³) into the soil and excavating the soil in the ring. The sample was then shipped to the Quaternary Pedology and Soil Characterization Laboratory in Reno, NV and analyzed for soil texture and bulk density using the laser light scattering method (Digisizer, Micromeretics, Norcross, GA) and a soil oven, respectively. On paved plots, the surface clast layers were carefully removed before collecting samples.

A mini-disk tension infiltrometer (MDTI) was used to calculate the saturated hydraulic conductivity ($K_s$) by measuring the cumulative outflow under three different tensions (-6 cm, -3 cm and -0.5 cm) (Caldwell et al., 2008). Though measurements at these test plots were taken at successively higher distances from a shrub (*Larrea tridentata*), only those measurements furthest from the shrub were used. Moreover, it is
noted that the rock clasts were removed before conducting the MDTI tests. So the measured $K_s$ will be compared only with the optimized $K_s$ for unpaved plots.

### 4.3 Green-Ampt infiltration

Under steady-state conditions and before ponding, the infiltration rate equals the rainfall intensity. The integrated version of Green-Ampt after ponding can be expressed as the following equations (Mein and Larson, 1973; Chu, 1978):

\[ K[t-(t_p-t_s)] = I - S(\theta_s - \theta_f) \ln \left( 1 + \frac{I}{S(\theta_s - \theta_f)} \right) \quad t > t_p \quad (4.1) \]

\[ K_s t_s = I_p - S(\theta_s - \theta_f) \ln \left( 1 + \frac{I_p}{S(\theta_s - \theta_f)} \right) \quad (4.2) \]

where $I$ is the vertical cumulative infiltration depth; $S$ is the soil capillary pressure at wetting front; $\theta_s$ and $\theta_f$ are saturated and initial water content respectively; $K_s$ is effective hydraulic conductivity; $t_p$ is the ground ponding time; $I_p$ is the cumulative infiltration depth at ponding time; and $t_s$ is a virtual time determined by equation (4.2). To implicitly calculate the $I$ in equation (4.1), five parameters have to be provided before the calculation: $K_s$, $S$, $\theta_s$, $\theta_f$, and $t_p$. In equation (4.1), parameters $S$, $\theta_s$, and $\theta_f$ are always of a form of $S \times (\theta_s - \theta_f)$. We reduce the number of fitting parameters to two, by designating the product $(\theta_s - \theta_f)$ as $M$; we then search only for $K_s$ and $MS$. In equation (4.2) $t_p$ is designated as the time when surface runoff is observed in all four quadrants. The reason not to consider the initial ponding time is that the WCR was inserted in the upslope of the plot. Therefore the initial ponding time in the upslope quadrant is assumed to be equivalent to the ponding time when ponding occurred in the whole plot. Hence, the associated $I_p$ was determined based on the WCR reading at time $t_p$. 

91
4.4 Parameter estimation approaches

The Levenberg-Marquardt algorithm (Marquardt, 1963) is an efficient optimization routine in hydrologic studies, and has been used in numerical codes for some time (i.e., HYDRUS-2D, Simunek et al., 1999). It is a numerical solution for the nonlinear least squares problem to minimize the following objective function:

\[ OF = \sum_{i=1}^{n} (y_i - f(x_i, \beta))^2 \]  

(4.3)

where \( y_i \) is the observed value and \( f(x_i, \beta) \) is the optimized function using the optimized parameters vector \( \beta \). It is noted that \( f(x_i, \beta) \) in this study is solved implicitly through equation (4.1) by using Newton method.

Under the two parameter conditions, the function can be written as (More et al., 1980):

\[ f(K, MS) = I - MS \ln \left( 1 + \frac{I}{MS} \right) - K \left[ t - \left( t_p - t_i \right) \right] \]  

(4.4)

and the required Jacobian matrix can be written as:

\[ \frac{\partial f}{\partial K} = -(t - (t_p - t_i)) \]  

(4.5)

\[ \frac{\partial f}{\partial MS} = -\ln(1 + \frac{I}{MS}) - \frac{I}{(1 + I/MS)MS} \]  

(4.6)

The general objective of the Levenberg-Marquardt algorithm is to minimize the sum of the square residuals by gradually changing optimized parameters.

In addition to the parameter estimation scheme and field measurements, we also used one forward calculation approach. The forward approach derives the parameters using a pedotransfer function (PTF) based on the soil texture and bulk density.
Calculations were done with the program Rosetta (Schaap et al., 2001). In this study, an empirical method described in Rawls et al. (1983) was used to build the empirical relationship between the PTF estimated hydraulic properties and wetting front capillary pressure $S$. The relevant parameters can be estimated using the approach described by Lenhard et al. (1989).

4.5 Results and discussions

4.5.1 Infiltration comparisons

Table 4.1 summarizes the surface runoff characteristics (as shown by the first five columns) and the collected surface runoff (the sixth column) on both paved and unpaved plots. In terms of the averaged timing, observed runoff on unpaved plots (B) was a little bit more delayed than the observed runoff on paved plots (A) except the time when a continuous flow connection was observed from the back to the front of the rainfall simulator (column 5 in Table 4.1). However, t-test (for normal distributions) or Mann-Whitney Rank Sum Test (for non-normal distributions) showed no significant differences between two plots in any of the runoff characteristics (Table 4.1), demonstrating that the surface clasts had very small effects on runoff generation.

Figure 2 shows the cumulative infiltration curves and the associated ponding times (dashed lines) for six pairs of test locations. Cumulative infiltration was calculated using the following equation:

$$I = \sum_{j=1}^{n} (\theta_i - \theta_j) z$$

(4.7)

where $z$ is the effective sampling depth of the WCR (6.5 cm). In most cases, the cumulative infiltration curves reached either constant values, or were slowly trending
upward, linear in time. This shows that the wetting fronts had passed the end of the WCR probe by completion of the test. The slight increase in infiltration depth with time reflects the slow release in entrapped air behind the wetting front. The behavior seen here was also described by Noborio et al. (1996). In their study, time domain reflectometry was used to trace the movement of the wetting front. Negative discrepancies between the measured and calculated infiltration in table 4.2 also demonstrated that some portions of the infiltrated water were not measured by the WCR.

In terms of the calculated total infiltration (Table 4.2), averaged values of 3.791 cm and 3.061 cm on paved and unpaved plots, respectively, showed a slightly higher infiltration on paved plots. Measured infiltration also showed a larger value on paved plots (1.976 cm vs. 1.949 cm). However, similar to the runoff characteristics presented in Table 4.1, no statistically significant difference was found between these six pairs of test locations (p=0.816). We did find, though, a high correlation ($r^2 = 0.925; p = 0.008$) between the calculated cumulative infiltration at site pairs of A (paved) and B (unpaved), illustrating the similarity between sites in close physical proximity. This similarity overwhelmed the differences introduced by the presence of the desert pavement surface, even considering that these sites were replicates. The results show that infiltration character in the paired test plots, were more similar than the infiltration character observed between paired test plots. Table 4.3 shows the soil texture of collected samples in all 12 test plots. When comparing data between Table 4.2 and Table 4.3, soil structure was correlated to the total infiltration. For example, a negative correlation coefficient ($r^2 = -0.62$) was found between the percentages of sand and total infiltration. The plots with low surface runoff (i.e., RFS5A and RFS5B in Table 4.2) were found in soils with higher
sand content (Table 4.3). When comparing relationships between runoff depth, soil texture and bulk density using the Pearson Product Moment Correlation test (SigmaStat, v3.5), the results showed that runoff was negatively correlated to sand content (p=0.032), positively correlated to silt content (p=0.008), and inversely proportional to bulk density, though not significantly (p=0.065).

In general, on plots with desert pavements (plots A), after the precipitation began, two trends were observed: a relatively rapid initial increase in infiltration rate (as inferred by the infiltration depth) followed by a relatively low infiltration rate (e.g., RFS 6A at about 300 s in Figure 4.2). The initially high values are likely attributed to either the high hydraulic gradient in the initially dry Av horizon (initial water contents measured with the WCR ranged from 0.043 to 0.073 cm$^3$ cm$^{-3}$), or the movement of the wetting front through the upper layer of rock clasts and silt/clay infilling. As the wetting front moved downward through the intact Av horizon and encountered the interface between the Av horizon and the coarser (B horizon) material underneath it, the Av horizon was more likely to retain the infiltrated water because of its high clay and silt content. Including the possibility that the soil textural contrasts were sufficient to induce a capillary break, these factors explain the rate change in cumulative infiltration curves on paved plots. However, the magnitude and timing of this change in infiltration rate differed from site to site, exhibiting spatial variability (Figure 2) of texture and (likely) the thickness of the Av horizons.

The abrupt change in infiltration rate was seen only on a few unpaved (B) plots, (e.g. RFS5B), where the Av horizon was not heavily disturbed when the overlying clasts were removed. But in most other cases, the cumulative infiltration gradually increased
until the wetting front reached the end of the probe (e.g. RFS7B). These results indicate that when clasts were removed, the fine-grained aeolian-deposited silt and clay found between the clasts, no longer formed a distinct surface layer, so the infiltration rate in these cases was governed by the underlying Av horizon (which is now the surface layer). Thus, the results show that the characteristics of the infiltration curve were altered by the disturbance, but that the cumulative infiltration was not affected. Similar to results observed on the paved (A) plots, strong spatial variability existed across the site.

Moreover, although Green-Ampt theory assumes that ponding occurs as long as the infiltration rate is less than the rainfall intensity, ponding and surface runoff were not observed immediately on either paved or unpaved plots, even though the early-time infiltration rate, estimated with the WCR, was lower than the rainfall intensity. The lack of observed runoff during this early time period, could be explained by the potential lateral flow of water beneath or between the clasts but still above the denser and intact Av horizon; furthermore, the results could be explained by soil heterogeneity, in which deeper infiltration of water occurred in soil not monitored by the WCR. The assumption of the soil heterogeneity in the vertical direction (e.g., cracks between soil peds) was observed by Meadows et al. (2007) when their dye experiments were conducted on the Qf3 surface, in the same region.

4.5.2 Parameter estimation

As described above, Green-Ampt parameters were initially estimated by using the PTF approach (see section 4.4) from soil analyzed using laser light scattering. In most runoff plots where the infiltration curve flattened with time, only part of the infiltration curve was chosen. For these cases, we isolated the cumulative infiltration curve, and
focused on data collected after the ponding was observed and before the wetting front migrated below the surface layer or the end of the probe. Fig. 4.3 shows the measured infiltration curves (based on the recorded water content change), infiltration calculated from the PTF parameter sets, and infiltration calculated from the optimized parameters. Table 4.4 summarizes the initial and optimized parameters, as well as the $K_s$ value obtained from the MDTI measurement.

Based on Fig. 3, infiltration using the initial parameters obtained by the PTF method significantly underestimated the overall infiltration in 11 out of 12 test plots, as measured by the WCR. However, simulated infiltration rates matched the measured infiltration rates in all plots when using optimized parameters in all plots, indicating that the Levenberg-Marquardt algorithm is effective in this study. In Table 4.4, in terms of the averaged $K_s$ value, differences between the paved and unpaved groups were smaller before the optimization (3.73 cm/day vs. 3.83 cm/day) than after the optimization (1.79 cm/day vs. 3.12 cm/day). Considering that the initial parameters were estimated based on the soil texture and bulk densities, soil structure associated with pavement formation increased the $K_s$ differences between paved and unpaved plots.

On average, the optimized $K_s$ values are almost 4.8 times and 8.2 times larger than the PTF estimated $K_s$ values on paved and unpaved plots, respectively (Table 4.4). Conversely, the optimized $K_s$ values were is 4.5 times smaller than the $K_s$ value obtained from the MDTI method on the unpaved plots. Individual comparisons also show a large variability. For example, on RFS4A, optimized $K_s$ is 21 times larger than the initial $K_s$ value obtained from the PTF. However, in the adjacent RFS4B plot, optimized $K_s$ is only 87% of the initial $K_s$. For the $MS$ value, the discrepancies between the optimized and
unoptimized values were much smaller. Both t-test and Mann-Whitney tests showed no statistically significant differences between the optimized and unoptimized $M_S$ values. Note that an unusually high optimized $M_S$ value (RFS7A of 215.5) was removed as an outlier before the group comparison. As a result, it is concluded that the underestimation of the total infiltration is mainly due to the underestimated $K_s$ based on the PTF approach.

The hydraulic conductivity values estimated from the PTF approach and measured from the MDTI are saturated hydraulic conductivities ($K_s$). But the hydraulic conductivity values used in equation (4.1) are effective hydraulic conductivities ($K_e$). Large discrepancies between the hydraulic conductivities from these different sources illustrated that the PTF-estimated or field-measured $K_s$ cannot be directly used in the Green-Ampt infiltration model. The Handbook of Groundwater Engineering (Delleur, 1999) suggested using half of the measured $K_s$ in the Green-Ampt model. Given that the MDTI measured $K_s$ was 4.5 times larger than the optimized $K_s$ (or $K_e$), the suggested adjustment would reduce this underestimation by about 50%, if other parameters are fixed.

4.6 Concluding statements

Although slight differences were observed between paved and unpaved plots in terms of averaged total infiltration and timings of surface runoff generation, analyses showed that the differences were not statistically significant. However, desert pavement did affect the infiltration rate when water moved through interfaces between the clast surface to the Av horizon and further down to the underlying coarser material. Moreover, even though the surface morphology of the desert pavement surfaces appear uniform,
without micro-topography or indications of bioturbation, the results showed significant variability of soil texture, thus leading to variability of hydraulic conductivity. By optimizing the Green-Ampt model parameters, differences between the PTF estimations, MDTI measurements and Green-Ampt parameters were mainly in effective hydraulic conductivities. More specifically, by directly using $K_s$ in the Green-Ampt model, PTF underestimated $K_e$ and MDTI overestimated $K_e$. On the contrary, there were no significant differences in estimating the $M_S$ value in all plots.

Due to the limited in-situ measurements (six for each group), statistical analyses were limited between the unoptimized and optimized $K_e$. Moreover, no correlation was observed between estimated and measured $K_s$ and $K_e$, although using half of the MDTI $K_s$ could increase the accuracy level by about 50%. Specifically, to extend the application of the PTF approach to Green-Ampt model on desert pavement, we suggest conducting more in-situ measurements and calibration, so that a site specific relationship between the estimated $K_s$ and model $K_e$ can be derived. It will provide an attractive way to estimate infiltration parameters for predictive modeling by only collecting a few soil samples and analyzing their physical properties.

4.7 Acknowledgements

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4.8 References


Table 4.1 Runoff characteristics on all twelve rainfall simulator (RFS) plots

<table>
<thead>
<tr>
<th>*RFS#</th>
<th>Ponding (s)</th>
<th>Initial runoff on surface (s)</th>
<th>Runoff in all quadrants (s)</th>
<th>Flow connection back to front (s)</th>
<th>Flow to trough (s)</th>
<th>Surface runoff (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2A</td>
<td>68</td>
<td>114</td>
<td>218</td>
<td>340</td>
<td>194</td>
<td>3.132</td>
</tr>
<tr>
<td>2B</td>
<td>60</td>
<td>90</td>
<td>145</td>
<td>270</td>
<td>225</td>
<td>3.019</td>
</tr>
<tr>
<td>3A</td>
<td>40</td>
<td>121</td>
<td>252</td>
<td>249</td>
<td>256</td>
<td>2.521</td>
</tr>
<tr>
<td>3B</td>
<td>60</td>
<td>131</td>
<td>162</td>
<td>224</td>
<td>305</td>
<td>2.799</td>
</tr>
<tr>
<td>4A</td>
<td>49</td>
<td>130</td>
<td>183</td>
<td>N/A</td>
<td>170</td>
<td>4.422</td>
</tr>
<tr>
<td>4B</td>
<td>96</td>
<td>179</td>
<td>200</td>
<td>239</td>
<td>233</td>
<td>3.949</td>
</tr>
<tr>
<td>5A</td>
<td>116</td>
<td>180</td>
<td>300</td>
<td>560</td>
<td>804</td>
<td>0.522</td>
</tr>
<tr>
<td>5B</td>
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<td>130</td>
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<td>214</td>
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<td>3.964</td>
</tr>
<tr>
<td>7A</td>
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<td>119</td>
<td>138</td>
<td>253</td>
<td>219</td>
<td>3.568</td>
</tr>
<tr>
<td>7B</td>
<td>80</td>
<td>105</td>
<td>155</td>
<td>192</td>
<td>240</td>
<td>4.749</td>
</tr>
<tr>
<td><strong>Difference</strong></td>
<td>No(t) (p=0.408)</td>
<td>No(t) (p=0.604)</td>
<td>No(t) (p=0.587)</td>
<td>N/A</td>
<td>No(MW) (p=0.394)</td>
<td>No(t) (p=0.815)</td>
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<tr>
<td>Averaged A</td>
<td>63</td>
<td>124</td>
<td>200</td>
<td>306</td>
<td>300</td>
<td>2.97</td>
</tr>
<tr>
<td>Averaged B</td>
<td>75</td>
<td>134</td>
<td>240</td>
<td>228</td>
<td>325</td>
<td>3.16</td>
</tr>
</tbody>
</table>

*The number of the plots starts from 2 due to a failed first test in the same test project and the number of that test was named as 1

**t-test (normal distribution) and Mann-Whitney Rank Sum Test (non-normal distribution) were conducted to compare the two groups (A plots and B plots)
Table 4.2 Water mass balance calculations (precipitation=6.75 cm)

<table>
<thead>
<tr>
<th>RFS#</th>
<th>Measured surface runoff (cm)</th>
<th>Calculated cumulative infiltration (cm)</th>
<th>Measured cumulative infiltration</th>
<th>Percent Difference (%)</th>
</tr>
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<tbody>
<tr>
<td>2A</td>
<td>3.132</td>
<td>3.624</td>
<td>2.171</td>
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<tr>
<td>2B</td>
<td>3.019</td>
<td>3.737</td>
<td>2.074</td>
<td>-44.5</td>
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<tr>
<td>3A</td>
<td>2.521</td>
<td>4.236</td>
<td>1.391</td>
<td>-67.2</td>
</tr>
<tr>
<td>3B</td>
<td>2.799</td>
<td>3.958</td>
<td>2.691</td>
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<td>2.334</td>
<td>2.672</td>
<td>14.5</td>
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<td>4B</td>
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<td>2.808</td>
<td>1.515</td>
<td>-46.1</td>
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<td>1.807</td>
<td>-71.0</td>
</tr>
<tr>
<td>5B</td>
<td>0.496</td>
<td>6.261</td>
<td>1.710</td>
<td>-72.7</td>
</tr>
<tr>
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<td>3.629</td>
<td>3.127</td>
<td>1.586</td>
<td>-49.3</td>
</tr>
<tr>
<td>6B</td>
<td>3.964</td>
<td>2.793</td>
<td>1.937</td>
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<td>3.188</td>
<td>2.230</td>
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<tr>
<td>7B</td>
<td>4.749</td>
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<td>1.768</td>
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<td>Averaged A</td>
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<td>3.791</td>
<td>1.976</td>
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<td>Averaged B</td>
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<td>3.061</td>
<td>1.949</td>
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</tbody>
</table>
Table 4.3 Soil texture and bulk density of soil collected at runoff plots after completion of the runoff tests

<table>
<thead>
<tr>
<th>RFS#</th>
<th>Sand(%)</th>
<th>Silt(%)</th>
<th>Clay(%)</th>
<th>BD(g cm⁻³)</th>
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</thead>
<tbody>
<tr>
<td>2A</td>
<td>44.2</td>
<td>32.3</td>
<td>23.4</td>
<td>1.70</td>
</tr>
<tr>
<td>2B</td>
<td>35.3</td>
<td>34.3</td>
<td>30.3</td>
<td>1.86</td>
</tr>
<tr>
<td>3A</td>
<td>39.4</td>
<td>34.4</td>
<td>26.1</td>
<td>1.98</td>
</tr>
<tr>
<td>3B</td>
<td>42.2</td>
<td>28.5</td>
<td>29.3</td>
<td>1.86</td>
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<tr>
<td>4A</td>
<td>42.0</td>
<td>32.0</td>
<td>26.0</td>
<td>1.64</td>
</tr>
<tr>
<td>4B</td>
<td>47.4</td>
<td>26.2</td>
<td>26.3</td>
<td>1.74</td>
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<tr>
<td>5A</td>
<td>67.8</td>
<td>21.3</td>
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<td>1.95</td>
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<tr>
<td>5B</td>
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<td>8.3</td>
<td>1.98</td>
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<td>37.4</td>
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<td>21.7</td>
<td>1.60</td>
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<tr>
<td>7B</td>
<td>48.4</td>
<td>38.8</td>
<td>12.8</td>
<td>1.79</td>
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Table 4.4 Comparison of unoptimized and optimized parameters

<table>
<thead>
<tr>
<th></th>
<th>Kₑ (cm/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RFS2A RFS2B RFS3A RFS3B RFS4A RFS4B RFS5A RFS5B RFS6A RFS6B RFS7A RFS7B</td>
</tr>
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- PTF-estimated using pedotransfer function, OP-optimized parameters, TI-MDTI measurement
Figure 4.1 (a) Rainfall simulator; (b) Runoff collecting trough
Figure 4.2 Accumulated infiltration and associated ponding times at six pairs of test locations. Note that the first 240 second measurements on RFS5A were missed due to accidentally turning off the data logger. In this figure, “A” represents the plots with desert pavement and “B” represents the plots with no desert pavement.
Figure 4.3 Accumulated infiltration curves calculated from the measured, PTF derived, and optimized Green-Ampt parameters
Figure 4.3 (continued). Accumulated infiltration curves calculated from the measured, PTF derived, and optimized Green-Ampt parameters
CHAPTER 5

CONCLUSIONS

5.1 Conclusion

Three research studies related to modeling soil moisture dynamics in the southwestern United States were presented in this dissertation. In general, it is demonstrated that numerical modeling was capable of simulating physical hydrologic processes. However, appropriate boundary conditions and model parameters have to be determined to obtain reliable results, but due to lack of observations and measurement in these arid and semi-arid regions, numerical modeling approaches used in this study are often the only tools available to understand hydrologic processes under a variety of conditions. The models used in this study are all physically based; however the approaches become more important when the empirical correlations are affected by environmental changes such as global warming and vegetation coverage. For example, if woody plants at the Lucky Hills 104 site were affected by human activities, then recalibration of new parameters might be limited only to the interception model. On the contrary, many more measurements of surface runoff have to be conducted before building a new and stable empirical correlation and the process often is time and budget
More specifically, the first study investigated how different boundary conditions could lead to different simulated chloride profiles preserved in the near surface soil in the northern Mojave Desert. The results showed that the multi-phase paleo-water fluxes and chloride transport in the soil were controlled by the total amount of water entering the soil through precipitation, the precipitation intensity, and the vegetation root distributions. However, more studies should be conducted to exploit other factors that may explain the current observed chloride peak. For example, preferential flow may increase flow velocity of water and transport chloride into deeper soils; or, the chloride concentration in precipitation could also change over thousands of years. This study indicated that numerical models can be used to predict possible hydrologic responses to future climate change. Factors affecting the boundary conditions should thus be incorporated into the model by providing reasonable changes in trends. The results showed that numerical modeling is an important tool for addressing water movement issues in the northern Mojave Desert, because of the difficulty in accurately measuring subsurface water fluxes in this region. The results also showed the roles that climate patterns and plant roots play in moisture dynamics in vadose zone systems. Therefore, in the future, collecting more detailed information should be focused on those dominating controlling factors.

In the second study, surface runoff was simulated in the Walnut Gulch experimental watershed based on historical precipitation and runoff data. The study used a two-dimensional diffusion wave model that can precisely calculate surface runoff on hill slopes. The soil hydraulic properties were derived using a PTF program and three different sampling strategies were tested. Results indicated that the cokriging approach
has the ability to capture the spatial patterns of runoff (and hence infiltration), although very limited basic soil information (e.g., soil texture) was provided. The study indicated that basic soil texture analyses and the PTF approach can help improve the confidence level of the model, as long as the appropriate sampling strategy is used. Therefore, the study described a quick and relatively reliable way to simulate surface runoff from the collection of only soil texture information and conditioned geostatistical sampling.

Although the efficiency of the PTF method has already been discussed under many circumstances, spatial patterns of soil texture were captured and successfully transformed to the spatial patterns of infiltration parameters, which were reflected by the simulated hydrographs. Moreover, the study showed the significant role of interception in calculating surface runoff depths. The results suggest that interception models and the associated parameters be further explored in rainfall-runoff models because they affect the water mass balance. Errors caused by neglecting interceptions cannot be compensated only by improving the efficiency of water flow solutions.

In the third and final study, we conducted a rainfall simulator test on a desert pavement found on an alluvial fan in the Mojave Desert Preserve, CA. The pavement surfaces on six of twelve test plots were removed to assess the influence of the desert pavement surface itself on infiltration rates. No significant statistical differences were found between the paved and unpaved test plots; but, the desert pavement did affect the infiltration patterns featured by the different infiltration patterns. The results indicated that removing the surface clasts has little effect on the total infiltration, but that spatial heterogeneity of soil physical properties (e.g., soil texture), however, had a larger effect on infiltration rates than the desert pavement itself. Moreover, the Levenberg-Marquardt
optimization method demonstrated that the numerical calibration can improve the predicted Green-Ampt parameters especially the effective hydraulic conductivities, if the PTF approach is desired.

Previous studies have shown that rainfall simulator test results can be used to derive curve numbers (CNs) for use in rainfall-runoff models (e.g., Young et al., 2007). This study provided a numerical solution for alternative (Green-Ampt) infiltration parameters by taking advantage of the same measured data. Obtaining both surface runoff parameters and infiltration parameters in one experiment is encouraging because they are two major controlling factors in rainfall-runoff models. More studies should be conducted in the future to analyze the correlation between effective hydraulic conductivities and wetting front capillary pressure heads, as this relationship may affect the efficiency of the L-M optimization through the creation of local minima.

The three research studies did not describe the development of new hydrologic models. However, they illustrated new approaches to better interpret existing models and to profoundly understand the physical hydrologic processes in arid and semi-arid regions. The focus of the study, therefore, was to use numerical approaches to better understand physical processes in arid and semi-arid regions, rather than to improve the numerical solutions themselves. Approaches and results in this dissertation could be important references for future studies.

Through these studies, the findings can be applied more widely to other studies. For example, the possible explanations for chloride peak in the thick vadose zone were discussed based on the multi-case simulations and the conceptual model can be used to predict the future response of hydrologic processes to climate change. Also, results from
the second study (Chapter 3) can be extended to other ungauged watersheds to improve the reliability of flood predictions. Finally, the infiltration tests on the desert pavement (Chapter 4) pointed out the potential future directions on the possible improvement of Green-Ampt infiltration model in desert areas. Though the three research studies were conducted in different locations, the common element of the studies is arid environments that are being tested; thus, the approaches could be extrapolated to sites with similar hydrologic characteristics and in particular, arid climate conditions.

Based on the results in this dissertation, further work will focus on interactions between vegetation and soil moisture in desert areas with thick vadose zones, to better understand the influence of soil properties on water budgets in these water limited systems. If the study considers potential climate change, subsequent changes of plants and soil physical properties should also be incorporated. In addition, the methods used to generate model parameters will be extended to humid regions and other studies areas that need to account for spatial variability. The relatively simple sample analysis and PTF approaches can bridge the gap between requirements for modeling accuracy and difficulties in obtaining reliable model parameters. Finally, more infiltration data will be collected on different aged alluvial fans to better understand the effects of pedologic evolution on soil hydraulic properties and the impacts to surface runoff potential.

5.2 References
APPENDIX

Texture information of 66 soil samples

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*A-Interspace samples, B-Undercanopy samples*
VITA

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22-30.

Dissertation Title: Spatiotemporal variation in soil moisture and hydraulic properties and
their impacts on rainfall-runoff and infiltration processes

119
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Committee Chair, Dr. Matthew Lachniet, Ph.D
Committee Chair, Dr. Ganqing Jiang, Ph.D
Graduate Faculty Representative, Dr. Jichun Li, Ph.D