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Quantifying Evapotranspiration and Water Table Interactions in Regions of Shallow Groundwater: Sensitivity to Soil Properties, Vegetation, and Climate Variability

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QUANTIFYING EVAPOTRANSPIRATION AND WATER TABLE INTERACTIONS
IN REGIONS OF SHALLOW GROUNDWATER: SENSITIVITY TO SOIL
PROPERTIES, VEGETATION, AND CLIMATE VARIABILITY

by

Mehmet Evren Soylu

A DISSERTATION

Presented to the Faculty of
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Major: Natural Resource Sciences

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Evapotranspiration (ET) is an important component of the water and energy balance, yet it is also one of the most challenging components to estimate. There has been great effort to understand the nature of controlling mechanisms and interactions between ET and other earth system processes. The controlling factors of ET can be grouped into two broad categories – namely moisture availability and energy availability (e.g., solar radiation). Soil moisture is a key factor that most of the land surface hydrologic processes are dependent on. While plant water use is mainly controlled by radiation, temperature is another key factor for ET in terms of controlling the atmosphere’s moisture demand. In this study, the overall goals are to: 1) quantify the impact of groundwater and climate on ET and other components of the surface water and energy balance, 2) assess the observed and modeled interactions among ET and groundwater when the water table is close to the surface, and 3) determine the interdependencies among interannually varying climatic variables and their combined effect on the surface energy and water balance.

First, we investigated the role of different numerical model parameterizations in quantifying the impact of groundwater on root zone soil moisture and ET – as well as model sensitivity to soil texture and water table depth – by comparing land surface ET models with varying complexity in a shallow water table environment (i.e., a riparian
wetland in south central Nebraska, USA). Then, the impact of ET on groundwater was examined by analyzing diurnal water table fluctuations at multiple observation wells at the wetland field site. In addition, we proposed a new method to estimate ET more effectively than existing methods by using Fourier series to represent diurnal variations in water level hydrographs. Finally, we used a high-resolution, distributed land surface hydrologic model (the Integrated Biosphere Simulator) to evaluate the impact of interannual climate variation, vegetation type, and groundwater depth on variations in ET across the central U.S.

Key Words: Evapotranspiration, groundwater, diurnal water table fluctuations, climate variability
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CHAPTER 1 : INTRODUCTION

As the world population grows, agricultural production – which relies heavily on the available water supply – is intensifying in order to provide more food. Groundwater is one of the main sources of water for irrigation in many regions around the globe. However, over-extraction of groundwater can have potentially serious impacts on ecosystems by causing declines in surface water level and streamflow, reduction in available water for vegetation, land subsidence, and seawater intrusion (Zekster et al. 2004). To mitigate such damages, efficient and sustainable management of groundwater and surface water resources is vital. The main challenge for sustainable management is to understand the water and energy balances and the impacts of climate and humans on available water resources. The components of the land surface water balance include precipitation, runoff, infiltration, and evapotranspiration (ET). Even though measuring each of these components has some associated difficulty, estimation of ET – which is the second major component of the water cycle after precipitation – can be very challenging. The main factors influencing land surface ET include precipitation, solar radiation, temperature, wind speed, and humidity (among others). Groundwater depth is also a crucial factor affecting ET in areas where the groundwater is shallow (such as riparian zones and wetlands).

There are several studies that have focused on the potential impacts of climate change on water resources (IPCC, 2001; Najjar 1999; Chiew and McMahon, 2002), with somewhat less attention paid to direct human impacts. Yet it is reported that human impact such as land use change and groundwater pumping may exceed the effects of climate change on water resources, especially in arid and semi-arid regions (Vorosmarty
et al., 2000). Recently, there have been an increasing number of studies that have focused on differentiating the relative effects of human impact and climate change on streamflow depletions in heavily irrigated basins (Ma et al., 2007; Scanlon et al., 2007; Wang and Cai, 2009). Understanding the factors causing declines in streamflow are crucial, especially in trans-boundary basins that are required to take measures to prevent streamflow and groundwater depletion.

One region where significant depletions in streamflow and groundwater levels have been recorded is the Republican River basin, which crosses the borders of Nebraska, Colorado, and Kansas. Although well-specified water allocation rules were set by the Republican River Compact in 1948, which was signed by the three states, Nebraska has faced legal challenges from Kansas over excessive water usage in the basin. After Kansas filed a lawsuit, Nebraska turned to the difficult task of regulating groundwater use, and the state was faced to pay $73 million in damages in 2007. As part of the effort to increase streamflow rates, Nebraska removed invasive plant species along the riparian corridors of the Republican River during 2007 and 2008. Recent studies by Cutrell (2010) and Lenters et al. (2011) investigated the surface energy and water balance of a riparian wetland dominated by the invasive species *Phragmites australis*. They concluded that these phreatophyte species consume a significant amount of water and that lower ET rates could potentially be achieved through removal of the invasive plants (depending on the subsequent land surface and atmospheric conditions after vegetation removal).

Even though high ET rates associated with establishment of invasive vegetation species along a riparian zone may partially explain long-term depletions in streamflow, insights into the impacts of climate change and human activities on streamflow and
groundwater are also critical. Therefore, factors affecting components of the surface water and groundwater balance need to be analyzed. Precipitation is the primary input to streamflow (through baseflow and surface runoff), while riparian ET and diversions can induce significant withdrawals from the stream. For the groundwater balance, recharge is generally assumed to be the only input, while pumpage, baseflow, and riparian ET represent the main sources of water loss.

The impact of precipitation (as well as other climatic factors) on streamflow in the Republican River basin has been studied by Szilagyi (2001), who found that while the mean precipitation rate has not changed over time, the frequency of storms has increased. Szilagyi (2001) used a model to simulate the effects of changing storm frequency and concluded that reductions in streamflow could not be explained by precipitation trends. To quantify the influence of irrigation wells on streamflow in one of the main tributaries of the Republican River, Burt et al. (2002) applied a multiple regression model and found a strong negative correlation between streamflow and the number of wells. Wen and Chen (2006) also studied the possible causes of streamflow decline by examining trends in precipitation, and they suggested that the main factor in streamflow depletion is groundwater withdrawal. Moore and Rojstaczer (2000) reported that surface water availability for ET has been doubled since the 1940’s over the Great Plains because of groundwater pumping for irrigation. They studied the effect of irrigated water on precipitation and concluded that there is some evidence to support the idea that rainfall has been enhanced by the presence of irrigation. The impact of solar radiation on water resources over the Mississippi River basin has been reported as not significant (Qian et
al., 2007; Teuling et al., 2009), but Milly and Dunne (2001) noted an increase in basin ET – driven by both higher precipitation and increases in consumptive water use.

Even though there is a tendency to attribute streamflow decline in the Republican River basin primarily to irrigation-related groundwater extraction, climatic variables may also play a significant role, at least at the subbasin level. To examine the impacts of climate variables and groundwater on streamflow, linear regressions were calculated between observed streamflows (in some selected subbasins) and precipitation, temperature, humidity, and mean groundwater levels. Three subbasins were selected based on annual groundwater level data availability from the USGS well observation network, and 20 wells (distributed homogeneously) were analyzed for each subbasin, depending on their proximity to the streambed. Average annual groundwater levels are plotted in Figure 1.1.a, which shows that the most severe groundwater decline was observed in Frenchman Creek, with an average trend of about –34 cm/year between 1978 and 2007. At South Fork, the rate of groundwater decline is about –15 cm/year between 1970 and 2007, and – unlike other basins – the streamflow trend observed at Medicine Creek is not statistically significant (roughly –2 cm/year).
Correlation coefficients between streamflow and various climatic and groundwater variables are shown in Table 1.1 for both the “early” period (1948-1969) and “recent” period (1970’s through 2007). The results show that there is generally a statistically significant relationship between annual mean streamflow and precipitation, and – in some cases – between streamflow and other climatic variables as well (such as humidity and temperature). In the two subbasins where groundwater decline is significant (Frenchman and South Fork), precipitation and humidity are the main factors associated with interannual variations in streamflow during the “early period”. (The strong correlation with humidity may simply be a reflection of its association with precipitation, although changes in humidity can also alter ET rates.) After heavy groundwater usage begins in the 1970’s, changes in groundwater levels explain up to 90% of the streamflow variability (Table 1.1, Frenchman Creek). During this later time period, climatic variables such as precipitation and humidity are less strongly associated with changes in streamflow. At Medicine Creek, where groundwater levels have remained essentially unchanged since heavy groundwater irrigation started, all four climatic variables that were examined continue to show statistically significant relationships with changes in streamflow. The base flow index (BFI), which was calculated on the basis of a digital filter algorithm (Nathan and McMahon, 1990), is a measure of the relative contribution of baseflow to total streamflow (Table 1.1). In all three subbasins, BFI values during the
recent period were higher than during the early period, reflecting a greater influence from groundwater.

Table 1.1. Correlation coefficients between observed annual mean streamflow and annual mean precipitation ($P$), maximum daily temperature ($T_{\text{max}}$), diurnal temperature range ($DTR$), relative humidity ($RH$), baseflow index ($BFI$), and annual change in groundwater level ($\Delta GW$) for three subbasins of the Republican River basin. Bold numbers indicate significant correlations ($p < 0.05$). The “early period” covers 1948-1969, while the “recent period” runs through 2007 and begins in the 1970’s (based on the earliest date when groundwater data are available – Frenchman: 1978, South Fork: 1970, and Medicine: 1974).

<table>
<thead>
<tr>
<th>Correlation coefficients</th>
<th>Early Period</th>
<th>Recent Period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P$</td>
<td>$T_{\text{max}}$</td>
</tr>
<tr>
<td>Frenchman</td>
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<td>South Fork</td>
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The results of this basic analysis show that changes in groundwater level are strongly associated with streamflow variability in highly groundwater-irrigated areas such as the Frenchman Creek and South Fork subbasins; however, the influence of climatic variables is not small enough to be ignored. In fact, climate variability is more important than groundwater levels in influencing streamflow variability in the Medicine Creek subbasin, where groundwater level trends are relatively muted. However, climate variables are also highly interdependent on each other, and so analyzing their influence and sensitivities requires great care in interpretation.
In the remainder of this study, several analyses are performed to quantify the impact of groundwater and climate forcing on the surface energy and water balance, as well as the sensitivity of observed and modeled ET to groundwater when the water table is close to the surface. Additionally, the interdependencies among climate variables and their combined effect on the surface energy and water balance are investigated. Diurnal groundwater variations in response to daily ET were also examined at a wetland field site in south central Nebraska. After an extensive review of the literature, a new method is proposed to estimate ET more effectively than existing methods on the basis of Fourier analysis of hourly water level hydrographs. This method is likely to be helpful to decision-makers and water resource managers for accurately estimating ET (and in a cost-efficient manner) in areas where groundwater interacts strongly with the vegetation root zone.

This dissertation is organized into four chapters. Chapter 1 (i.e., the current chapter) presents an introduction, while Chapter 2 discusses the sensitivities of land surface model-derived ET estimates to the inclusion of groundwater effects, including factors such as model complexity, parameterizations, solution types, and soil parameters. This is followed in Chapter 3 by the development of a new cost-effective technique for estimating riparian ET from diurnal groundwater fluctuations, with an application to a riparian wetland field site in the Republican River basin that is dominated by an invasive plant species, *P. australis*. Finally, in Chapter 4, the sensitivity of growing season ET to interannual variations in climate, vegetation, and groundwater depth is examined for the state of Nebraska (and surrounding regions) using a dynamic vegetation land surface model. This latter study includes the effects of interdependencies among climate
variables and utilizes a high-resolution, long-term (60-year), summer-mean climatic dataset to assess the impacts of spatial and temporal variability on ET and other components of the land surface water balance.

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**Introductory Statement for Chapter 2**

The following chapter is the first in a series of investigations that evaluates interactions between ET and groundwater. This chapter provides insights about groundwater and ET relationships by utilizing observations (and modeling) from a wetland field site in south-central Nebraska. The role of different numerical model parameterizations in quantifying the impact of groundwater on root zone soil moisture and ET is examined, as well as the model sensitivity to soil texture and water table depth. Models with various complexities are compared across a range of water table depths, similar to what might be found in shallow water table environments (e.g., wetlands and riparian zones).
CHAPTER 2: QUANTIFYING THE IMPACT OF GROUNDWATER DEPTH ON EVAPOTRANSPIRATION IN A SEMI-ARID GRASSLAND REGION

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ABSTRACT

Interactions between shallow groundwater and land surface processes play an important role in the ecohydrology of riparian zones. Some recent land surface models (LSMs) incorporate groundwater-land surface interactions using parameterizations at varying levels of detail. In this paper, we examine the sensitivity of land surface evapotranspiration (ET) to water table depth, soil texture, and two commonly used soil hydraulic parameter datasets using four models with varying levels of complexity. The selected models are Hydrus-1D, which solves the pressure-based Richards equation, the Integrated Biosphere Simulator (IBIS), which simulates interactions among multiple soil layers using a (water-content) variant of the Richards equation, and two forms of a steady-state capillary flux model coupled with a single-bucket soil moisture model. These models are first evaluated using field observations of climate, soil moisture, and groundwater levels at a semi-arid site in south-central Nebraska, USA. All four models are found to compare reasonably well with observations, particularly when the effects of groundwater are included. We then examine the sensitivity of modelled ET to water table
depth for various model formulations, node spacings, and soil textures (using soil hydraulic parameter values from two different sources, namely Rawls and Clapp-Hornberger). The results indicate a strong influence of soil texture and water table depth on groundwater contributions to ET. Furthermore, differences in texture-specific, class-averaged soil parameters obtained from the two literature sources lead to large differences in the simulated depth and thickness of the “critical zone” (i.e., the zone within which variations in water table depth strongly impact surface ET). Depending on the depth-to-groundwater, this can also lead to large discrepancies in simulated ET (in some cases by more than a factor of two). When the Clapp-Hornberger soil parameter dataset is used, the critical zone becomes significantly deeper, and surface ET rates become much higher, resulting in a stronger influence of deep groundwater on the land surface energy and water balance. In general, we find that the simulated sensitivity of ET to the choice of soil hydraulic parameter dataset is greater than the sensitivity to soil texture defined within each dataset, or even to the choice of model formulation. Thus, our findings underscore the need for future modelling and field-based studies to improve the predictability of groundwater-land surface interactions in numerical models, particularly as it relates to the parameterization of soil hydraulic properties.

**INTRODUCTION**

Shallow groundwater in river valleys, riparian zones, and wetlands interacts with soil, vegetation, and climate through capillary rise and direct root water uptake from the water table, influencing land surface processes. Unlike deep water table conditions, a shallow groundwater table maintains elevated soil moisture in the root zone (Chen and Hu, 2004). Since land surface processes (e.g., evapotranspiration, runoff, and infiltration) are
strongly dependent on soil moisture, incorporating groundwater in land surface models (LSMs) is crucial for realistic representations of hydrologic processes in watersheds (Niu et al., 2007; Yeh and Eltahir, 2005; York, 2002; Maxwell and Kollet, 2008). Yet, little is known about the impacts of groundwater on land surface fluxes over different time and space scales. In the absence of detailed field observations, numerical models are currently being used to explore the role of groundwater in simulated land surface fluxes (Fan et al., 2007; Liang et al., 2003; Maxwell et al., 2007).

In a shallow, unconfined aquifer, water can move upward from the water table to relatively drier soil surface layers through capillary flux. Quantifying capillary flux to the root zone depends on soil hydraulic properties, groundwater table depth, and the distribution of soil matric potential throughout the unsaturated zone. A number of approaches have been proposed to simulate this process in LSMs by linking the unsaturated zone with the water table. The majority of recent LSMs employ the Richards equation to simulate water movement in the unsaturated zone, while representing groundwater as a simple unconfined, lumped aquifer and treating the water table as a constant-head lower boundary condition by keeping lower soil layers saturated (Yeh and Eltahir, 2005; Niu et al., 2007; Fan et al., 2007). Maxwell and Miller (2005) presented a more complex modelling approach by integrating groundwater, subsurface flow, and overland flow processes in a coherent, numerical model framework. In their study, a groundwater flow model, ParFlow – which solves the Richards equation both in variably saturated and fully saturated conditions – was coupled to an LSM (the Community Land Model) to simulate the energy and water balance of the land surface. In a series of papers, Maxwell and co-workers (Maxwell and Miller, 2005; Kollet and Maxwell, 2008)
illustrated how incorporating groundwater leads to more realistic patterns of soil moisture and runoff on the landscape. Using ParFlow, Ferguson and Maxwell (2010) recently showed that the sensitivity of hydrologic response to climate change is strongly related to the inherent feedbacks between groundwater and land surface processes, especially in regions with a shallow water table. Furthermore, the magnitude and seasonality of these feedbacks are also sensitive to the direction of climate change.

The Richards equation is the most widely accepted, physically based model used to simulate variably saturated flow in porous media:

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

where \( \theta \) is volumetric water content \([L^3 L^{-3}]\), \( K(h) \) is unsaturated hydraulic conductivity \([L T^{-1}]\), \( h \) is matric head \([L]\), \( z \) is the (positive upward) vertical coordinate \([L]\), and \( S \) is the rate of root water uptake \([L^3 L^{-3} T^{-1}]\). The Richards equation can be written in three basic forms: (1) a pressure-based form (i.e., \( h \)-based), (2) a volumetric water content-based form (i.e., \( \theta \)-based), and (3) a mixed form, such as that shown in Eq. (1) or by Celia et al. (1990).

Solving the Richards equation requires the representation of \( \theta \) and \( K \) as functions of \( h \). (Brooks and Corey, 1966; Clapp and Hornberger, 1978; van Genuchten, 1980; Rawls et al., 1982). However, due to the highly nonlinear nature of these functions, analytical solutions of the Richards equation only exist for very simplified boundary conditions and specific forms of the moisture-pressure relations (Zlotnik et al., 2007). Therefore,
numerical techniques are needed to solve the Richards equation for more general applications (Warrick, 2003).

Many numerical studies have used either $h$-based or $\theta$-based forms of the Richards equation to describe water flow in the unsaturated zone (e.g. Hills et al., 1989; Kirkland et al., 1992). Overall, the numerical solution of the $\theta$-based Richards equation has been found to yield more accurate mass balance and computational efficiency in relatively dry soils and is, therefore, often preferred in most LSMs that neglect the role of groundwater (Dickinson et al., 1993; Sellers et al., 1996). However, application of the $\theta$-based form is problematic when dealing with saturated soil layers, since – unlike pressure head – soil moisture does not vary within a homogeneous and inelastic saturated porous medium (Celia et al., 1990; Pan and Wierenga, 1995; Zeng and Decker, 2009; de Rooij, 2010). Nevertheless, the $\theta$-based form of the Richards equation has been used in some LSMs that incorporate groundwater (i.e., saturated soil layers) below the unsaturated zone (Kim and Eltahir, 2004; Yeh and Eltahir, 2005). Because of the various drawbacks of the $h$- and $\theta$-based forms of the Richards equation, some studies have combined the two forms into one equation (e.g. Allen and Murphy, 1986; Celia et al., 1990). The mixed form of the Richards equation provides solutions in terms of pressure head, while conserving mass better than the $h$-based solution.

On the other end of the spectrum, simple analytical solutions have also been employed to couple groundwater and land surface processes in some LSMs. One such model is the Gardner-Eagleson (G-E) model that estimates a steady rate of capillary flux to the land surface based on the water table depth (Gardner, 1958; Eagleson, 1978; Famiglietti and Wood, 1994). The analytical form of the original G-E model is derived
from the Darcy-Buckingham equation and is based on assumptions of steady-state capillary flux and a completely dry soil surface. The latter assumption can lead to over-predictions of the capillary flux, especially during wet periods, while the former assumption neglects changes in flux rates within the soil profile. These assumptions limit the general use of the analytical model, making numerical solutions preferable in many instances, such as time-varying simulations of land surface fluxes and soil moisture (Ridolfi et al., 2008; Laio et al., 2009).

Recently, models similar to the G-E model (with varying degrees of complexity) have been proposed to relax the dry soil assumption in the analytical solution. For example, Bogaart et al. (2008) offered a set of closed-form expressions, based on the Darcy-Buckingham equation, which accounts for both root-zone soil moisture and water table depth. Vervoort and van der Zee (2008) provide a piecewise linear equation for calculating soil water flux from the water table, which depends on the potential capillary flux and the actual evaporative demand. They then couple the equation to a stochastic soil moisture accounting model to provide continuous simulations of water table and land surface linkages. Similarly, Ridolfi et al. (2008) suggested an analytical framework to couple soil moisture dynamics and groundwater fluctuations under bare soil conditions, which was later extended to vegetated conditions by Laio et al. (2009).

Despite these previous efforts, there is still a limited amount of research assessing the utility of different numerical and analytical models for realistic representations of groundwater and land surface coupling. The current study investigates the impacts of different model parameterizations on our ability to quantify the role of groundwater in land surface processes. We also examine the sensitivity of the various models to soil
texture and water table depth. Four models are selected for this study: 1) the Hydrus-1D model (Simunek et al., 2005), 2) the Integrated Biosphere Simulator (IBIS; Foley et al., 1996; Kucharik et al., 2000), and 3-4) two variants of the G-E model that are coupled with a bucket-type soil moisture model using successive steady-state flux conditions. Model values for soil hydraulic parameters are obtained from two soil texture-based lookup tables that are commonly used by LSMs (Table 2.1), namely the parameter sets of Rawls et al. (1982) and Clapp and Hornberger (1978). These soil parameter datasets are hereafter referred to as R-1982 and CH-1978, respectively.

Among the models selected for this study, Hydrus-1D has the most complex parameterization for the vertical movement of water for models that use the mixed ($\theta$- and $h$-based) form of the Richards equation. The IBIS model serves as an intermediate-complexity LSM with multiple buckets that exchange soil water based on the $\theta$-based Richards equation. Finally, the coupled G-E / single-bucket soil moisture model represents the simplest scenario by assuming steady-state conditions, rather than explicitly transient solutions. Lateral movement of water is not considered for any of the models used in this study. In what follows, we first describe each of the models, followed by a limited model verification study in a semi-arid region with a shallow groundwater table (south-central Nebraska, USA). We then investigate and compare the sensitivity of the various models to water table depth, soil texture, soil hydraulic parameters, and node spacing. Finally, we discuss the results of the model simulations and suggest directions for future research.
MODEL DESCRIPTIONS

Hydrus-1D model

In this study, the Hydrus-1D model (Simunek et al., 2005) is selected to represent models that employ a one-dimensional, finite-element solution of the Richards equation (in the “mixed” form). Hydrus-1D has been previously verified using analytical solutions under certain boundary conditions (Zlotnik et al., 2007) and has also been successfully used in numerous studies for predicting observed evapotranspiration (ET) and soil moisture (e.g., Scott et al., 2000; Scanlon et al., 2002).

Hydrus-1D solves Eq. (1) for variably saturated flow in homogenous and rigid porous media. In solving Eq. (1), Hydrus-1D calculates the root water uptake term, \( S(h) \), according to the method proposed by Feddes et al. (1978, p. 20):

\[
S(h) = \mu(h) S_p,
\]

where \( S_p \) is the potential root water uptake rate \([\text{L}^3 \text{L}^{-3} \text{T}^{-1}]\) (i.e., the potential volume of water removed from a unit volume of soil per unit time). When integrated over the rooting depth, \( S_p \) becomes identical to the potential rate of evapotranspiration \( (ET_p) \) at the surface (assuming a fully vegetated surface with no intercepted or bare-soil evaporation).

The term \( \mu(h) \) is a dimensionless, prescribed function of pressure head \((0 \leq \mu(h) \leq 1)\) which introduces soil moisture limitation to the uptake of water by roots:

\[
\mu(h) = \begin{cases} 
0 & \text{if } h \leq h_w, \\
\frac{h - h_w}{h^* - h_w} & \text{if } h_w < h \leq h^*, \\
1 & \text{if } h^* < h
\end{cases}
\]
where \( h_w \) and \( h^* \) are pressure heads at the wilting point and drought-induced incipient stomata closure point, respectively. Below \( h_w \), plants cannot extract water, and \( \mu(h) \) equals zero. Between \( h_w \) and \( h^* \), root water uptake is limited by soil moisture and increases linearly with pressure head as the soil gets wetter. Above \( h^* \), plant transpiration (and likewise the root water uptake) is not constrained by soil moisture.

In order to run Hydrus-1D, lower and upper boundary conditions need to be specified for the finite-element solution scheme. The lower boundary condition is set as free drainage (i.e., “no groundwater”) or as a constant pressure head to represent the groundwater table. The upper boundary condition, on the other hand, is specified by atmospheric factors, namely precipitation input and evaporative demand. Surface runoff occurs when the precipitation rate exceeds the soil infiltration capacity. More specifically, the upper boundary condition is obtained by applying the following two limiting conditions at the soil surface (Neuman et al., 1974):

\[
\left| K(h) \left( \frac{\partial h}{\partial z} + 1 \right) \right| \leq |E_{\text{max}}| \quad \text{at } z = 0, \quad (4a)
\]

and

\[
h_{\text{min}} \leq h \leq 0 \quad \text{at } z = 0, \quad (4b)
\]

where \( E_{\text{max}} \) [L T\(^{-1}\)] is the maximum potential rate of evapotranspiration (\( ET_P \)) or infiltration (\( I_{\text{max}} \)) under the current atmospheric conditions, and \( h_{\text{min}} \) is the minimum pressure head [L] allowed at the soil surface. This upper boundary condition can switch from a prescribed flux to a prescribed pressure head to ensure that the two limiting conditions in Eq. (4) are met (Simunek et al., 2005).
In all of the model simulations used in this study, the CH-1978 soil parameter functions are used to relate soil water content to pressure head and unsaturated hydraulic conductivity (with $h < h_{ae} < 0$ for unsaturated conditions):

$$h(\theta) = h_{ae} \left( \frac{\theta}{\theta_s} \right)^{-b},$$

(5a)

$$K(\theta) = K_s \left( \frac{\theta}{\theta_s} \right)^{2b+3},$$

(5b)

where $\theta_s$ is the saturated volumetric water content $[L^3 L^{-3}]$ (also equal to porosity), $h_{ae}$ is the air entry (bubbling) pressure [L], $K_s$ is saturated hydraulic conductivity $[L T^{-1}]$, and $b = \lambda^{-1}$ is a soil index (with $\lambda$ being equal to the pore size distribution index; Brooks and Corey [1966]).

**Integrated Biosphere Simulator (IBIS)**

IBIS is a dynamic global vegetation model (DGVM) that integrates various terrestrial ecosystem processes within a single, physically consistent framework (Foley et al., 1996). IBIS simulates the land surface energy, water, and carbon balance, vegetation dynamics and phenology, and canopy physiology (Foley et al., 1996; Kucharik et al., 2000; Lenters et al., 2000; Li et al., 2005). Here we discuss the components of IBIS that are most relevant to the focus of this paper.

The land surface transfer scheme (LSX) of Pollard and Thompson (1995) is used within IBIS to model exchanges of momentum, energy, and water mass in the soil-vegetation-atmosphere continuum (Thompson and Pollard, 1995a, b). In its standard
version, IBIS simulates energy and water exchange in two canopy layers (upper and lower), three snow layers, and 11 soil layers with varying thicknesses. Hourly meteorological inputs include air temperature, relative humidity, incoming solar radiation, precipitation, and wind speed. The soil sub-model in IBIS simulates soil temperature, water content, and ice content in each of the 11 soil layers and solves the \( \theta \)-based form of the Richards equation:

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left( D(\theta) \frac{\partial \theta}{\partial z} \right) + \frac{\partial K(\theta)}{\partial z} - S, \tag{6}
\]

where \( D(\theta) = K(h)(\partial h/\partial \theta) \) is the moisture diffusivity [L\(^2\) T\(^{-1}\)].

For a given soil layer, \( i \), the root water uptake term, \( S_i \), is calculated from plant transpiration according to:

\[
S_i = T \cdot F_i, \tag{7}
\]

where \( T \) is the sum of the upper and lower canopy transpiration [L\(^3\) L\(^{-3}\) T\(^{-1}\)], and \( F_i \) is the water uptake fraction [-], which is a function of root distribution and soil water content:

\[
F_i = \frac{R_i A_i}{\sum_i R_i A_i}, \tag{8}
\]

\( R_i \) is the root biomass in soil layer \( i \), and \( A_i \) is a stress factor related to soil water availability:

\[
A_i = 1 - \frac{\ln(1 + 799 \cdot \exp[-12 \cdot \theta_a])}{\ln(800)} \tag{9}
\]

\( \theta_a \) is the plant available water fraction and is calculated in each soil layer as:
where $\theta$ is volumetric water content [$L^3 L^{-3}$], $\theta_w$ is the wilting point [$L^3 L^{-3}$], and $\theta_{fc}$ is field capacity [$L^3 L^{-3}$].

The transpiration functions in IBIS are based on the work of Pollard and Thompson (1995):

$$T_u = \frac{\rho C_u}{(1 + r_u C_u)}(1 - f_u^{wet})(q_{sat}(L_u) - q_u)LAI_u,$$  \hspace{1cm} (11a)

$$T_l = \frac{\rho C_l}{(1 + r_l C_l)}(1 - f_l^{wet})(q_{sat}(L_l) - q_l)LAI_l,$$  \hspace{1cm} (11b)

where the subscripts $u$ and $l$ represent the upper and lower canopy, respectively, $\rho$ is the density of near-surface air [$M L^{-3}$], and $f_u^{wet} = \min(0.8, W_{u\|}/W_{u\|}^{max})$ is the fraction of leaf area wetted by intercepted water or snow (where $W$ is the intercepted liquid or snow on a unit leaf/stem area [$M L^{-2}$]). Other variables in Eq. (11) include leaf temperature, $L$ (in °C), as well as the heat/vapor transfer coefficient between canopy and air $C$ [$L T^{-1}$], calculated as $C_{u\|} = \delta \sqrt{U_{u\|}/\varepsilon}$, where $\delta = 0.01$ m s$^{-0.5}$, $U$ is wind speed [m s$^{-1}$], and $\varepsilon = 0.01$ m is the fetch length for leaves and stems. Finally, $q_{sat}$ is the saturation specific humidity at the leaf temperature [$M M^{-1}$], $q$ is the ambient specific humidity within the canopy [$M M^{-1}$], $LAI$ is the single-sided canopy leaf area index [$L^2 L^{-2}$], and $r$ is the stomatal resistance per unit leaf area [$T L^{-1}$], which is a function of photosynthetically active radiation, temperature, vapour pressure deficit, and available soil water content.

Total “actual” ET is calculated as the sum of: 1) total transpiration ($T = T_u + T_l$), 2)
evaporation of water intercepted by vegetation, and 3) evaporation of water from the soil surface (Pollard and Thompson, 1995).

The upper boundary in the IBIS soil model is specified by an infiltration rate that is equal to the water throughfall rate (plus snowmelt) minus evaporation. If the upper soil layer is saturated, or throughfall minus evaporation exceeds the maximum possible infiltration rate, then a surface “puddle” accumulates to a maximum depth, beyond which surface runoff occurs. IBIS does not explicitly represent water table dynamics. Instead, the lower boundary condition is allowed to vary from 100% free drainage to zero flux (or anywhere in between, based on an empirical coefficient ranging from 0 to 1). In this study, representation of groundwater as a lower boundary condition is required in order to determine the groundwater contribution to surface ET. To do so, the bottom flux boundary condition in IBIS is changed to a fixed soil moisture boundary condition by forcibly saturating the soil layers below the top of the capillary fringe. Yeh and Eltahir (2005) applied a similar adjustment to the IBIS model to incorporate the influence of groundwater. In the current study, the average thickness of the capillary fringe for sand, silt loam, silty clay loam, and clay was set to 5 cm, 32.5 cm, 45 cm, and 32.5 cm, respectively. This is based on the work of Mausbach (1992), who reported these values for wet soil environments and over a narrower range than the air-entry values of CH-1978 and R-1982 (which are listed in Table 2.1).

The “default” soil depth (250 cm) and soil layer thicknesses in IBIS are meant to coincide with the CONUS-Soil dataset, which is based on the USDA State Soil Geographic Database (STATSGO). As a result, the standard thicknesses of the 11 soil layers are 5 cm (layers 1 and 2), 10 cm (layers 3-5), 20 cm (layers 6-8), and 50 cm (layers
9-11). These intervals are too coarse to capture some of the finer soil moisture gradients and changes in groundwater level that are examined in this study. To overcome this limitation, as well as to ensure that the IBIS simulations are directly compatible with the smaller node spacing of the Hydrus-1D simulations, we changed the soil layer thicknesses in IBIS to a fixed 2.5-cm interval throughout the soil column (100 layers total, to a depth of 250 cm).

**Coupled root-zone and steady-state capillary flux models**

**Gardner-Eagleson (G-E) model**

The G-E model offers an analytical solution to calculate a constant rate of capillary flux from the water table to the unsaturated zone under steady-state soil moisture conditions (i.e., $\partial \theta / \partial t = 0$). The derivation of the G-E model was first given by Gardner (1958) and later modified by Eagleson (1978). Neglecting root water uptake, the vertical capillary flux, $v$ [L T$^{-1}$] (positive upwards), can be calculated from Eq. (1) to form the Darcy-Buckingham equation:

$$v = -K(h) \left( \frac{\partial h}{\partial Z} + 1 \right) = K(\psi) \left( \frac{\partial \psi}{\partial Z} - 1 \right),$$  \hspace{1cm} (12)

where $\psi = -h = |h|$ is the soil suction head in the unsaturated zone (since $h < 0$). Eq. (12) can be rearranged and integrated from the water table depth to the upper boundary at the soil surface (or the root zone) to solve for $Z_{gw}$, the depth-to-groundwater:

$$Z_{gw} = \int_{\psi_0}^{\psi_c} \frac{d\psi}{1 + (v/K(\psi))},$$  \hspace{1cm} (13)
where \( \psi_u \) is the soil suction head at the upper boundary [L]. In order to solve Eq. (13), Gardner (1958) used the empirical expression \( K(\psi) = \frac{a}{(\psi^n + c)} \), where \( a, n, \) and \( c \) are constants, and \( n \) was varied over a range of 1 to 4 (Gardner, 1958). Neglecting \( c \), which is small compared to \( \psi^n \), it can be shown from Eq. (5) that \( a = K_s |h_{ac}|^n \), and that \( n \) is related to the pore size distribution index through \( n = 2 + 3 \lambda = 2 + 3/\beta \). Thus, \( K(\psi) \) reduces to the form of Brooks and Corey (1966) and Campbell (1974):

\[
K(\psi) = K_s \left( \frac{|h_{ac}|}{\psi} \right)^n. \tag{14}
\]

Substituting Eq. (14) into Eq. (13) yields:

\[
Z_{gw} = \int_0^{\psi_u} \frac{d\psi}{1 + \alpha \psi^n}, \tag{15a}
\]

where

\[
\alpha = \frac{\nu}{K_s |h_{ac}|^n}. \tag{15b}
\]

Under the assumption of constant capillary flux \( (\nu) \), Gardner (1958) showed that Eq. (15) can be solved analytically for certain \( n \) values. One such analytical solution arises under the assumption of a completely dry soil surface (i.e. \( \psi_u \to \infty \)), which results in a strong upward gradient and the following equation for capillary flux:

\[
\nu = B K_s \left( \frac{|h_{ac}|}{Z_{gw}} \right)^n, \tag{16}
\]
where \( B \) is a parameter that depends solely on the value of \( n \) and is often taken from a lookup table. Values of \( B \) from Gardner (1958) are listed in Table 2.2.

In addition to the solution of Gardner (1958), Ripple (1972) suggested various graphical solutions to Eq. (15), and Anat et al. (1965) developed some approximate solutions in the case of \( n > 1 \). Warrick (1988) extended the analytical solutions of Eq. (13) for various \( n \) values using the Brooks-Corey retention curve model. However, these solutions cannot be explicitly written in terms of \( v(h_{\text{nl}}, Z_{gw}) \) and \( \psi(v, Z_{gw}) \). An approximate analytical model based on the results of Gardner (1958) was presented by Eagleson (1978) and later modified by Salvucci (1993). Eagleson (1978) suggested a continuous relationship to extend \( B \) over the full range of soil index values using the following empirical function:

\[
B = 1 + \frac{3}{2(n-1)}. \tag{17}
\]

Substituting Eq. (17) and \( n = 2 + 3/b \) into Eq. (16) yields the “original G-E model” form of the capillary flux that is used in this paper:

\[
v = K_s \left[ 1 + \frac{3}{2(6/b)} \left( \frac{h_{\text{nl}}}{Z_{gw}} \right)^{2+3/b} \right]. \tag{18}
\]

It is important to note here that in Eq. (18), the soil surface is assumed to be dry \( (\psi_u \rightarrow \infty) \). To allow continuous modelling of soil moisture and ET under varying atmospheric evaporative demand and groundwater table elevations, the original G-E model (Eq. 18) and a modified form of the G-E model are coupled to a bucket-type vadose zone hydrology model. In the “modified G-E model,” instead of assuming a dry
soil surface, we use the actual (depth-averaged) soil moisture in the root zone. For this purpose, the soil suction head used as the upper limit of the integral in Eq. (15) is calculated by solving Eq. (5a) for $|h|$ using the depth-averaged, root-zone soil moisture. This modification requires the integration of Eq. (15), which does not have a general analytical solution. Therefore, we use the composite trapezoidal rule to numerically integrate Eq. (15) and thereby calculate the capillary flux to the root zone.

**Bucket hydrology model**

Both forms of the G-E capillary flux model are coupled to a leaky bucket-type hydrology model by adding the steady-state groundwater capillary flux to the root zone at each time step of the model iteration, similar to Brolsma and Bierkens (2007). The rate of change in the depth-averaged soil moisture in the root zone is calculated according to:

$$
\frac{d s}{d t} = I - E T_a(s) - L_r(s) + v(s, Z_{gw}),
$$

(19)

where $\phi$ ($= \theta_b$) is porosity $[L^3 L^{-3}]$, $Z_r$ is rooting depth $[L]$, $s = \theta / \theta_s$ [-] is the degree of saturation within $Z_r$, $I$ is infiltration rate $[L T^{-1}]$, $ET_a$ is actual ET $[L T^{-1}]$, and $L_r$ is leakage from the root zone $[L T^{-1}]$. (Note that the capillary flux into the root zone, $v$, is independent of $s$ for the case of the “original” G-E model, as given by Eq. [18].) The infiltration rate is defined as:

$$
I = \begin{cases} 
\min[P_r, K_s] & P_t > C_{\text{int}} \\
0 & P_t \leq C_{\text{int}} 
\end{cases}
$$

(20)

where $P_r$ is rainfall rate [L T$^{-1}$], $P_t$ is total cumulative rainfall [L] during a given rain event, and $C_{int}$ is canopy interception [L]. Runoff is generated when rainfall rate exceeds $K_s$ and the canopy can no longer intercept additional precipitation.

Leakage from the root zone is calculated according to Campbell (1974):

$$L_r(s) = \begin{cases} 
0 & s \leq s_{fc} \\
K_s s^{2.43} & s_{fc} < s \leq 1
\end{cases},$$

(21)

where $s_{fc}$ is the degree of soil saturation at field capacity. $ET_a$ is calculated by reducing the potential ET rate by a soil moisture limitation function similar to that described in Eq. (3) (see also Laio et al., 2001):

$$ET_a(s) = \begin{cases} 
0 & s \leq s_w \\
ET_p \left( \frac{s - s_w}{s - s^*} \right) & s_w < s \leq s^* \\
ET_p & s^* < s < 1
\end{cases},$$

(22)

where $s_w$ and $s^*$ are the degree of soil saturation at the wilting point and at the threshold for incipient stomata closure, respectively. In the application of the bucket model, $ET_p$ is estimated from the Priestley-Taylor equation (Priestley and Taylor, 1972).

As noted earlier, two forms of the G-E model are used in this study. In the first application, we use the original G-E model (Eq. 18) for calculating $v$ in the soil water balance equation (Eq. 19). This version (which we refer to as “G-E-bucket model-1”) represents a one-way coupling, in the sense that the root zone receives a capillary flux that is independent of soil moisture fluctuations in the root zone. In the second version (referred to as “G-E-bucket model-2”), the capillary flux is directly coupled to the root-
zone soil moisture in a quasi-steady-state manner. In order to accomplish this, a value for \( \psi_u \) is first obtained for each model iteration using the root-zone soil moisture from the previous time step (i.e., solving Eq. (5a) for \(|h|\)). Then, for a given \( Z_{gw} \), Eq. (15) is integrated numerically to solve for \( v \). Finally, this calculated \( v \) is added to the soil water balance in the root zone. In simulations with no groundwater (i.e., free drainage), \( v \) is simply set to zero (for both G-E models). The models are run at a daily time step using the analytical method of Laio et al. (2001).

**MODEL EVALUATION AND EXPERIMENTAL DESIGN**

In this section, we first evaluate the models against field observations of soil moisture for a ~5-month period during the growing season of 2009 (using local meteorology and water table depth as model drivers). The field site is located at a riparian wetland in the semi-arid region of south-central Nebraska (USA). Observed groundwater levels are introduced as the lower boundary condition for each model, and calculated soil moisture levels in the root zone are compared against those observed in the field. Later in section 3.3, we describe the experimental design used to explore the sensitivity of modelled ET to soil texture, water table depth, model formulation, and node spacing. A long-term (10-year) climate dataset from a nearby meteorological station is used as the driver for these latter simulations. Groundwater levels are again introduced as the lower boundary condition, except that multiple 10-year simulations are performed across a wide range of water table depths (which are held fixed during each simulation). A summary of the models, boundary conditions, and simulation periods is presented in Table 2.3. Results from the model sensitivity experiments are discussed in section 4.
Field site and observational data

A limited model-data comparison study was conducted at a riparian wetland field site in the Republican River basin of south-central Nebraska, USA (Fig. 2.1) to assess the viability of the models used in this study. The climate of this site is generally semi arid, with a mean annual precipitation of 430 mm. Approximately 80% of this precipitation occurs between April and September. Irrigated croplands are common in the region, with limited trees except in riparian zones near the Republican River and other areas where the water table is shallow. Valley wetlands with exposed water tables are generally occupied by tall grasses and open water (maximum depth ~1 m). The wetland field site is an oxbow channel located at 40°17.91’ N and 99° 57.90’ W, with an elevation of 664 m above sea level (ASL) (Fig. 2.1). The channel is approximately 900 m long and 50 m wide, with a water depth that ranges from approximately 0–60 cm. The wetland typically experiences groundwater discharge from spring to early summer and recharge from mid summer to early autumn (Cutrell, 2010). Both banks of the wetland channel are partially covered by old-growth cottonwood trees (Populus deltoides), while the channel itself is dominated by tall, perennial grass (primarily Phragmites australis, or common reed).

Hourly water level measurements were obtained using a series of piezometers (3 m long) and Level TROLL 300 transducers (In-Situ, Inc.). Five piezometers were deployed in the field – two in each of the southern and northern banks, and one in the wetland. Soil moisture profiles were monitored at two locations along the southern bank of the channel, where the overstory vegetation is sparse cottonwood, and the understory is short grass. The measurements were made using soil water content reflectometers (model CS616, Campbell Scientific, Inc.), positioned horizontally at approximately 10, 20, and 50 cm
below the soil surface. We selected monitoring sites devoid of tree roots to avoid complications due to transpiration from the upper canopy. Meteorological measurements were also made near the middle of the wetland (Fig. 2.1) to provide estimates of air temperature, relative humidity, wind speed, precipitation, and radiation (solar, longwave, and net radiation). These are used as inputs to the IBIS model, as well as for calculating $ET_p$ in the Hydrus-1D and G-E-bucket models (see Eqs. [4] and [22]). Figure 2.2.a shows the observed daily precipitation and depth-to-groundwater that were used to drive the model simulations during the 2009 evaluation period.

A previous, detailed energy balance study of the wetland site (Cutrell, 2010) found that the Priestley-Taylor method provides very good estimates of $ET_p$ during the main growing season (when water is abundant and vegetation is green). Therefore, we employ the same method here to calculate $ET_p$ as input for the Hydrus-1D and G-E-bucket models during the model evaluation portion of this study. (A different method, described in section 3.3, is used to estimate $ET_p$ for the model sensitivity experiments.) We use a constant Priestley-Taylor coefficient of 1.26 (as in Cutrell, 2010), as well as the direct field measurements of net radiation to calculate $ET_p$. Ground heat flux is assumed to be 10% of net radiation, which is similar to values found in other studies (e.g., Kustas et al., 1989).

Although the understory cover of the modelled domain is grass, the solar radiation reaching the understory surface is attenuated by the sparsely distributed cottonwood trees of the upper canopy. To account for this attenuation of radiation in the Priestley-Taylor estimate of $ET_p$, we employ the method of Ritchie (1972), which uses Beer’s Law to calculate attenuated net radiation ($R_a$) according to $R_a = R_n \cdot e^{-kLAI}$, where $R_n$ is measured
net radiation, LAI is the leaf area index of the upper canopy, and $k = 0.5$ is the extinction coefficient. (For consistency, a similar attenuation was applied to the incoming solar radiation input for the IBIS model.) Upper canopy LAI is derived from MODIS imagery (MOD15A2) at a temporal resolution of 8 days, with LAI reaching a peak of \(~3\). Since the narrow band of cottonwood trees covers only a small area in a 1-km by 1-km MODIS pixel, we selected a larger coverage area (slightly south of the wetland) that contained the same canopy type and nearly identical cover density (as observed in the field and from areal photos). Figure 2.2.b shows the resulting $ET_p$ that was calculated from the Priestley-Taylor method using the observed and attenuated net radiation. It is evident from this figure that despite the peak in solar radiation around late June, the “attenuated $ET_p$” reached its maximum around early May and declined thereafter (due to overstory canopy development). Thus, the impact of increased upper-canopy LAI on attenuated $ET_p$ is most significant from about mid June onward.

Model evaluation using field observations

Using the meteorological observations as upper boundary conditions, simulated soil moisture values from the Hydrus-1D, IBIS, and G-E-bucket models were compared with volumetric water content measurements collected along the southern bank of the wetland (Fig. 2.3). To provide a “control” for assessing model sensitivity to groundwater, we first ran the simulations assuming free-drainage conditions (i.e., no groundwater influence). Under this condition, the G-E-bucket models reduce to a single-bucket soil moisture model. Subsequently, we replaced the lower boundary condition of the models with the timeseries of observed water table depth that was measured along the southern bank of the wetland (Fig. 2.2a).
The Hydrus-1D and IBIS simulation domains are one-dimensional, vertical soil columns that are 250 cm deep, with uniform soil characteristics and a node spacing of 2.5 cm (Table 2.3). Vegetation type is assumed to be grass in all models (specifically C3 grass in IBIS), and we use a uniform root distribution that is 50 cm deep (based on previously reported root depths in grasslands studies such as Jackson et al., 1996 and Wang et al., 2008). Simulated soil moisture outputs for the Hydrus-1D and IBIS models are obtained at 10, 20, and 50 cm below the soil surface, which is consistent with the field observations. The two G-E-bucket models provide depth-averaged volumetric water content for the entire 50-cm root zone. To be consistent among the different models, therefore, we use only the depth-averaged, root zone soil moisture when comparing the modelled and observed volumetric water content. The soil type employed in the models is sand, using representative soil parameter values from R-1982 (Table 2.1). The simulations were initialized using the observed soil moisture profile, and no adjustments were made to the soil parameters to attempt to “calibrate” the models. Separate, detailed parameter optimizations – which could have improved the simulation results for the IBIS and Hydrus-1D models – were not applied, as this was not the intent of the paper. Rather, our goal is to show the models’ performance using standard soil moisture parameters that are based solely on soil texture (Table 2.1).

The results of Figure 2.3 indicate that, despite the range of complexities among the models, each one showed improvements in the soil moisture simulation when groundwater was introduced as the lower boundary condition. Somewhat surprisingly, the volumetric water content predicted by the simpler G-E-bucket models showed the best agreement with the observed soil moisture timeseries. The overall influence of
groundwater in the modelled soil moisture was to reduce the daily variability and increase the mean daily soil moisture, especially from early May to mid July (Fig. 2.3). This time period is when the water table depth was relatively shallow (roughly 75–100 cm below the surface; Fig. 2.2a). In addition, the improvement in simulated soil moisture during this high-water-table period was most dramatic for the Hydrus-1D and G-E-bucket model simulations, whereas the response in IBIS was somewhat muted. This suggests a weaker sensitivity of the IBIS model to water table variations when the depth-to-groundwater is ~75 cm or deeper (at least for sand, using R-1982 parameters). The Hydrus-1D and G-E models, on the other hand, show a greater sensitivity to the presence of groundwater, suggesting a deeper simulated “critical zone” (also discussed in section 4). As $ET_p$ and water table depth continued their seasonal decline beyond mid July (Fig. 2.2), the differences in soil moisture between the simulations with and without groundwater diminished considerably (Fig. 2.3). Finally, we note that the model evaluation simulations were also run using the CH-1978 soil hydraulic parameters. These additional simulations (not shown) resulted in an increase in mean soil moisture in all models (compared to the R-1982 runs), but the general shape of the pulse-decay behaviour was not altered notably.

Experimental design: Model sensitivity experiments

The goal of the model sensitivity analysis is to evaluate the role of soil texture, water table depth, model formulation, and node spacing in determining mean annual ET. Although it has been suggested that the use of soil texture alone is often insufficient for estimating soil hydraulic parameters (Gutmann and Small, 2005), the availability of global soil texture maps makes it a commonly used predictor of soil hydraulic parameters.
for hydrologic and land surface modelling purposes. Thus, in the first set of sensitivity experiments (Table 2.3), we run Hydrus-1D using CH-1978 and R-1982 texture-specific, class-averaged values for four different soil textures (Table 2.1) under varying water table depths. Two different node spacings are used (1.5 cm and 30 cm). In the second set of experiments, the IBIS model and both forms of the G-E-bucket model are individually compared with Hydrus-1D to investigate the role of model differences and complexities in determining the ET response to varying water table depths. Simulations using free-drainage lower boundary conditions are also compared between IBIS and Hydrus-1D.

Since the observational dataset from the wetland field site covers only one growing season (2009), measurements from a long-term meteorological station near Champion, Nebraska (a grassland site) were used to drive the model sensitivity experiments. Mean hourly and daily data were obtained from the High Plains Regional Climate Center (HPRCC) at the University of Nebraska-Lincoln for a 10-year period (1999–2008). The HPRCC station is located approximately 150 km west of the field site at 40°24.00’ N and 101°43.20’ W at an elevation of 1028 m ASL. Measured variables include air temperature, relative humidity, incoming solar radiation, precipitation, and wind speed. Air temperature and net radiation are used to calculate $ET_p$ via the Priestley-Taylor method (for the Hydrus-1D and G-E-bucket models). Net radiation is calculated as 63% of incoming solar radiation (based on a linear regression using data collected at the field site; $r^2 = 0.96$), and 10% of the net radiation is assumed to go into ground heat flux. It should be noted that IBIS is the only model used in this study that explicitly simulates snow or frozen soil processes. Precipitation and soil moisture in the Hydrus-1D and G-E-bucket models, on the other hand, are assumed to be unfrozen, regardless of the time of
year. This simplification is not expected to have a significant impact on the simulated mean annual ET, since the vast majority of the land surface latent heat flux in this mid-latitude location occurs during the warm season.

The vegetation type in all four models is specified as grass (C3 grass for IBIS), with a root depth of 50 cm and a uniform root distribution. It is important to note that differences in root distribution have been shown to influence transpiration rates and groundwater recharge (e.g., Finch, 1998; Small, 2005; Collins and Bras, 2007). Although examining such impacts is beyond the scope of the present study, it would be interesting to include the effects of root distribution in future studies of groundwater-land surface coupling. Similarly, the sensitivity analysis presented in this paper should also be extended to other vegetation types. However, conducting this initial analysis with a shallow-rooted vegetation type is important for laying the groundwork for future studies of groundwater impacts on ET in the presence of more complex root distributions and deep-rooted water uptake.

For the first set of simulations (which involves only Hydrus-1D; Table 2.3), the lower boundary condition was set to a constant pressure head to represent a fixed water table depth. The depth was varied from 100 cm to 1400 cm (in increments of 100 cm). 10-year simulations were run at a daily time step for each of the two node spacings, two soil parameter datasets, four soil textures, and 14 water table depths (i.e., a total of 224 simulations). To minimize the influence of initial soil moisture conditions on the results, a “spin-up” period of 10 years or more was applied to each Hydrus-1D simulation, in which forcing data from the first year (1999) was run for multiple years until the year-end soil moisture profile no longer varied with time. The model was then run at a daily time
step from 1999-2008, and mean annual ET values were calculated from this 10-year average.

In the second set of simulations, a similar experimental design was used to compare the IBIS and G-E-bucket models with Hydrus-1D (see Table 2.3). As before, both the CH-1978 and R-1982 soil parameter datasets were used, and 10-year simulations were performed to calculate the mean annual ET. Both of the G-E-bucket models were run at a daily time step and across the same range of water table depths described above for the Hydrus-1D simulations. The IBIS model, on the other hand, runs at an hourly time step and has a total soil depth of 250 cm (see section 2.2). Thus, an additional set of Hydrus-1D simulations was performed (with an hourly time step, 2.5-cm node spacing, and 250-cm total soil depth), so as to be directly compatible with the IBIS results. Water table depths for the IBIS and Hydrus-1D comparison runs varied across 11 irregularly spaced intervals from 5–225 cm (with finer intervals near the surface), and a free-drainage simulation was also performed for each model. A 5-year spin-up period was applied to the IBIS simulations, while the G-E-bucket models were initialized by setting the soil moisture to field capacity (i.e., no spin-up period was required for the shallow, single-bucket models).

Finally, we note one additional modification to the Hydrus-1D hourly simulations that was implemented in order to provide a more direct comparison with the IBIS simulations, and this involves the calculation of $ET_p$ (and hence, $ET_a$). While Hydrus-1D calculates $ET_a$ based on available water content and prescribed $ET_p$ (which we estimate from the Priestley-Taylor relationship), IBIS calculates $ET_a$ based on the sum of transpiration, intercepted evaporation, and bare soil evaporation (see section 2). Therefore, to ensure
the use of similar atmospheric forcing in both models (i.e., that the \(ET_p\) used in Hydrus-1D is similar to what would be estimated by IBIS), we performed a set of IBIS simulations in which all soil layers were saturated (for all soil texture classes). The IBIS-simulated \(ET_a\) from these “saturated” runs was then used as the \(ET_p\) input for Hydrus-1D (see Table 2.3). (No such adjustment was required for the G-E / Hydrus-1D comparisons, since both models use the Priestley-Taylor method to calculate \(ET_p\)). It was found that the IBIS-estimated mean annual \(ET_p\) for the 10-year period (1052 mm) was only 2% higher than that calculated from the Priestley-Taylor method (1034 mm).

**RESULTS AND DISCUSSION: MODEL SENSITIVITY EXPERIMENTS**

We present the results of the model sensitivity analysis in terms of the ratio of actual to potential ET (i.e. \(ET_a / ET_p\)), where both \(ET_a\) and \(ET_p\) represent 10-year annual mean values. This ratio represents the fraction of atmospheric evaporative demand that is actually utilized for ET. As such, \(ET_a / ET_p\) characterizes the degree of water or energy limitation, with high (low) values of \(ET_a / ET_p\) indicating energy-limited (water-limited) conditions. \(ET_a / ET_p\) can be compared to \(P/ET_p\) (often referred to as the “humidity index;” Porporato et al., 2004), where \(P\) is the annual mean precipitation. Although non-zero surface runoff and/or groundwater recharge would generally imply that \(ET_a / ET_p \leq P/ET_p\) (in the long-term mean), capillary flux from groundwater can often lead to \(ET_a / ET_p \geq P/ET_p\), particularly in dry regions. (Irrigation can also lead to \(ET_a\) rates in excess of \(P\), but this is not something that we examine here.) In the present study, the humidity index at the long-term HPRCC meteorological station was found to be \(P/ET_p = 0.41\). Thus, values of \(ET_a / ET_p\) in excess of 0.41 would be indicative of a groundwater contribution to \(ET_a\), with \(ET_a / ET_p\) approaching 1.0 as the water table reaches the surface. As the water
table depth increases, however, $ET_a/ET_p$ converges toward $P/ET_p$ in this semi-arid climate, resulting in limited runoff or groundwater recharge (Zhang et al., 2008).

Influence of water table depth, soil parameters, and node spacing on $ET_a$

Results of the Hydrus-1D sensitivity analysis are illustrated in Fig. 2.4, which shows the simulated $ET_a/ET_p$ as a function of water table depth for both large and small node spacing, two soil parameter datasets (Table 2.1), and four different soil texture classes. In all cases, we find that $ET_a/ET_p$ is roughly equal to 1.0 for very shallow water tables, but asymptotically approaches $P/ET_p = 0.41$ as the water table depth increases. In a numerical modelling study using a fully coupled groundwater / vadose zone / land surface model, Kollet and Maxwell (2008) described the “critical zone” as the region in which a strong correlation exists between $ET_a/ET_p$ and water table depth, and they found this zone to occur at depths of 100–500 cm in their study area (Oklahoma, USA; generally loam and loamy sand soil textures). The results of Fig. 2.4 generally agree with those of Kollet and Maxwell (2008), but clearly show that the depth and thickness of the modelled critical zones depend strongly on the soil type and (especially) the source from which the texture-specific, class-averaged values are obtained. Among the four soil textures used, silt loam shows the thickest (and deepest) critical zone, while sand shows the thinnest (Fig. 2.4). Clay and silty clay loam tend to exhibit the shallowest critical zone, except when using the R-1982 soil parameter dataset (in which case sand shows the shallowest critical zone).

The critical zones simulated by Hydrus-1D are significantly deeper (for all four soil types) when using the CH-1978 soil parameters instead of the R-1982 parameters. In most cases, the critical zone is also thicker (especially for sand and silt loam). These
results indicate that LSMs that simulate coupled water table dynamics in semi-arid regions are likely to produce more surface ET (for the same water table depth) when using CH-1978 values for a given soil texture rather than the R-1982 values (unless the water table depth is well above or well below both critical zones). This could lead to a negative feedback, whereby the water table elevation declines until surface ET is sufficiently reduced to reach a steady-state water balance. As a result, the simulated water table depth, in the long-term mean, would be deeper in the case of the CH-1978 values. According to Fig. 2.4, this difference in water table depth could be very large (e.g., greater than ~5 m in the case of sand, or ~10 m in the case of silt loam).

Conversely, LSMs that model capillary flux, but with fixed water table depths, are likely to simulate significantly different ET$_a$ values (and root-zone soil moisture), depending on the soil parameter dataset that is used. This difference would be particularly large when the imposed water table depth lies somewhere between the depths of the two critical zones (Fig. 2.4). In our own study, the ET$_a$ simulated by Hydrus-1D is up to a factor of 2.4 larger (i.e., 1.0 / 0.41) when CH-1978 parameters are used instead of R-1982 (e.g., for silt loam at a water table depth of ~700 cm; or sand at a water table depth of ~300 cm). These large differences in ET$_a$ would cause significant discrepancies in the partitioning of available energy into latent and sensible heat flux in LSMs that use fixed water table depths in semi-arid regions. As noted above (and in Fig. 2.4), the discrepancies become significantly minimized only if the water table depth is extremely shallow or if it drops below the deepest of the two critical zones. In the latter case, ET$_a$/ET$_p$ converges to a common value of P/ET$_p$ (for dry climates), regardless of the soil parameter dataset that is chosen. For wetter climates, the asymptotic value of ET$_a$/ET$_p$
would be less than $P/ET_p$ due to the increased partitioning of precipitation into runoff. This would also mean that the different soil parameter simulations would not necessarily converge to the same value (due to the impacts of soil physics on runoff processes). Even for the semi-arid region studied here, we note that some of the asymptotic $ET_a/ET_p$ ratios are slightly lower than $P/ET_p$, showing subtle differences depending on soil texture (e.g., $ET_a/ET_p$ being lowest for sand). Lower values of $ET_a/ET_p$ for coarser soil texture are consistent with other modelling and water balance studies in this region (Wang et al., 2009a, b), as well as studies in other semi-arid locations (e.g. Small, 2005).

Although there are relatively few previous studies that have shown the sensitivities of surface ET to soil hydraulic properties in areas where groundwater is an important contributor to ET, various modelling studies have shown significant uncertainties in simulated groundwater recharge (Schaap and Leij, 1998; Schaap et al., 2001; Wang et al., 2009b). Faust et al. (2006) also examined the effects of chosen pedotransfer functions on the prediction of potential recharge rates and patterns, and they found that different pedotransfer functions can produce up to an order-of-magnitude variation in the total recharge simulated by a basin-scale hydrologic model. Nolan et al. (2007) pointed out that uncertainty in soil hydraulic parameters can also lead to a higher spatial variability in estimated recharge.

The effects of node spacing on the Hydrus-1D-simulated $ET_a/ET_p$ are illustrated in Fig. 2.4 by the vertical “error” bars (i.e., 1.5-cm node spacing for the squares / circles vs. 30-cm node spacing for the thin vertical lines). The results show that the use of a coarser node spacing leads to higher $ET_a$ in all cases, with the difference being largest for water table depths within the critical zone (generally 100–600 cm). In some cases, the
simulated $ET_a/ET_p$ for 30-cm node spacing can be up to 60% larger than that for 1.5-cm spacing (Fig. 2.4), but otherwise the differences are generally small. Associated with the higher $ET_a/ET_p$ is a slight deepening of the simulated critical zone (by ~50–100 cm) when using the 30-cm node spacing. It should be noted that other investigations using the Richards equation (van Dam and Feddes, 2000) have shown that a node spacing of ~5 cm or larger may not correctly estimate evaporation and infiltration, especially in layers close to the surface and with a shallow water table. Nevertheless, the results of the current study show that the use of two widely varying node spacings in Hydrus-1D generally leads to only moderate differences in simulated $ET_a$, except when the water table depth is within the critical zone, in which case the discrepancies can be non-trivial. Even in the latter case, however, the uncertainties due to node spacing are much less than those associated with the choice of soil hydraulic parameters (Fig. 2.4).

**Hydrus-1D / IBIS model comparison**

To investigate the sensitivity of $ET_a/ET_p$ to differences in the numerical solution of the Richards equation (as a function of water table depth), we compare the IBIS and Hydrus-1D model simulations (described in section 2.3 and Table 2.3). As noted earlier, IBIS employs the commonly used, mass-conservative, $\theta$-based form of the Richards equation, while Hydrus-1D uses the mixed $\theta$- and $h$-based form. Both model simulations use identical node spacing (2.5 cm), soil depth (250 cm), and atmospheric forcing (at least in terms of $P$ and IBIS-estimated $ET_p$). The results are shown in Fig. 2.5 for four soil types, 11 water table depths (ranging from 5–225 cm), and both soil parameter datasets (i.e., CH-1978 and R-1982).
In general, IBIS simulates considerably lower $ET_a$ than Hydrus-1D (by up to a factor of three), particularly for intermediate water table depths that are between the models’ two simulated critical zones (Fig. 2.5). Only when the water table is extremely shallow (~5–25 cm) do the models show good agreement (and not surprisingly, considering they use the same $ET_p$). One might also expect both models to converge to a similar value of $ET_a/ET_p$ (equal to $P/ET_p$) when the water table is very deep, as was found in Fig. 2.4 for Hydrus-1D (at depths of ~300–800 cm for R-1982 parameters, or > 1400 cm for CH-1978). However, the shallow soil depth in IBIS (Fig. 2.5) prevents us from determining the precise water table depth at which this might occur. Moreover, some of the asymptotic $ET_a/ET_p$ values for IBIS actually fall well below $P/ET_p$, particularly in the case of sand, which is coarser and allows for greater recharge (Fig. 2.5a). This was also found for Hydrus-1D (Fig. 2.4a), although the effect is more pronounced in the case of IBIS. For additional comparison, Table 2.4 shows results from simulations with no groundwater at all (i.e., using free-drainage lower boundary conditions and R-1982 soil parameters). Without the influence of groundwater, the $ET_a/ET_p$ values in Hydrus-1D fall somewhat below $P/ET_p = 0.41$ and vary slightly by soil texture. IBIS, on the other hand, exhibits even lower values of $ET_a/ET_p$, particularly for sand ($ET_a/ET_p = 0.248$). Thus, there is a tendency for IBIS to simulate lower $ET_a$ than Hydrus-1D (and, therefore, greater surface runoff and/or recharge), with or without the influence of groundwater. (It should also be noted that this conclusion doesn’t change if the free-drainage simulations are run with CH-1978 parameters instead of R-1982.)

In conjunction with the lower values of $ET_a$, IBIS also simulates a shallower critical zone than Hydrus-1D (Fig. 2.5; also alluded to earlier in section 3.2), regardless of which
soil parameter dataset is used. In other words, a shallower water table is needed (in IBIS) in order to simulate the same rate of $ET_a$ as Hydrus-1D (Fig. 2.5). This suggests greater capillary flux and root water uptake in Hydrus-1D, as compared to IBIS (given the same water table depth). (A higher rate of root water uptake could also explain the stronger “no-groundwater” response that was found in the Hydrus-1D-simulated soil moisture shown earlier in Fig. 2.3.) Since surface ET in dry climates (or dry seasons) is often maintained through capillary rise from the water table, this is a critical issue in terms of vegetation dynamics, as well as surface energy, water, and carbon fluxes (Nepstat et al., 1994).

The difference in critical zone depths simulated by IBIS and Hydrus-1D is ~100 cm when using the R-1982 soil parameters (Fig. 2.5), and considerably larger when using CH-1978 values (Figs. 2.4 and 2.5). These model-related differences are comparable to the “uncertainty” in IBIS-simulated critical zone depth that is associated with using different soil parameter datasets (Fig. 2.5). In contrast, Hydrus-1D exhibits a much greater sensitivity to the choice of soil hydraulic parameters (Fig. 2.4), showing differences in critical zone depth of over 1000 cm between R-1982 and CH-1978. These results indicate that resolving issues related to proper soil parameterizations is extremely important and, in some cases, more important than even the choice of which model to use. In terms of critical zone depth, however, IBIS shows considerably less sensitivity to the choice of soil hydraulic parameters than Hydrus-1D.
**Hydrus-1D / G-E-bucket model comparison**

In Fig. 2.6, we examine the sensitivity of simulated $ET_a/ET_p$ to three model formulations: 1) G-E-bucket model-1, 2) G-E-bucket model-2, and 3) Hydrus-1D. Identical soil parameter values and climate forcing are used in both models (Table 2.3), and the water table depths vary from 100–1000 cm (in increments of 100 cm). In general, the models agree well with each other, especially for sand and silty clay loam. The simulated critical zones are similar for the two models (in terms of both depth and thickness), except in the case of clay (with R-1982 soil parameters). The latter scenario shows a thicker critical zone in the Hydrus-1D model (~500 cm) as compared to both of the G-E-bucket models (~250 cm). Another model-related difference that is evident in the clay / R-1982 scenario (Fig. 2.6.d) is the simulation of lower $ET_a/ET_p$ values by Hydrus-1D (as compared to both of the G-E-bucket models) when the water table is shallow (< 200 cm). This pattern reverses for deeper water tables (> 300 cm), where Hydrus-1D instead converges to a higher $ET_a/ET_p$ value than that of the G-E models. The asymptotic value of $ET_a/ET_p$ in Hydrus-1D (for clay) is almost identical to $P/ET_p$, whereas the G-E-model converges to a notably lower value (implying non-zero recharge and/or surface runoff, similar to what was found for IBIS in Fig. 2.5 and Table 2.4).

As was shown earlier for Hydrus-1D, the $ET_a/ET_p$ ratios simulated by both of the G-E-bucket models are very sensitive to the choice of soil hydraulic parameters (R-1982 and CH-1978). In fact, the soil parameter-related differences shown in Fig. 2.6 are much larger than the differences in $ET_a/ET_p$ among the three model simulations. Given the wide range in complexity among all four models examined in this study, this again highlights the importance of using proper soil hydraulic parameters in modelling the response of
surface ET to fluctuations in water table depth (particularly near the critical zone). The results of Fig. 2.6 also suggest that simpler models that are more computationally efficient (such as the G-E-bucket model) can be effectively used to simulate groundwater impacts on ET<sub>a</sub>, so long as the soil hydraulic parameters are properly specified.

**SUMMARY AND CONCLUSIONS**

Soil moisture in the root zone is a critical mediator of land surface-atmosphere interactions and vegetation dynamics. In regions with shallow groundwater, capillary rise from the water table can be a significant source of moisture to the root zone. In this study, we examined the role of different numerical model parameterizations in quantifying the impact of groundwater on root zone soil moisture and ET, as well as model sensitivity to soil texture and water table depth. The four models used in this study are: 1) the Hydrus-1D model (Simunek et al., 2005), 2) the Integrated Biosphere Simulator (IBIS; Foley et al., 1996; Kucharik et al., 2000), and 3-4) two variants of the Gardner-Eagleson (G-E) model that are coupled with a bucket-type soil moisture model using successive steady-state flux conditions. The G-E model offers an analytical solution to calculate a constant rate of capillary flux from the water table to the unsaturated zone under steady-state soil moisture conditions. Model values for soil hydraulic parameters were obtained from two soil texture-based lookup tables that are commonly used by LSMs (Table 2.1), namely the parameter sets of Clapp and Hornberger (1978) and Rawls et al. (1982).

The models were first evaluated using observations from a semi-arid field site in a region with shallow groundwater (located in south-central Nebraska, USA). Root-zone soil moisture and water table fluctuations were measured at the field site for a ~5-month
period during the 2009 growing season. All models compared well with observations when using water table depth as a lower boundary condition and soil hydraulic parameters from Rawls et al. (1982). The simulations worsened considerably under free-drainage boundary conditions (i.e., no groundwater influence). Soil moisture was more accurately simulated in the two G-E models than both Hydrus-1D and IBIS, while IBIS showed the lowest sensitivity to the presence/absence of groundwater. Use of the Clapp and Hornberger (1978) parameter dataset led to significant overestimates of mean soil moisture in all models (but with little change in simulated variability). Sensitivity analysis of the models to water table depth, soil texture, node spacing, and soil parameters revealed several key findings that are summarized below.

Model simulations showed that the depth and thickness of the critical zone, which is the zone of strongest influence of water table on surface ET, is (in most cases) significantly affected by soil texture. The simulated critical zone for silt loam, for example, was found to be much deeper and thicker than that for sand (regardless of model choice or soil parameter dataset). On the other hand, the impact of soil hydraulic parameters on surface ET was generally found to be much larger than that of soil texture. Clapp and Hornberger (1978) soil parameters consistently produced much deeper critical zones than those obtained using the Rawls et al. (1982) parameters. Significant differences in actual evapotranspiration ($ET_a$) were also found (up to a factor of 2.4) as a result of using different soil parameters, particularly when water table depths were located between the two simulated critical zones. Such differences could introduce a significant bias in the partitioning of available energy into latent and sensible heat fluxes in LSMs, as well as errors in predicting water table position in coupled (two-way) land
surface-groundwater models. For very deep water tables or free-drainage conditions (i.e., no influence from groundwater at all), the difference in simulated $ET_a$ between the two soil parameter datasets became much smaller, but not necessarily negligible. Only for extremely shallow water tables did the models converge to identical values of $ET_a$ (equal to $ET_p$). The use of a much larger node spacing in Hydrus-1D (30-cm instead of 1.5-cm) led to a slightly deeper critical zone (by ~50–100 cm) and higher simulated $ET_a$ rates (particularly when the water table depth was within a range of ~100–600 cm). In general, however, the effects of node spacing were found to be significantly less than those related to soil hydraulic parameters.

The Hydrus-1D and IBIS models were used to examine the implications of using different forms of the Richards equation. IBIS uses the $\theta$-based form, while Hydrus-1D solves the mixed $\theta$- and $h$-based form. The two models were found to be in good agreement with each other only in cases of very shallow water table (5-25 cm, depending on soil texture). Moderate agreement was also evident under free-drainage conditions, with IBIS simulating 18–32% lower $ET_a$ than Hydrus-1D (and, therefore, greater recharge). When the water table was near the critical zone, however, there was a much greater difference between the $ET_a$ values predicted by the two models. Regardless of the soil parameters and texture type, Hydrus-1D consistently predicted a higher $ET_a/ET_p$ ratio than IBIS. Especially for sand and clay, the difference was as high as a factor of two to three. This difference would have a major impact on regional energy and water balance predictions. We attribute the disagreement between the two models largely to differences in the form of the Richards equation, since both models used similar forcing, node spacing, and soil parameters. On the other hand, the models’ different formulations for
calculating $ET_a$ could also be leading to some of the discrepancies (despite the use of identical $ET_p$). Finally, we note that IBIS was found to have a lower sensitivity to soil hydraulic parameters than Hydrus-1D. The parameter-related differences in IBIS-simulated $ET_a/ET_p$, however, were by no means negligible (and, in fact, were comparable to the inter-model differences).

The two variants of the G-E-bucket model were also compared to Hydrus-1D and, overall, were found to be in slightly better agreement with Hydrus-1D than IBIS. The models showed good agreement with Hydrus-1D in predicting $ET_a/ET_p$ for most soil textures (especially sand and silty clay loam), although some discrepancies were found when soil parameters from Rawls et al. (1982) were used. In the case of clay, for example, the two G-E-bucket models converged to a lower value of $ET_a/ET_p$ (at deep water table depths) than was simulated by Hydrus-1D (implying greater recharge in the G-E models, as was also found for IBIS). At water table depths less than ~200 cm, however, the G-E-bucket models simulated higher values of $ET_a/ET_p$ (for clay) than Hydrus-1D. Overall, the three-model comparison clearly showed that simulations of surface ET (in the presence of groundwater) are much more sensitive to the choice of soil hydraulic parameters than to the choice of model formulation. As noted above, even IBIS showed a sensitivity to soil hydraulic parameters that was comparable to the inter-model differences in $ET_a/ET_p$. Thus, we conclude that resolving issues related to the parameterization of soil hydraulic properties is of utmost importance, as these parameters were found to play a larger role than other factors such as node spacing, soil texture, or even the choice of model.
It has been previously shown that neglecting the role of groundwater in LSMs may result in significant errors in the surface energy and water balance, especially in areas where the water table is shallow (e.g., Kollet and Maxwell, 2008; Maxwell and Kollet, 2008). We show in this new study that even coupled models may lead to inaccurate results, depending on the choice of soil parameters and solution methods that are used for simulating the interaction between saturated and unsaturated zones. Hence, further studies are needed that integrate field measurements with modelling to better understand and predict the coupling of groundwater with the land surface and overlying atmosphere. Our own study has examined model- and soil parameter-related sensitivities using validation and forcing data from a semi-arid, grassland location. It would be valuable to extend this study to other regions with different climate, land cover, and soil types to assess the universality of the current findings. In particular, field studies which explicitly measure $ET_a$ as a function of water table depth and soil parameters (e.g., using eddy covariance, energy balance, or lysimeter techniques) would be especially useful for testing and validating coupled groundwater-land surface hydrologic models.

**ACKNOWLEDGEMENTS**

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Table 2.1. Soil hydraulic parameters used in the model simulations (see section 2 for variable definitions).

|                | $K_s$ (m/day) | $|h_{we}|$ (cm) | $\phi$   | $b$     | $s_w$ | $s^*$ |
|----------------|---------------|----------------|----------|---------|-------|-------|
| **Clapp and Hornberger (1978)** |               |                |          |         |       |       |
| Sand           | 15.21         | 12.10          | 0.395    | 4.05    | 0.106 | 0.331 |
| Silt Loam      | 0.62          | 78.60          | 0.485    | 5.30    | 0.304 | 0.727 |
| Silty Clay Loam| 0.15          | 35.60          | 0.477    | 7.75    | 0.373 | 0.675 |
| Clay           | 0.11          | 40.60          | 0.482    | 11.40   | 0.522 | 0.782 |
| **Rawls et al. (1982)** |               |                |          |         |       |       |
| Sand           | 5.20          | 7.26           | 0.437    | 1.69    | 0.007 | 0.109 |
| Silt Loam      | 0.16          | 20.76          | 0.501    | 4.74    | 0.214 | 0.567 |
| Silty Clay Loam| 0.04          | 28.08          | 0.471    | 6.62    | 0.356 | 0.713 |
| Clay           | 0.01          | 37.30          | 0.475    | 7.63    | 0.415 | 0.758 |

$^\dagger$ Parameters are calculated using soil water potentials from Laio et al. (2001)
Table 2.2. $B$ values used by Gardner (1958) for determining capillary flux as a function of soil index, $n$ (see Eq. [16]). The analytical solution of Gardner (1958) assumes a completely dry surface, and the $B$ values listed here are similar to those calculated by means of Eq. 17 (which is used in the G-E model).

<table>
<thead>
<tr>
<th>$n$</th>
<th>$B$</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/2</td>
<td>3.77</td>
</tr>
<tr>
<td>2</td>
<td>2.46</td>
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<tr>
<td>3</td>
<td>1.76</td>
</tr>
<tr>
<td>4</td>
<td>1.52</td>
</tr>
</tbody>
</table>
Table 2.3. Model characteristics, boundary conditions, and experimental design for the model-observation evaluation period (i.e., short-term simulations) and the model sensitivity experiments (i.e., long-term simulations). See section 3 for further details.

<table>
<thead>
<tr>
<th>Model</th>
<th>Time Step</th>
<th>Lower Boundary</th>
<th>Upper Boundary</th>
<th>Domain</th>
<th>Soil Depth</th>
<th>Simulation Length</th>
<th>$ET_p$ Calculation</th>
<th>Node Spacing</th>
<th>Soil Parameter Dataset</th>
<th>Water Table Increments</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model evaluation experiments (Short-term simulations; Figure 2.3)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydrus-1D</td>
<td>Hourly</td>
<td>Free drainage or constant pressure head</td>
<td></td>
<td>1-D vertical soil column</td>
<td>250 cm</td>
<td>5 months</td>
<td>Priestley - Taylor</td>
<td>2.5 cm</td>
<td>R-1992</td>
<td>Observed water table depths</td>
</tr>
<tr>
<td>G-E bucket models</td>
<td>Daily</td>
<td>Free drainage or constant capillary flux</td>
<td>1-D vertical soil column</td>
<td>N/A</td>
<td>N/A</td>
<td>5 months</td>
<td>Priestley - Taylor</td>
<td>N/A</td>
<td>R-1992</td>
<td>Observed water table depths</td>
</tr>
<tr>
<td>IBIS</td>
<td>Hourly</td>
<td>Free drainage or constant soil water content</td>
<td>Atmospheric forcing</td>
<td>1-D vertical soil column</td>
<td>250 cm</td>
<td>5 months</td>
<td>N/A</td>
<td>2.5 cm</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Model sensitivity experiments (Long-term simulations; Figures 2.4, 2.5, and 2.6)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydrus-1D</td>
<td>Daily</td>
<td>Constant pressure head</td>
<td>1-D vertical soil column</td>
<td>1500 cm</td>
<td>10 years</td>
<td></td>
<td>Priestley - Taylor</td>
<td>1.5 and 30 cm</td>
<td>R-1982 and CH-1978</td>
<td>1 m</td>
</tr>
<tr>
<td>G-E bucket models</td>
<td>Daily</td>
<td>Constant capillary flux</td>
<td>1-D vertical soil column</td>
<td>N/A</td>
<td>N/A</td>
<td>10 years</td>
<td>Priestley - Taylor</td>
<td>N/A</td>
<td>Variable increments from 5–25 cm</td>
<td></td>
</tr>
<tr>
<td>IBIS</td>
<td>Hourly</td>
<td>Free drainage or constant soil water content</td>
<td>1-D vertical soil column</td>
<td>250 cm</td>
<td>10 years</td>
<td>N/A</td>
<td>2.5 cm</td>
<td></td>
<td>R-1982 and CH-1978</td>
<td>Variable increments from 5–25 cm</td>
</tr>
<tr>
<td>Hydrus-1D</td>
<td>Hourly</td>
<td>Free drainage or constant pressure head</td>
<td>1-D vertical soil column</td>
<td>250 cm</td>
<td>10 years</td>
<td></td>
<td>IBIS $ET_a$ (saturated)</td>
<td>1.5$^a$ or 2.5 cm</td>
<td></td>
<td>1 m$^a$ or variable increments from 5–25 cm</td>
</tr>
</tbody>
</table>

$^a$ The first and second terms refer to comparisons with the G-E bucket and IBIS models, respectively.
Table 2.4. Long-term mean annual $ET_a/ET_p$, as simulated by IBIS and Hydrus-1D in the 10-year model sensitivity experiments (Table 2.3) using free-drainage lower boundary conditions. Soil hydraulic parameters from Rawls et al. (1982) are used in the simulations.

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>IBIS</th>
<th>Hydrus-1D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>0.248</td>
<td>0.365</td>
</tr>
<tr>
<td>Silt Loam</td>
<td>0.326</td>
<td>0.396</td>
</tr>
<tr>
<td>Silty Clay Loam</td>
<td>0.314</td>
<td>0.389</td>
</tr>
<tr>
<td>Clay</td>
<td>0.305</td>
<td>0.378</td>
</tr>
</tbody>
</table>
Figure 2.1 Map showing the location of the piezometers, soil moisture reflectometers, and meteorological station at the wetland field site in the Republican River basin, as well as the location of the HPRCC climate station in Champion, Nebraska.
Figure 2.2. (a) Observed daily precipitation and water table depth for the field site in south-central Nebraska during the 2009 growing season. (b) Daily ETp (calculated from the Priestley-Taylor equation) and “attenuated ETp” for the understory vegetation (based on LAI-reduced net radiation due to overstory vegetation).
Figure 2.3. Observed and simulated depth-averaged soil moisture (i.e., volumetric water content down to 50 cm) for the (a) two G-E bucket models, (b) Hydrus-1D model, and (c) IBIS model during the 2009 model evaluation period (see Table 2.3). Simulation results using free drainage as the lower boundary condition are represented by blue dashed lines. Green dots show the daily mean soil moisture observations from the field site.
Figure 2.4. Long-term mean annual $ET_a/ET_p$ versus water table depth, based on the daily Hydrus-1D 10-year simulations (see Table 2.3). Shown are model results for (a) sand, (b) silt loam, (c) silty clay loam, and (d) clay. Dashed and solid lines indicate model solutions using Clapp and Hornberger (1978) and Rawls et al. (1982) soil parameters, respectively (both with 1.5-cm node spacing). Vertical “error bars” represent solutions using 30-cm node spacing, while empty squares or circles indicate solutions that did not converge using a 30-cm nodal distance. The horizontal, dashed line (in grey) indicates the 10-year mean annual $P/ET_p$ ratio, where $ET_p$ is calculated from the Priestley-Taylor
relationship. Gray shaded and hatched areas represent approximate critical zones for R-1982 and CH-1978 soil parameters, respectively.

Figure 2.5. Same as in Fig. 4, except for hourly Hydrus-1D (black) and IBIS (red) 10-year simulations (see Table 2.3). The node spacing in all simulations is 2.5 cm, and $ET_p$ is calculated based on $ET_a$ from the “saturated” IBIS run.
Figure 2.6. Same as in Fig. 4, except for daily Hydrus-1D (black) and G-E-bucket model (1-blue, 2-yellow) 10-year simulations (see Table 2.3). The node spacing in the Hydrus-1D simulation is 1.5 cm, and $ET_p$ is calculated from the Priestley-Taylor relationship.
Introductory Statement for Chapter 3

In Chapter 2, the impact of groundwater on the surface energy and water balance was examined by exploring the sensitivities to various water table depths, models, and soil hydraulic parameters. Although the depth-to-groundwater was prescribed across a wide range of fixed values (i.e., from the surface to beyond the critical zone), these values were not allowed to vary during the course of the growing season in the model simulations. In other words, the impact of water table depth on land surface processes (e.g., ET) was studied from a “one-way” perspective, without examining fully coupled, two-way interactions (such as the feedback of ET on groundwater levels). In reality, however, ET often has a strong influence on groundwater levels (across a wide range of timescales), especially if phreatophytic vegetation exists in a shallow water table environment and directly consumes groundwater through its roots. In the following chapter, the impact of diurnal variations in ET on groundwater fluctuations is examined by analyzing multiple water level observations at the wetland field site described previously in Chapter 2. These observations are used to develop a new empirical method for estimating daily ET rates more accurately than existing methods that utilize water level hydrographs in areas where groundwater interacts with the vegetation root zone. A modified “saturated specific yield” is also developed to aid in understanding and interpreting ET-groundwater interactions in saturated environments (including conditions with standing water).
CHAPTER 3: ON EVAPOTRANSPIRATION AND SHALLOW GROUNDWATER FLUCTUATIONS: A FOURIER-BASED IMPROVEMENT TO THE WHITE METHOD AND THE ROLE OF SPECIFIC YIELD UNDER SATURATED CONDITIONS

This chapter has been submitted to Water Resources Research

ABSTRACT

Evapotranspiration (ET) is a significant component of the water and energy balance in wetlands and riparian zones, yet it is also one of the most challenging components to estimate. Diurnal water table fluctuations are often used to estimate daily groundwater consumption by phreatophytes, which are typically considered to be one of the major contributors to the total ET in riparian zones. Methods using groundwater hydrographs directly measure plant water consumption and are cost effective, but significant uncertainties often exist, and more accurate techniques continue to be developed. In this study, we propose a new Fourier-based method for calculating groundwater ET consumption using a moving, multi-day sine function to capture robust, diurnal water table fluctuations across daily to seasonal timescales. The technique is tested and calibrated in a *Phragmites australis*-dominated riparian wetland in south-central Nebraska by comparing the results with detailed energy balance estimates of ET (broken down into transpiration and surface water evaporation components). The results show that the new Fourier technique performs significantly better than the commonly used White method, regardless of the size of the multi-day moving window that is applied to each method. In addition, the concept of “saturated” specific yield (in concert with
hydraulic head measurements) is introduced to allow the method to be applied across a
gradient of water table depths (from unsaturated conditions to regions of standing water).
Specific yield estimates at the study site are found to vary significantly in space and time,
responding strongly (and inversely) to temporal variations in water table depth. Spatial
variations in specific yield are weaker, but more complex, showing an increase in specific
yield as groundwater nears the surface, but declining thereafter as one moves into regions
of standing water.

INTRODUCTION

Evapotranspiration (ET) of shallow groundwater is a crucial component of both the
surface and subsurface water balance in riparian systems. Previous studies have shown
that groundwater has a significant effect on the energy and water balance of riparian
zones and wetlands, where groundwater elevates soil moisture and/or ET rates from
phreatophytic plants [Chen and Hu, 2004; Maxwell and Kollet, 2008; Soylu et al., 2011].
Upward capillary flux of groundwater and uptake by phreatophytes result in a significant
increase in latent heat flux, which subsequently modifies other components of the energy
and water balance, as well as land-atmosphere interactions. Understanding the surface
energy and water balance requires proper quantification of ET. However, determining the
amount of groundwater that contributes to surface ET is challenging [Shah et al., 2007;
Martinet et al., 2009]. Riparian zone ET can be estimated by a number of methods such
as lysimeters, isotopic tracers, micrometeorological techniques, water balance residuals,
diurnal water table fluctuations, and sap flow measurements. However, many of these
methods are difficult to implement in areas of phreatophyte plant communities and
groundwater-fed wetlands, particularly in narrow riparian corridors [Loheide et al., 2005; Lautz, 2007].

The primary meteorological driver of ET is solar radiation, which has a pronounced diurnal cycle. In response to ET, shallow groundwater tables also show similar diurnal fluctuations, particularly where significant phreatophyte vegetation is present. Therefore, the main advantage of estimating ET by means of diurnal water table fluctuations is that the water loss due to evapotranspirative water consumption by phreatophytes is directly measured through water level change [White, 1932; Meyboom, 1967; Gerla, 1992; Loheide et al., 2005]. Cost effectiveness and relatively simple numerical calculations are other important advantages of this ET estimation method. Even though this technique has some advantages over other methods, it is hindered by a number of sources of uncertainty. Even the most widely used ET estimation technique that employs diurnal water table fluctuations – the White method [White, 1932] – has undergone numerous modifications due to a variety of uncertainties and deficiencies [e.g. Meyboom, 1965; Engel et al., 2005; Gribovszki et al., 2008; Loheide, 2008], many of which relate to the estimation of specific yield in shallow water table environments [e.g., Loheide et al., 2005; Shah and Ross, 2009].

In the current study, we propose a new groundwater ET estimation method that utilizes a partial (24-hour) Fourier series along a moving, multi-day window to more effectively capture the full diurnal cycle associated with water table fluctuations. This technique is tested and calibrated in a Phragmites australis-dominated riparian wetland in south-central Nebraska (using independent energy balance measurements of evapotranspiration) and is found to perform better than the White method, both on the
“standard” daily timescale and when using a 3-day (or longer) moving average. Application of the new technique requires measurements of diurnal groundwater fluctuations, an estimate of specific yield, and the use of a scaling factor that is largely dependent on the ambient solar cycle at the study site (which can be approximated using clear-sky values). Given the predominantly saturated conditions at our wetland field site, special care is taken to discuss the interpretation of specific yield for this particular type of application, including defining a new “saturated specific yield” and investigating its dependency on depth-to-groundwater. In the following sections, we discuss some of the background and theory for estimating ET from water table fluctuations, followed by a description of the new methodology, an application of the technique to the riparian study site, and a discussion of the results and conclusions.

BACKGROUND AND THEORY: THE WHITE METHOD

As noted earlier, the primary diurnal control on plant water use is solar radiation, particularly in energy-limited regions such as riparian zones. On clear days, incoming shortwave radiation increases rapidly after sunrise, reaches its maximum around midday, and decreases rapidly as sunset approaches. The daytime portion of this diurnal cycle can be significantly modified by the presence of cloud cover, often showing complex temporal patterns. In response to solar radiation, plants transpire water during the day, and the upward flow of groundwater due to plant water consumption is (generally) more rapid than the rate of groundwater recovery, which causes a decline in water table during the daytime [White, 1932]. In addition to solar radiation, of course, there are many other factors that control the rate of riparian ET and associated diurnal water table fluctuations. Soil type, vegetation cover, and other meteorological conditions such as wind speed, air
temperature, and vapor pressure deficit also affect plant water use and the magnitude of diurnal water table fluctuations [Butler et al., 2007; Campbell and Norman, 1998]. At nighttime, however, photosynthesis ceases, thereby halting the transpiration-driven decline in water table, allowing the water level to increase gradually in response to groundwater recovery (a process which is not limited to just the nighttime period). Thus, it is important to note that both plant water use and groundwater recovery contribute to the pattern of diurnal fluctuations in water table depth.

In many shallow groundwater environments, ET from phreatophytic plants is associated with water withdrawals from both the vadose and saturated zones, since the plant root depth generally extends into both regions [Shah and Ross, 2009]. Therefore, total water use by phreatophytic plants – which is fundamentally equal to the transpiration rate \((T)\) – is comprised of ET from the vadose zone and \(ET_G\) [L T\(^{-1}\)], which is the portion of transpiration that is drawn directly from groundwater [Mould, et al., 2010]. It is the latter of these two terms that leads most directly to the observed diurnal fluctuations in water table. Typically, however, vadose zone and groundwater sources of total transpiration are not explicitly distinguished, and so \(T\) is often assumed to be equal to \(ET_G\). For intermediate water table depths, this can sometimes lead to an underestimate of the total transpiration [e.g., for depths of 80–160 cm; Shah and Ross, 2009]. Thus, important modifications to the calculation of specific yield are often required in shallow water table environments in order to correct for the “missing” vadose zone component, leading to complex dependencies of specific yield on depth-to-groundwater [Shah and Ross, 2009]. Taking such modifications into consideration, however, \(ET_G\) and
groundwater recovery lead to a net change in water storage that can be quantified according to the following governing equation [Loheide, 2008]:

\[
S_y \frac{dZ_{wt}}{dt} = r(t) - ET_G(t),
\]

where \( S_y \) is the specific yield [-], \( dZ_{wt}/dt \) is the time rate of change in the height of the water table [L T\(^{-1}\)], and \( r \) is the net groundwater recovery to/from a given area [L T\(^{-1}\)]. (Note that when using the land surface as the datum, the water table “depth” is actually equal to \(-Z_{wt}\), although the terms water table “height, depth, and level” are often used interchangeably.) Equation (1) can be integrated over a time interval, \( \Delta t \) (e.g., one day), to solve for the total accumulated \( ET_G \):

\[
T_{tot} = \int_{\Delta t} ET_G \, dt = \int_{\Delta t} r \, dt - S_y \Delta Z_{wt},
\]

where \( T_{tot} \) is the total transpiration [L] during the time interval \( \Delta t = t - t_0 \) (which is assumed to be short enough that \( S_y \) is constant), and \( \Delta Z_{wt} \) is the observed change in water table height [L] during the same time interval. Note that equation (2) can also be written as:

\[
T_{tot} = \left( \frac{1}{\Delta t} \int_{\Delta t} r \, dt \right) \Delta t + S_y (\bar{r}_{gw} \Delta t + s),
\]

where \( r_{gw} = r/S_y \) is the rate of change in water table depth due solely to the effects of groundwater recovery [L T\(^{-1}\)], \( s = -\Delta Z_{wt} \) is the observed decrease in storage [L] (i.e., increase in depth-to-water-table, positive downward), and the overbar indicates a temporal average over the time period \( \Delta t \). In the rare instance that \( r_{gw} = 0 \) (i.e., no
groundwater recovery), it is evident from equation (3) that the daily total $ET_G (= T_{tot})$ is simply the product of the specific yield, $Sy$, and the daily drop in groundwater storage ($s > 0$).

White [1932] observed diurnal groundwater level changes in Escalante Valley, Utah. He found that the water table fluctuations only existed where the water table was shallow and where the surface was covered with vegetation. White [1932] proposed a method to estimate daily total $ET_G$ (equivalent to $T_{tot}$) from diurnal water table fluctuations using an equation similar to equation (3) [e.g., see Gribovszki et al., 2010]:

$$ET_G = Sy \cdot (24r_{gw} \pm s).$$

(4)

In applying the White method (equation (4)) to estimate 24-hr total $ET_G$, $r_{gw}$ is simply taken to be the hourly rate of water table rise between midnight and 4:00 A.M. (using all available data points within that period), and $s$ is the observed net rise or fall of the water table during the 24-hr period (i.e., $s = |\Delta Z_{wt}|$, and the $+$ or $-$ in equation (4) are used in the case of water table fall or rise, respectively). This methodology, therefore, assumes that the groundwater recovery rate is constant during the 24-hr period and that the interval between midnight and 4:00 A.M. is an appropriate time period for estimating this “constant” rate (i.e., when any influence from ET is likely to be absent). Figure 3.1a illustrates the application of the White method for a sample groundwater time series observed at our field site (described later). An inherent difficulty in applying the White method (and similar techniques) is an accurate determination of the specific yield, $Sy$. It is also possible for the groundwater recovery rate to vary within a 24-hr period. These
and other limitations to the White method have been previously discussed in the literature [e.g., *Healy and Cook*, 2002; *Loheide et al.*, 2005; *Schilling*, 2007].

The primary source of error in estimating $ET_G$ is related to the determination of specific yield [Meyboom, 1965; *Loheide et al.*, 2005; *Shah and Ross*, 2009; *Logsdon et al.*, 2010]. Specific yield is defined as the volume of water released under gravity from storage per unit cross sectional area per unit decline in water table [*Freeze and Cherry*, 1979]. For deep water table environments, the specific yield is often taken to be simply the difference between soil water content at saturation and at field capacity [*Shah and Ross*, 2009]. However, this definition of specific yield is simply a function of the soil or aquifer properties and does not explicitly account for the period of time during which the release of water takes place (i.e., the release time), nor the effect of a shallow water table on vadose zone soil water content. The release of water via gravitational forces can last many years, depending on soil type. Therefore, a modified “readily available specific yield” ($S_y^*$) has been proposed as a more appropriate parameter for providing improved estimates of ET from diurnal water table fluctuations [Meyboom, 1965; *Loheide et al.*, 2005]. $S_y^*$ is lower than $S_y$ and can be described as the volume of water that is released from the vadose zone (per unit drop in water table per unit area) during the time frame of the diurnal fluctuations. Other studies of groundwater fluctuations have accounted for the effects of shallow water table by using the term “apparent specific yield” [e.g. *Duke*, 1972; *Crosbie et al.*, 2005; *Schilling* 2007], which is defined as the “change in soil water storage per unit area per unit change in water table depth.” *Shah and Ross* [2009] refer to this term as “equilibrium specific yield,” noting that it can be calculated as the difference between the saturated water content and the actual water content (within the vadose
zone), and that it is also equivalent to the “depth-compensated specific yield” used by Loheide et al. [2005]. Gerla [1992] proposed yet another approach based on the ratio of water table rise to infiltration. Importantly, Duke [1972], Sophocleous [1985], Healy and Cook [2002], and many of the other studies already mentioned have shown that specific yield is highly variable in shallow water table environments and that it depends not only on soil texture, but also on the water table depth and its rate of change.

As noted above, another potential source of error in the White method is the assumption of a constant 24-hr recovery rate to estimate daily $ET_G$ (equation (4)). In fact, it has been shown that groundwater recovery rates can (and should) vary throughout the course of the day and night [Gribovski et al., 2008; Loheide, 2008], and that this variation can have an impact on subsequent estimates of daily $ET_G$. Perhaps more importantly, the White method’s use of only a short, 4-hour interval to estimate the constant rate of groundwater recovery can lead to large uncertainties. This is due not only to potential temporal variations in recovery rate, but also the fact that measurement errors can be exacerbated by the short observational interval (particularly if groundwater measurements are made at hourly or coarser time scales). These uncertainties are evident in the 4-day example shown in Figure 3.1a, which reveals large day-to-day variations in groundwater recovery estimates, as well as significant hour-to-hour variations in water table depth (which, in turn, affect the accuracy of the 4-hour extrapolation to daily values).

Some studies have recommended modifications to the White method (and/or estimates of specific yield) in order to improve its performance [e.g., Meyboom, 1965; Engel et al., 2005; Loheide et al., 2005; Gribovski et al., 2008], while others have
developed new techniques to estimate $ET_G$ [Loheide, 2008; Schilling, 2007; Czikowsky and Fitzjarrald, 2004]. For example, Meyboom [1965] proposed a correction to the White method and suggested that specific yield should be decreased by 50% in order to avoid overestimation of $ET_G$. Another improvement to the estimation of specific yield was proposed by Loheide et al. [2005], who used a variably saturated, two-dimensional numerical model to investigate the impacts of soil texture, water table depth, and elapsed time of drainage. Loheide et al. [2005] presented a means of estimating the “depth-compensated” readily available specific yield for various soil textures and water table depths. Engel et al. [2005] added a parameter to the White method to account for changes in regional water level, while Gribovski et al. [2008] proposed a method to calculate sub-daily $ET_G$ rates based on variations in groundwater recovery. In another study, Schilling [2007] observed stepwise patterns in water table observations (at corn and grass sites), in which water table declines were found during day time, followed by almost no groundwater recovery during the night. He developed a method to calculate daily and hourly $ET_G$ rates from the stepwise observations. Later, Loheide [2008] extended Schilling’s [2007] method for areas in which groundwater recovery is non-zero during the night. He improved and generalized Schilling’s method to estimate hourly and even sub-hourly $ET_G$. Gribovszki et al. [2010] provide a detailed historical review of $ET_G$ estimation methods that utilize diurnal fluctuations in water table depth (as well as diurnal variations in streamflow).

**IMPROVED METHODOLOGY: A FOURIER APPROACH**

Despite the obvious periodic (and often sinusoidal) nature of diurnal fluctuations in shallow groundwater levels (e.g., Figure 3.1), relatively few studies have employed the
use of Fourier series to examine rates of evapotranspiration. Most of these previous studies have focused on diurnal variations in streamflow \cite[e.g.,][]{Czikowsky2004, Lundquist2002, Bren1997}. For example, \cite{Czikowsky2004} studied diurnal streamflow signals over small watersheds in the eastern U.S. and found that the diurnal variations could be adequately described using a Fourier series methodology. In particular, they applied a partial Fourier series (i.e., a repeating, 24-hr sine curve) to a 3-day moving window of de-trended streamflow data. Various coefficients were calculated by empirically fitting the streamflow data to the following time series function:

\begin{equation}
Z(t) = A \cdot t + D + B \sin \left[ 2\pi \frac{(t + E)}{24} \right],
\end{equation}

where $Z$ is the stream discharge or stage [L], $t$ is time (in units of hours), $A$ is the 3-day trend [L hr$^{-1}$], $D$ is the mean bias [L], $B$ is the diurnal amplitude [L], and $E$ is the diurnal signal phase [hr]. \cite{Czikowsky2004} used this method to quantify daily to seasonal changes in the magnitude of diurnal fluctuations in streamflow. Together with other methods and observations, they used this information to infer seasonal variations in regional ET, such as the changes that occur at the onset of spring (e.g., leaf emergence).

The approach used by \cite{Czikowsky2004} – and as described by equation (5) – is relatively simple to apply and has been found to provide a good characterization of seasonal variations in ET for various watersheds. To our knowledge, however, this method has not been used in conjunction with estimates of specific yield to directly calculate the rate of $\text{ET}_G$ in riparian systems. \cite{Czikowsky2004}, for example, used the magnitude of the diurnal streamflow fluctuations to infer relative
variations in ET (by normalizing the diurnal fluctuations by the daily total streamflow),
but they did not utilize this method to explicitly calculate absolute rates of ET (e.g., in
mm day$^{-1}$).

In the current study, we adopt the “Fourier method” of Czikowsky and Fitzjarrald [2004] and modify it to estimate daily (and longer) ET$_G$ from diurnal fluctuations in shallow groundwater. We then apply the method to field data collected at a riparian wetland site (in south-central Nebraska, USA) and compare the results to those obtained from the White method. The goals of this study, therefore, are to: (1) develop a technique for estimating daily to seasonal ET$_G$ from diurnal water table fluctuations by means of a moving Fourier series, (2) test and calibrate the White and Fourier methods using independent energy balance observations of ET$_G$ from the field site (a process which also leads to estimates of specific yield), (3) compare the relative performance of the White and Fourier methods, and (4) examine the effects of water table depth on specific yield.

Similar to the approach of Czikowsky and Fitzjarrald [2004] – and supported by observations such as Figure 3.1b – we assume that groundwater levels can be properly represented using a multi-day, moving 24-hr sine function, as described by equation (5). By empirically fitting this equation to the observed groundwater levels, the mean bias and trend over the multi-day period are effectively removed, leaving only the main parameter of interest – the diurnal amplitude, $B$. An example of the results of this fitting procedure is shown in Figure 3.1b for a 3-day moving window. In contrast to Czikowsky and Fitzjarrald [2004], however, we do not restrict our study to 3-day periods, but instead apply the method across a variety of window sizes (from 1- to 7-day intervals) to test their relative effectiveness. As such, our analysis does not resolve sub-daily variations in
ET_G, but instead focuses on variations that range across timescales of days to weeks (or longer). There is, of course, a trade-off in utilizing longer or shorter time windows in applying the Fourier method. Larger time windows provide more opportunity for diurnal signal “detection,” but at the expense of not resolving higher frequency variations in ET_G (e.g., daily or less), which are either muted or not detected at all. Smaller time windows, on the other hand, are more effective at resolving day-to-day variability, but have fewer data points with which to detect a robust diurnal amplitude.

In order to apply the Fourier method to the estimation of ET_G, we must first relate equation (5) to the governing equation for shallow groundwater fluctuations (equation (1)). To do this, we start with a time-integrated form of equation (1) (i.e., similar to equation (2)) to relate the height of the water table (Z_wt) to the cumulative effects of groundwater recovery and transpiration (as a function of time):

\[ S_y \Delta Z_{wt} = S_y [Z_{wt}(t) - Z_0] = \sum_{\Delta} [r(t) - ET_G(t)] = r \Delta t - \sum_{\Delta} ET_G(t), \]  

(6)

where Z_0 is an arbitrary initial water level, and we have chosen – at least at this stage – to use the more “general” definition of specific yield, Sy, rather than some of the alternative formulations (for reasons described later). Similar to the White method, equation (6) assumes that the groundwater recovery rate is constant over the time period of interest (\( \Delta t = t - t_0 \)), which has allowed \( r \) to be pulled out of the summation on the right hand side. Although this assumption can potentially be problematic (as noted earlier), we would argue that this drawback is more than made up for by the fact that the Fourier method takes into account the full diurnal cycle (and, in some cases, over multiple days). The White method, on the other hand – while also assuming a constant daily recovery rate –
does so by simply extrapolating to a 24-hr period using a small number of data points over a short, 4-hour interval.

Combining equation (6) with equation (5) by setting \( Z = Z_{wt} \) (and \( t_0 = 0 \)), we arrive at:

\[
Z_{wt}(t) = Z_0 + r_{gw} t - \frac{1}{S_y} \sum_{\Delta t} ET_G(t) = D + A \cdot t + B \sin \left[ \frac{2\pi (t+E)}{24} \right].
\] (7)

At first glance, it might appear from equation (7) that the mean and trend \((D + A \cdot t)\) are entirely accounted for by the initial water level and accumulated groundwater recovery \((Z_0 + r_{gw} t)\). This would leave the cumulative \( ET_G \) term to be associated solely with the sine function on the right hand side – i.e., a diurnal fluctuation in water level with a peak-to-trough “range” of \(2B\). Importantly, however, this is not the case. Rather, the observed water level trend, \( A \cdot t \), actually represents the combined effects of both groundwater recovery and cumulative transpiration. Thus, \( ET_G \) contributes significantly to the trend in water level and, in fact, is responsible for the entire trend when the groundwater recovery rate is zero. As a result, the process of de-trending the water level time series – by removing \((D + A \cdot t)\) in equation (7) (and any associated trend on the left hand side) – actually removes a significant portion of the cumulative \( ET_G \) signal, thereby weakening the diurnal rise and fall that is subsequently observed in the de-trended \( Z_{wt} \) time series (relative to the original \( Z_{wt} \)). The only term on the right hand side of equation (7) that remains after the de-trending process, then, is the aforementioned sine function, with amplitude \( B \) (i.e., peak-to-trough range = \(2B\)). Although this diurnal amplitude is precisely what the Fourier method is intended to measure (which is also why the de-trending procedure is applied in the first place), we demonstrate in the following section
(and Figure 3.2) that simply equating the daily total transpiration to \( Sy(2B) \) results in a significant underestimation of \( ET_G \). This artifact of the de-trending process, however, can be easily corrected through the use of a simple scaling factor, as described below.

**Scaling Factor and Its Estimation**

To illustrate the effects of the de-trending process (as well as groundwater recovery) on the diurnal amplitude, we examine two idealized scenarios in Figure 3.2, which shows the hourly transpiration rate, cumulative \( ET_G \), hypothetical water level (multiplied by specific yield), and de-trended water level time series. The two synthetic water level time series (i.e., \( Sy \cdot Z_{WT} \)) were created from equation (6) by assuming \( Z_0 = 0 \), \( t_0 = 0 \), and \( r = 0.2 \) mm hr\(^{-1}\) (i.e., constant), while applying an \( ET_G(t) \) that varied on an hourly basis but maintained a constant daily rate of 6 mm day\(^{-1}\). These specific numerical values were chosen for the sake of illustration purposes only and do not have an impact on the resulting calculation of the \( ET_G \) “scaling factor,” which depends only on the shape and duration of the diurnal transpiration curve. (In theory, a similar adjustment factor to correct for diurnal variations in groundwater recovery rate, \( r \), could also be introduced, but this is beyond the scope of the current study and is likely to be of less importance than accounting for the overall impacts of de-trending on the diurnal amplitude.)

In both scenarios shown in Figure 3.2, it is clear that the amplitude of the diurnal fluctuations in each of the various time series gets progressively weaker as each step is applied. For example, when a periodic, 12-hr square wave (Figure 3.2a) is used to simulate transpiration (at a maximum rate of 0.5 mm hr\(^{-1}\)), the cumulative \( ET_G \) time series shows a daily range of 6 mm (Figure 3.2c), as would be expected. Ultimately, this is the
parameter that the Fourier method seeks to recover, since it represents the total daily transpiration. However, this daily range is reduced to 3.6 mm when a constant groundwater recovery rate of 0.2 mm hr$^{-1}$ is applied (Figure 3.2e). De-trending the overall time series reduces the diurnal range even further (to $2B = 3$ mm), resulting in a value which is exactly half the original diurnal range of 6 mm. Thus, a “scaling factor” of $k = 2.0$ must be applied to recover the initial $ET_G$ (i.e., the actual daily transpiration). This can be represented by the following simple expression:

$$ET_G = Sy \cdot k(2B).$$

(8)

In fact, it turns out that $k = 2.0$ is the appropriate scaling factor for any 12-hr square wave, regardless of the transpiration rate or constant $r$ value that is chosen (since $r$ is also removed in the de-trending process). Note from equation (8) that one could also simply “absorb” $2k$ into the definition of specific yield, which would create values of $Sy$ that are roughly four times larger than the actual value. Especially given the time-varying nature of the scaling factor, however, we chose to directly account for $k$ so that the artificial “filtering” effects of the de-trending process could be effectively removed. This also allows for a more direct comparison of the calculated $Sy$ values with those from previous studies.

In the second, and more realistic scenario shown in Figure 3.2 (right-hand panels), the hourly transpiration time series was given the same shape as a theoretical clear-sky solar radiation curve (based on the latitude of our field site, but scaled to produce the same daily total $ET_G$ of 6 mm). In this case, the original diurnal amplitude in Figure 3.2d was reduced even further by the de-trending process (Figure 3.2h), resulting in a larger
scaling factor of \( k = 2.12 \). Thus, the magnitude of \( k \) is found to be dependent on the shape (and duration) of the diurnal transpiration curve, which is largely a function of solar radiation (at least during the growing season). To examine the range of potential values that may exist for this scaling factor, we repeated the above process using observed, hourly incoming solar radiation data from our field site (for 2009) to represent the diurnal shape of the \( ET_{G}(t) \) curve. Each day’s hourly solar radiation values were accumulated iteratively over multiple days, then the time series was de-trended, and the scaling factor was calculated. This was repeated for each day of the growing season, and the resulting scaling factors are shown in Figure 3.3. The magnitude of the scaling factor was found to range from a minimum of \( \sim 1.6 \) to a maximum of \( \sim 2.2 \), with a mean value of 1.9. Larger scaling factors tend to occur during days that have a “flatter” diurnal pattern or longer length-of-day (as evidenced by the obvious seasonal cycle, which peaks in late June). The observed scaling factors in Figure 3.3 are used later in the analysis (together with energy budget-derived observations of \( ET_{G} \)) to arrive at estimates of specific yield, based on equation (8).

Since observations of incoming solar radiation may not always be available for applying the Fourier method described here, we also tested the accuracy of simply using an hourly theoretical clear-sky curve to calculate the scaling factor for each day of the growing season. The results are compared with the actual daily values from 2009 (Figure 3.3). As might be expected, the clear-sky scaling factors are generally found to lie along an upper envelope of the observed daily values (roughly 8% higher than the polynomial fit to the observations). Thus, we find that it would be suitable to use scaling factors generated from theoretical clear-sky values, so long as a reduction of \( \sim 8\% \) is applied.
According to Figure 3.3, these “reduced” clear-sky estimates are typically within 10% of the actual daily values, and even a constant, mean scaling factor of 1.9 would be off by no more than ~18% on any given day. The option of using clear-sky values is obviously desirable, since such calculations only require knowledge of the latitude of the field site in question (and day of year). On the other hand, observations of incoming solar radiation also provide additional valuable information (i.e., not only for calculating the daily scaling factor, but also for estimating cloud cover, potential ET, etc.).

**STUDY SITE AND INSTRUMENTATION**

The wetland field site is located roughly 6 km west of Arapahoe, Nebraska (USA) at an elevation of 664 m above sea level (Figure 3.4). The climate of the site is sub humid to semi arid, with a mean annual precipitation of 600 mm. Approximately 80% of the annual precipitation occurs between April and September. Perennial standing water exists in the wetland channel, which is approximately 900 m long and 50 m wide, with a water depth that ranges (seasonally) from approximately 0–60 cm. The wetland receives a limited amount of water from a spring along the western end and occasionally loses water through a narrow channel to the east (but only during periods of high water level). In general, the flow of surface water into or out of the wetland is minimal, as most of the water enters through groundwater discharge and leaves through ET and groundwater recharge [Lenters et al., 2011]. A tall, invasive grass – *P. australis*, or “common reed” (maximum height 4.2 m) – is the dominant vegetation type in the wetland. Some native reeds are also present, as well as small patches of open water (Figure 3.4). The soil in the vicinity of the wetland is classified as a Gibbon soil [fine-silty, mixed, superactive, calcareous, mesic Fluvaquentic Endoaquolls; Soil Survey Staff, 2010].
Instrumentation at the field site includes numerous piezometers (Figure 3.4), water/soil temperature loggers, pressure transducers (for measuring surface and groundwater level), and a meteorological tower for monitoring the surface energy and water balance of the wetland. The tower height is 6.3 m, and it is positioned near the middle of the wetland. Atmospheric measurements include incoming solar radiation, wind speed and direction, precipitation, air temperature and relative humidity, net shortwave and longwave radiation, and barometric pressure. A large aperture scintillometer (LAS) system was also installed in the wetland to measure sensible heat flux. The LAS transmitter and receiver are positioned in such a way that the midpoint of the transect is near the meteorological tower (Figure 3.4). Most measurements were sampled every ten seconds (one second, in the case of the LAS data) and averaged to 10-minute, hourly, and daily means. Data were collected throughout the 2009 growing season (roughly mid April to early October). Additional details regarding the energy balance instrumentation, measurements, and data analysis can be found in Lenters et al. [2011].

The monitoring network for measuring subsurface hydrologic conditions includes five polyvinyl chloride (PVC) piezometers installed at various locations throughout the wetland (Figure 3.4). Each well contains a screen in the lower section that is 20 cm long, with a slot width of 0.2 mm, and the wells were deployed at an average depth of 2.0 m (measured from the upper portion of the screen to the soil surface). The hydraulic head within each piezometer, $h_{WT}$, was measured every 15 minutes using automated pressure transducers (Level TROLL 300, In-Situ, Inc.), and the data were averaged to 1-hour intervals. For the purposes of this study, we use the soil surface as our water level datum.
and convert the hydraulic head measurements to “depth to water table,” $D_{WT} = -h_{WT}$ (see discussion below). Two of the wells were located within the main channel of the wetland (well-1 and well-2; Figure 3.4), where standing water and dense, $P. australis$ vegetation were always present (mean $D_{WT} = -35$ cm; i.e., above ground level; Figure 3.5). The other three wells were deployed in unsaturated conditions (mean $D_{WT} = +60$ cm), with one positioned in the western portion of the wetland (well-3), and the other two located along the north bank (well-4) and south bank (well-5) of the central section of the wetland (Figure 3.4). Hydrographs from all five observation wells show a distinct pattern of diurnal fluctuations in depth-to-groundwater during the 2009 growing season, especially between mid-June and the end of September (Figure 3.5).

**WATER TABLE AND SPECIFIC YIELD UNDER SATURATED CONDITIONS**

It is important to note that the hydraulic head measurements collected in this study (when converted to $D_{WT}$) are similar – but not identical to – conventional depth-to-groundwater observations. Previous studies of diurnal water table fluctuations typically recommend continuous screening of the groundwater wells across the water table interface [e.g., Loheide et al., 2005]. However, continuous screening was not employed at our field site due to the prevalence of saturated conditions and standing water throughout most of the wetland. Especially for the two piezometers located within the wetland channel (which is where most of the $P. australis$ is also present), such screening would simply result in measurements of surface water level, which generally do not reflect a strong diurnal influence from $ET_G$. In fact, when compared with hydraulic head measurements at the various observation wells, the surface water level data exhibited diurnal fluctuations that were lagged in time and had significantly weaker amplitudes.
Short-term trends often showed moderate differences as well. An example of these contrasting temporal patterns is shown in the inset of Figure 3.5, which compares $D_{WT}$ at well-2 with nearby surface water level observations during a brief period in September (with other time periods showing similar behavior). The comparison reveals that diurnal fluctuations in surface water level are almost completely out of phase with measurements at well-2 (which, in contrast, shows an expected pattern of lower hydraulic head at the end of the day, rather than the beginning of the day).

These observations suggest that the transpiration-driven, daytime drawdown of hydraulic head (measured at ~2 m below the soil surface) has a dampened effect on surface water levels, and with a delay of up to half a day. Both of these characteristics can be explained by various factors, including the vertical separation between the piezometers and the water surface, the depth and vertical structure of the plant root system, variations in porosity (including the transition from soil to standing water), and the mean hydraulic conductivity at the field site (~0.73 m day$^{-1}$). (Direct evaporation from surface water, on the other hand, would have limited influence on the diurnal cycle during the growing season, given the high LAI of the $P. australis$ vegetation and subsequent low surface evaporation rates; see next section and Figure 3.6.) Thus, although hydraulic head and water table elevation are, on average, nearly identical for piezometers positioned so close to the water table, it is important to note the distinction between these two types of measurements. As noted above, this distinction becomes particularly critical when the water table is actually above ground level, since short-term fluctuations can differ considerably between the two types of observations. The distinction can also be important for interpreting mean $D_{WT}$ when the vertical separation
between the water table elevation and piezometer depth grows large. Although this was generally not the case at our field site (maximum separation of ~2.5 m), it is nevertheless a factor that should not be overlooked (e.g., when comparing results among the different observation wells). It should also be noted that – despite slight variations in surface elevation – each of the wells was deployed at roughly the same depth relative to the mean water table (ranging from ~1.6 to 2.1 m).

To our knowledge, previous studies of the impacts of $ET_G$ on diurnal fluctuations in water table have not been applied to situations where the water table is actually above ground level. This is important to note for two reasons. First of all, it means that we are not only testing a new methodology (i.e., the Fourier method, as compared to the White method), but we are also applying it to measurements of hydraulic head (due to the saturated conditions at our field site), rather than the more traditional depth-to-water-table (a subtle, but important difference). Thus, this is a rather unique application of the two methods and requires some “validation” in its own right. Secondly, because of the absence of a vadose zone at two of the five observation wells (and the fact that all five wells are screened below the water table), traditional interpretations of specific yield do not apply here – regardless of the form of $Sy$ that is used (e.g., apparent $Sy$, readily available $Sy^*$, etc.). Although Loheide et al. [2005] indicate that the concept of specific yield is “not valid” under saturated conditions, this is largely because $Sy^*$ is defined in terms of the release of soil water from the vadose zone and, hence, the change in soil water content (which would be zero under continuously saturated conditions). Instead, to deal with high water table environments (both saturated and unsaturated), we simply define a new “saturated specific yield,” $Sy_{sats}$ that is then used throughout the remainder
of this study. $S_{ysat}$ is defined here as “the volume of water withdrawn from the soil per unit cross sectional area per unit decline in hydraulic head, with the latter being measured at a known depth within the saturated zone.”

The primary distinction in this new definition of saturated specific yield (as compared to the standard definitions of $S_y$ or $S_y^*$) is that the “volume of water withdrawn,” according to $S_{ysat}$, is not dependent on any observed change in soil water content, but rather on the actual volume of water removed (in total) from the vadose and saturated zones (e.g., as driven by transpiration or artificial pumping). Note that this new definition of specific yield also results in $S_{ysat}$ being dependent on the depth at which the hydraulic head is measured – not because of variations in soil texture (although this may also play a role), but primarily because fluctuations in head generally become less responsive to $ET_G$ as the piezometer depth increases beyond the root zone (even though $ET_G$ itself may not be changing). This is similar to the concept of “water table extinction depth,” which has been described in previous studies [e.g., Shah et al., 2007]. Thus, if multiple observation wells are to be used to estimate a single value of $S_{ysat}$, it is important to place the piezometers at a consistent depth (and one that is both shallow, but still within the saturated zone). Alternatively, if the screen depths vary considerably, one can calculate a separate value of $S_{ysat}$ for each observation well. Finally, we note that defining a new “saturated” specific yield does not eliminate its dependency on temporal (or spatial) variations in depth-to-water-table (or, equivalently, hydraulic head) – similar to what has been discussed in previous studies regarding variations in equilibrium specific yield under shallow water table conditions [Loheide et al., 2005; Shah and Ross, 2009]. More specifically, since the concept of $S_{ysat}$ can be applied across both the saturated and vadose
zones (with the latter having variable soil water content), and since other factors continue to play a role as well (such as vertical variations in soil texture and/or root distribution), saturated specific yield will – like other forms of $Sy$ – continue to be dependent on changes in groundwater depth. This issue is carefully examined in later sections, after first applying the Fourier method to our field site by using energy balance measurements of $ET_G$ to arrive at estimates of $Sy_{sat}$.

RESULTS

Energy balance estimates of $ET_G$

Estimates of transpiration from the $P. australis$ vegetation (assumed equal to $ET_G$) were derived from energy balance measurements of the total ET (minus surface water evaporation). As described in greater detail by Lenters et al. (2011), data from the meteorological station and LAS were used to calculate the total rate of ET from the wetland (i.e. latent heat flux) as a residual from the energy balance, which can be written as:

$$\lambda(ET_{tot}) = R_n - H - \frac{\Delta S}{\Delta t},$$  \hspace{1cm} (9)

where $R_n$ is net radiation, $ET_{tot}$ [m s$^{-1}$] is the overall (i.e., “total”) wetland ET rate, $\lambda$ is the volumetric latent heat of vaporization [J m$^{-3}$], $H$ is sensible heat flux (measured directly from the LAS), and $\Delta S/\Delta t$ is the total rate of the heat storage in the wetland (including the water, soil, and vegetation). Each of the four terms in equation (9) is in units of W m$^{-2}$. The heat storage rate in the wetland was measured using multiple temperature sensors at
various heights throughout the canopy, water, and soil columns. Careful quality control and uncertainty analyses were undertaken to minimize errors and assess data uncertainty associated with the energy budget-derived ET estimates [as described by Lenters et al., 2011]. This earlier work has also shown that the LAS used in this study tends to overestimate sensible heat flux by ~7% in comparison with eddy covariance measurements. Therefore, the sensible heat flux values used in equation (9) were reduced by 7% from the original observations of Lenters et al. [2011].

The total ET in equation (9) can be broken down into its various components, which includes transpiration ($ET_G$), open water evaporation ($E_{ow}$), intercepted water evaporation ($E_{int}$), evaporation from water beneath the canopy ($E_{cw}$), and soil water evaporation from the unsaturated zone ($E_{unsat}$). Observations from the study site indicate that standing water was present throughout most of the wetland during the vast majority of the 2009 season. Thus, the soil was generally 100% saturated or – at most – had a very limited vadose zone (e.g., near the banks; Figure 3.5), indicating that $E_{unsat}$ can be ignored as an important contributor to the total ET. Intercepted evaporation ($E_{int}$) is also assumed to be negligible due to the relatively infrequent and short duration of precipitation events. However, given the significant amount of standing water in the wetland – both beneath the vegetation and exposed to the open air – neither of the surface water evaporation terms can be ignored ($E_{ow}$ and $E_{cw}$). Therefore, we separated $ET_{tot}$ into three components according to the surface area occupied by each component:

$$A_{tot} ET_{tot} = A_{ow} E_{ow} + A_{cw} E_{cw} + T_{tot},$$

(10)
where $A_{tot}$ [m$^2$] is the total area contributing to the energy balance-derived ET (i.e., roughly the “footprint” of the LAS and meteorological station), $A_{ow}$ is the area of open water contained within that footprint, $A_{cw}$ is the area of the standing water beneath the vegetation canopy, and $T_{tot} = A_{tot}ET_G$ is the transpiration rate [m$^3$ s$^{-1}$], expressed as a volumetric flux of water through the stems of the $P. australis$ vegetation. Dividing both sides of equation (10) by $A_{tot}$ and solving for $ET_G$, we get:

$$ET_G = ET_{tot} - f_{ow}E_{ow} - f_{cw}E_{cw},$$  

(11)

where $f_{ow}$ and $f_{cw}$ are the fractions of the wetland area occupied by open water and “under-canopy” water, respectively. Open water occupies approximately 9% of the total wetland area [Lenters et al., 2011], but the fractional coverage is much lower ($f_{ow} = 0.03$) in the portion of the wetland that lies within the footprint of the LAS (Figure 3.4). The remaining 97% of the wetland surface is comprised of standing water beneath the canopy ($f_{cw} = 0.91$) and stems protruding from the water (which account for ~6% of the surface area). (Note that the flux of water through the stems contributes to the transpiration term, $ET_G$, not to $E_{ow}$ or $E_{cw}$.)

Both $E_{ow}$ and $E_{cw}$ were determined using the Bowen ratio energy balance (BREB) method, which expresses the evaporation rate as:

$$E_{ow} = \frac{R_n - \Delta S_{ws}/\Delta t}{\lambda(1 + \beta_{ow})},$$  

(12a)

and

$$E_{cw} = \frac{R_n - \Delta S_{ws}/\Delta t}{\lambda(1 + \beta_{cw})},$$  

(12b)
where $R_{nc}$ is the canopy-attenuated net radiation (i.e., the portion that makes it to the water surface), $\Delta S_{es}/\Delta t$ is the rate of heat storage in the water and underlying soil, and $\beta$ is the Bowen ratio ($\beta = H/\lambda E$), which is calculated according to:

$$\beta_{ow} = \frac{\gamma(T_{ow} - T_{oa})}{(e_{sw} - e_{oa})}$$  \hfill (13a)$$

and

$$\beta_{cw} = \frac{\gamma(T_{cw} - T_{ca})}{(e_{sw} - e_{ca})},$$  \hfill (13b)$$

where $\gamma$ is the psychrometric constant, $T$ is temperature, $es$ is saturation vapor pressure, and $e$ is vapor pressure. The subscripts “ow” and “oa” refer to measurements taken at the open-water surface and open-air height (4.1 m), respectively, while “cw” and “ca” refer to the under-canopy water surface and within-canopy air height (2.2 m), respectively. The canopy-attenuated net radiation is calculated according to Beer’s law:

$$R_{nc} = R_n \exp(-k_{ext} LAI),$$  \hfill (14)$$

where $k_{ext} = 0.6$ is the extinction coefficient (based on estimates for $P. australis$ from Burba et al., 1999), and $LAI$ is the leaf area index (measured at the site).

Figure 3.6 shows the final estimates of $ET_G$ (on a 3-day running mean timescale), along with the total ET and surface water components for the 2009 growing season. Around the time of leaf emergence (April 20; Cutrell, 2010), transpiration from the $P. australis$ was negligible and did not first rise above zero until April 22 – when total ET was roughly 2 mm day$^{-1}$ (and, therefore, comprised entirely of evaporation from surface
water). By early to mid May, $ET_G$ rates had increased to become comparable to $E_{cw}$ (Figure 3.6), although open-water evaporation rates were still much higher ($E_{ow} \approx 5 \text{ mm day}^{-1}$). Continued plant growth and increases in LAI eventually led to significant attenuation of incoming radiation by early to mid June, accompanied by reductions in “under-canopy” $E_{cw}$ to generally less than 1 mm day$^{-1}$. Open-water evaporation rates remained high throughout the summer (up to $\sim8$ mm day$^{-1}$), but did not contribute significantly to the total ET due to the small fraction of open-water area (3%). The end result, then, is that transpiration rates ($ET_G$) were much lower than the total ET during the early part of the season (e.g., $\sim20–50\%$ lower during May) but were only slightly lower ($\sim5–20\%$) from about mid-June onward (Figure 3.6). As described below, these $ET_G$ observations were then combined with measurements of diurnal fluctuations in $D_{WT}$ at the various observation wells to arrive at estimates of saturated specific yield.

*Specific yield calculations*

Earlier in this study, we discussed the challenges of determining specific yield in shallow-water-table environments, and we noted the adoption of a new parameter, $Sy_{sat}$, to account for the (largely) saturated conditions at our field site. Along with the high degree of saturation and significant amount of standing water, the depth to water table, $D_{WT}$ (and associated hydraulic head), is quite variable throughout the 2009 growing season (Figure 3.5). Thus, we do not assume $Sy_{sat}$ to be constant, but rather, we explicitly investigate its dependency on $D_{WT}$. To calculate $Sy_{sat}$ at our field site, we used both the White and Fourier methods (equations (4) and (8), respectively) to solve for specific yield:
\[ Sy_{sat} = \frac{ET_G}{(24r_{gw} \pm s)} \] (15a)

and

\[ Sy_{sat} = \frac{ET_G}{k(2B)} \] , (15b)

where \( ET_G \) values were obtained by partitioning the total wetland ET using the BREB method (as described in the previous section). Data from each of the five observation wells were used to create plots of daily \( Sy_{sat} \) versus \( D_{WT} \) for both the White method (Figure 3.7a) and the Fourier method (Figure 3.7b), with the latter technique also being applied across a variety of moving windows (i.e., 3-, 5-, and 7-days; Figures 3.7c-e). The plots in Figure 3.7 not only illustrate the dependency of \( Sy_{sat} \) on water table depth, but they also provide insights into the performance of the different methods (e.g., as determined by the degree of scatter in the data). The results of Figure 3.7 are discussed below.

As noted earlier, we analyzed diurnal fluctuations in the observed hydrographs (Figure 3.5) during the main portion of the growing season (June 15–September 30, 2009), which is when the hourly variations in water table were most pronounced. It is clear from Figure 3.5 that the observed diurnal fluctuations increase in amplitude as the season progresses (during which time the depth-to-water-table also increases by \( \sim 40–80 \) cm). As described by equation (8), this increase in diurnal amplitude (i.e., \( 2B \)) is indicative of either an increase in \( ET_G \) and/or a decrease in \( Sy_{sat} \) (with the scaling factor, \( k \), playing a more limited role; Figure 3.3). Clearly \( ET_G \) by itself cannot explain the seasonal increase in diurnal water table fluctuations, since transpiration is declining during this time (Figure 3.6), primarily in response to decreases in incoming solar
radiation (Figure 3.3). Rather, the relationship between water table depth and the amplitude of the diurnal fluctuations mainly stems from changes in $S_y_{sat}$ (calculated according to equation (15) and plotted in Figure 3.7 as a function of $D_{WT}$). As illustrated in Figures 3.7a and 3.7b, both the White and Fourier methods yield similar values of $S_y_{sat}$, ranging from ~0.04 (for deep water tables) to ~0.4 (for shallow water tables), with a few outliers beyond these bounds. Both methods also display an inverse, exponential relationship between daily values of $S_y_{sat}$ and $D_{WT}$ (at each of the five observation wells). These results indicates that – during periods of high water table – transpiration withdraws more soil water from storage than would be expected from the otherwise limited diurnal fluctuations in water table (e.g., early in the season; Figure 3.5). Conversely, when the water table deepens, $S_y_{sat}$ becomes smaller (Figure 3.7) and $ET_G$ decreases, despite the larger observed diurnal fluctuations in water table depth (Figure 3.5).

The exponential relationship between $S_y_{sat}$ and water table depth (Figure 3.7) can be expressed as follows:

$$S_y_{sat} = a \cdot e^{-b \cdot D_{WT}},$$

where $a$ and $b$ are empirical coefficients determined individually for each observation well (based on the regressions between $S_y_{sat}$ and $D_{WT}$, and listed in Figure 3.7). The functional relationship is especially strong in the case of the Fourier method (Figure 3.7b), which shows considerably less scatter than the White method (Figure 3.7a), and the regression is improved even further when the size of the Fourier window is increased to 3-, 5-, and 7-day moving windows (Figures 3.7b-e). There are, however, “diminishing returns” as one expands the Fourier method beyond the 5-day timescale (presumably due
to trade-offs between sample size and temporal “smoothing”). Thus, we conclude that the Fourier technique performs best when 3-day and (especially) 5-day moving windows are applied.

Although equation (16) provides a convenient means of estimating $S_{y_{sat}}$ at our field site (based on depth-to-water-table), a drawback of the approach is that the empirical coefficients in Figure 3.7 are determined individually for each observation well. As mentioned earlier in the discussion of saturation specific yield, however, a “well-by-well” calibration was noted as a likely necessity if there were variations in piezometer depth (and associated hydraulic head) amongst the various wells. The five observation wells at our field site were deployed at a depth of ~2.0 m below the soil surface (ranging from 1.63 m for well-1 to 2.45 m for well-5), and this variation of ~0.8 m becomes 40% smaller if the piezometer depth, $D_p$, is calculated relative to the seasonal-mean water table depth, $D_{WT}$ (ranging from $D_p = 1.59$ m for well-3 to $D_p = 2.10$ m for well-2). However, the mean water table itself is slightly more variable – ranging from $D_{WT} = -0.43$ m at well-1 (i.e., standing water) to $D_{WT} = +0.74$ m at well-5 (i.e., a variation of ~1.2 m). These differences in $D_{WT}$ are readily apparent from the separation of curves in Figure 3.7. Temporal deviations in water table depth ($D_{WT}' = \pm 0.3$ m; Figure 3.5) contribute even further to the overall variability in $D_{WT} = D_{WT} + D_{WT}'$ (total range in water table depth of ~1.7 m; Figure 3.7). Thus, some of the well-to-well variations in regression coefficients ($a$ and $b$; equation (16)) could, indeed, be due to differences in seasonal mean water table depth at the various wells, with temporal changes in $D_{WT}$ contributing even further to variations in saturated specific yield (equation (16)).
Figure 3.7 shows that the empirical coefficients do, in fact, vary rather systematically from one well to another (particularly in the case of the Fourier method), and that this variation is largely a function of $\bar{D}_{WT}$. For example, the parameter $b$ (i.e., the slope of the lines in Figure 3.7) becomes progressively more negative as the mean depth-to-water-table increases. This indicates a stronger (weaker) sensitivity of $S_{Y_{sat}}$ to varying water table depth when the mean water table is deep (shallow). Similarly, the parameter $a$ (i.e., the “intercept” of the lines in Figure 3.7) also shows a systematic progression from one well to the next. These patterns are further illustrated in Figure 3.8, which shows both of the empirical parameters in equation (16) as a function of $\bar{D}_{WT}$ (i.e., for each of the five observation wells, based on the 5-day Fourier results from Figure 3.7d). The slope parameter ($b$) is found to vary roughly linearly with mean water table depth ($r^2 = 0.87$), while the intercept ($a$) shows a stronger, exponential relationship ($r^2 = 0.99$). Combining the regression equations in Figure 3.8 with that of equation (16), we arrive at a more general empirical relationship for estimating $S_{Y_{sat}}$ as a function of water table depth:

$$S_{Y_{sat}} = 0.240e^{-D_{WT}(2.43+1.15\bar{D}_{WT})+2.82\bar{D}_{WT}},$$

(17)

where both $D_{WT}$ and $\bar{D}_{WT}$ are in units of meters. Unlike equation (16), equation (17) does not require the use of different regression coefficients for each observation well at the field site, but instead simply uses 5-day ($D_{WT} = \bar{D}_{WT} + D_{WT}'$) and seasonal-mean ($\bar{D}_{WT}$) measurements of depth-to-water-table. Clearly, equation (17) still includes empirical coefficients that are specific to the field site in question. Nevertheless, this convenient functional relationship provides a useful framework for describing the dependency of $S_{Y_{sat}}$ on depth-to-groundwater for the shallow water table environment examined in this
study (see discussion section and Figure 3.12). It may also prove to be of significant utility (albeit with different empirical parameters) at other field sites that utilize multiple observation wells across a gradient of water table depths, particularly in saturated environments with time-varying depth-to-groundwater.

Evaluation of $ET_G$ estimates

Final estimates of $ET_G$ were determined from the observed diurnal water table fluctuations (Figure 3.5) using the White and Fourier methods (equations (4) and (8), respectively). $S_y_{sat}$ was calculated individually for each observation well (using equation (16) and the empirical coefficients from Figure 3.7), and then the five $ET_G$ estimates from each well were averaged together to create an overall time series of the “mean wetland” transpiration rate. Four time series were created using the Fourier method (using 1-, 3-, 5-, and 7-day moving windows), while two time series were created using the White method (i.e., the standard, daily method and – for comparison purposes – a 3-day moving average). Figure 3.9 shows a comparison of each of these six estimates with the observed $ET_G$ values derived from the BREB measurements. In addition to the “mean wetland” $ET_G$ values shown in Figure 3.9 (i.e., the red squares), we also show the individual $ET_G$ estimates from each of the five observation wells (i.e., the gray dots).

The results clearly show that the Fourier method performs significantly better than the White method, regardless of the size of the moving window that is applied. For example, comparisons of estimated and observed $ET_G$ values using the White method yield $r^2$ values of 0.14 and 0.39 for daily (Figure 3.9a) and 3-day (Figure 3.9b) timescales, respectively. The Fourier method, on the other hand, yields higher $r^2$ values of 0.47
(Figure 3.9c) and 0.62 (Figure 3.9d), respectively, and with lower RMSE values (1.77 and 1.16 mm) than the White method (2.65 and 1.69 mm). Use of a 5-day moving Fourier window shows the best correspondence with observed $ET_G$ values ($r^2 = 0.68$; RMSE = 0.98 mm; Figure 3.9e), while a larger window size of seven days results in a slightly poorer correspondence ($r^2 = 0.65$; RMSE = 0.99 mm; Figure 3.9f). Czikowsky and Fitzjarrald [2004] indicated in their study of diurnal streamflow fluctuations that the optimal window length is dependent on the regional climate, and they chose a 3-day running mean timescale for the eastern U.S. Our own results suggest that the optimal window length for estimating $ET_G$ in our study domain is five days, which is also consistent with the timescale of synoptic weather variability in this region. It should also be noted that when we applied a 5-day running mean to the 1-day Fourier $ET_G$ values, the overall comparison with observations over the 2009 season ($r^2 = 0.71$; RMSE = 1.01 mm) was comparable to that of the 5-day moving window results noted above. However, some of the short-term anomalies (relative to observations) tended to be more exaggerated. Thus, we conclude that the use of a broader Fourier window appears to be slightly more effective at calculating 5-day $ET_G$ values, rather than applying an “after-the-fact” moving average to 1-day $ET_G$ estimates.

To test the performance of the 5-day Fourier method using the more “general” expression for specific yield, we applied equation (17) to each of the five observation wells and compared the various $ET_G$ estimates (and the 5-well average) with the BREB-derived measurements of $ET_G$ (Figure 3.10). We find that the mean wetland $ET_G$ estimates compare very well with observations ($r^2 = 0.68$; RMSE = 1.01 mm) – comparable, in fact, to the accuracy obtained when calculating separate regression
coefficients for $S_{\text{ysat}}$ at each of the five observation wells (equation (16)), and then averaging the $ET_G$ values to form a “grand mean” (Figure 3.9e). However, it is also evident that the individual $ET_G$ estimates at specific wells are – in general – more poorly estimated when calculating $S_{\text{ysat}}$ from equation (17) rather than equation (16) (i.e., compare the gray dots in Figure 3.10 with those in Figure 3.9e). There is a tendency, for example, for transpiration rates to be overestimated when observed $ET_G$ rates exceed ~4.5 mm day$^{-1}$ (Figure 3.9e), and this discrepancy is even more prevalent when using the general form for $S_{\text{ysat}}$ (Figure 3.10). On the other hand, some of the $ET_G$ estimates at individual wells – even when using equation (17) – are actually found to correspond closely with observations (e.g., $r^2 = 0.72$ and RMSE = 0.97 mm for well-1; not shown).

Thus, we conclude that the more general formulation for $S_{\text{ysat}}$ – while appropriate for calculating average $ET_G$ across multiple observation wells – can vary greatly in its accuracy when applied to individual observation wells ($r^2 = 0.28$–0.72; RMSE = 0.97–1.61 mm).

Finally, to illustrate the temporal variability in $ET_G$ derived from the Fourier and White methods, Figure 3.11 shows time series of the predicted and observed 5-day $ET_G$ rates for the 2009 season. Fourier-based $ET_G$ values are shown using both formulations of $S_{\text{ysat}}$ (i.e., equations (16) and (17)), while the White method $ET_G$ values were first calculated on a daily basis (Figure 3.7a), but then averaged to a 5-day running mean to be consistent with the other three time series. Both the White and Fourier methods are found to capture the seasonal variability in $ET_G$ reasonably well, peaking in late June and declining through late September. The temporal correspondence with observed $ET_G$ is also very reasonable on shorter timescales, particularly in the case of the Fourier method.
There is a tendency, however, for the variability in $ET_G$ to be somewhat “exaggerated” by the diurnal fluctuations in water table, with larger maximums and smaller minimums than the observed $ET_G$ (Figure 3.11). These discrepancies are especially large in the case of the White method. And as might be expected from the results of Figure 3.10, the choice of whether to use equation (16) or (17) to calculate $S_{y_{sat}}$ is found to have little impact on the Fourier-based estimates of the “mean wetland” $ET_G$ (i.e., averaged across all five observation wells).

**DISCUSSION**

*Comparison of $ET_G$ methods*

The results of Figures 3.7–11 indicate that the Fourier method can be used as an improved alternative to the “standard White method” in estimating $ET_G$ from water table fluctuations. This conclusion holds true even if a multi-day moving window is used in both cases (with five days being determined as the “optimal” timescale for applying the Fourier method – at least for the field site in this study). The advantage of the 5-day moving window is that it allows one to sample over multiple diurnal periods and can overcome other difficulties often associated with measurements of water table depth (e.g., coarse sampling intervals or high-frequency noise). Similar to the White method, the Fourier technique is relatively easy to apply and requires only groundwater level observations, estimates of specific yield, and a local “scaling factor,” $k$, which can be estimated from observed (or theoretical clear-sky) solar radiation values.
Effect of water table depth on specific yield

The dependence of specific yield on water table depth has been previously analyzed in field observations [Schilling, 2007; Mould et al., 2010] and modeling studies [Duke, 1972; Loheide et al., 2005]. In general these two quantities have been found to show a close relationship, with $Sy$ typically decreasing as the water table rises. For example, Loheide et al. [2005] presented a graph of depth-compensated specific yield (based on an equilibrium equation), which shows a dramatic drop in $Sy$ as the water table depth decreases from 1 to 0 m. This behavior can be explained in terms of the reduction in available pore space within the vadose zone, which becomes thinner and more saturated as the water table rises. Schilling [2007] and Mould et al. [2010] provide field-based examples of variations in $Sy$ that show similar relationships to the model-based studies.

Unlike these previous studies, however, Logsdon et al. [2010] observed an inverse relationship between $Sy$ and $D_{WT}$ at certain depths, with $Sy$ decreasing from ~0.45 to 0.10 as the water table depth increased from 0.9 m to 1.3 m (and as $D_{WT}$ decreased from 0.9 m to 0.7 m). This relationship is similar to the findings that we presented earlier in Figure 3.7. Logsdon et al. [2010] also note that their field conditions violated the assumptions of the equation for depth-compensated specific yield reported by Loheide et al. [2005], such that the soil profile was not approaching equilibrium, and that transpiration was responsible for most of the water loss (rather than lateral drainage). Similar to the field conditions of Logsdon et al. [2010], our own study site is quite different from the environment described by Loheide et al. [2005], as water levels were either shallow or above ground level, resulting in a limited or absent unsaturated zone. An inverse relationship between $Sy$ and water table depth was also found in a modeling study by
Shah and Ross [2009], in which maximum simulated $Sy$ values (of ~0.3–0.4) occurred at water table depths of ~0.8–1.2 m [with lower values of $Sy$ as the water table deviated from this “optimal” depth, similar to Logsdon et al., 2010]. Shah and Ross [2009] showed that – under drying conditions (i.e., ET stress) – this augmented specific yield (at water table depths of ~1 m) was explained by enhanced contributions to $ET_G$ from non-groundwater storage (i.e., the vadose zone). Such behavior could also explain the increase in $Sy_{sat}$ observed at our own field site (with decreasing $D_{WT}$; Figure 3.7), at least for the observation wells that have a well-defined unsaturated zone.

Finally, we note that while other investigations have – in contrast to the current study – observed reduced diurnal groundwater fluctuations in conjunction with increases in depth-to-water-table [e.g., Butler et al., 2007], the reduction in diurnal amplitude found by Butler et al. [2007] was not attributed to increases in specific yield. Rather, they concluded that as the water table declined, fewer roots were able to utilize the available groundwater, such that after the maximum root depth was reached, no fluctuations were detected. This explanation relates to the concept of extinction depth, which is defined as the water table depth at which the fraction of ET contributed by groundwater becomes zero [Shah et al., 2007]. At our own wetland study site, the P. australis vegetation is located in a region of very shallow water table (and even standing water) throughout the growing season. Therefore, any relationships between diurnal water table fluctuations and temporal variations in depth-to-water-table are not likely to be related to extinction depth at the wetland field site. On the other hand, the use of piezometers that are not screened across the water table (i.e., hydraulic head, instead of water table depth), could potentially
lead to some impacts of root distribution, depending on the depths of the various piezometers (relative to each other and to the root depth of the *P. australis* vegetation).

Clearly the issue of shallow water table effects on specific yield is a complex one. Some of the studies referenced above imply the existence of a “peak” in specific yield at intermediate water table depths. None of these studies, however, have attempted to extend the results to conditions in which the water table is above the surface, partly because previous definitions of specific yield are ill defined in such saturated environments. In this study, we have introduced the concept of “saturated specific yield” (*Sy*<sub>sat</sub>) and investigated its dependency on seasonal-mean and temporally varying water table depths (Figures 3.7 and 3.8). An empirical relationship was arrived at (equation (17)), which relates *Sy*<sub>sat</sub> at our field site to depth-to-groundwater (both 5-day running mean *D<sub>WT</sub>* and seasonal-mean *D<sub>WT</sub>*). Figure 3.12 summarizes the dependency of *Sy*<sub>sat</sub> on variations in shallow water table depth, as predicted by this relationship. During the remainder of this discussion, we describe the results of Figure 3.12 and relate these findings to the conclusions of the previous studies discussed above.

Figure 3.12 was created from equation (17) by plotting *Sy*<sub>sat</sub> versus depth-to-groundwater (*D<sub>WT</sub>* in Figure 3.12a and *D<sub>WT</sub>* in Figure 3.12b). *Sy*<sub>sat</sub> curves are shown in Figure 3.12a for a series of fixed, seasonal-mean water table depths, *D<sub>WT</sub>* (ranging from –0.6 to +0.9 m), and across a range of temporal *D<sub>WT</sub>* anomalies, where *D<sub>WT</sub>* = *D<sub>WT</sub>* − *D<sub>WT</sub>* = ±0.3 m. Similarly, Figure 3.12b shows *Sy*<sub>sat</sub> curves for various fixed values of *D<sub>WT</sub>*', but plotted as a function of *D<sub>WT</sub>*. The ranges noted above were chosen based on the approximate bounds of the observed water table depths at the field site (e.g., Figures 3.5
and 3.7). Values outside this domain are shaded in gray in Figure 3.12. The reasoning behind separating $D_{WT}$ into seasonal-mean and time-varying components is related to the fact that $\bar{D}_{WT}$ is largely a function of space, rather than time. In other words, variations in $\bar{D}_{WT}$ primarily reflect changes in well location (and associated piezometer depth, distance below the water table, location within the root zone, etc.). $D_{WT}'$, on the other hand, represents temporal (i.e., 5-day) deviations from the long-term, seasonal mean. As such, Figure 3.12a can be interpreted as the “overall” impact of $D_{WT}$ on $S_{y_{sat}}$ (for various fixed locations, $\bar{D}_{WT}$, and across a range of temporal anomalies, $D_{WT}'$) – i.e., similar to what is plotted in Figure 3.7, but in a more summarized form (and with the x-y axes inverted). Figure 3.12b, on the other hand, more explicitly shows the impact of well location, $\bar{D}_{WT}$ (i.e., the vertical axis), on $S_{y_{sat}}$, while also illustrating the role of temporal anomalies (along the horizontal axis). In both panels, increases (decreases) in water table elevation are shown as a decrease (increase) in water table depth, denoted by a “−” (“+”).

The results of Figure 3.12 show a clear dependency of saturated specific yield on depth-to-water-table. Similar to Figure 7, Figure 3.12a demonstrates that – from a time-varying perspective – decreases in $D_{WT}'$ (for a fixed value of $\bar{D}_{WT}$) always lead to increases in $S_{y_{sat}}$, even in cases of standing water (i.e., $D_{WT} < 0$). This is also true for the seasonal-mean $\bar{D}_{WT}$, with the important exception that the saturated specific yield values actually begin to decrease once $\bar{D}_{WT}$ gets close to (or rises above) the land surface (Figure 3.12b). It is also evident from Figure 3.12 that changes in $S_{y_{sat}}$ at the wetland study site are much more sensitive to temporal variations in water table depth than to changes in the seasonal mean value (i.e., well location). For example, a 0.3-m change in $\bar{D}_{WT}$ leads to – at most – a change in $S_{y_{sat}}$ of 0.15, while a similar variation in $D_{WT}'$ can
result in changes in $S_{y_{sat}}$ that are up to three times larger (i.e., $\Delta S_{y_{sat}} = 0.45$; Figure 3.12b). It should be noted, however, that temporal variations in $S_{y_{sat}}$ become much more muted as the water table elevation drops significantly below or (especially) rises above the ground surface. The observed, seasonal-mean values of $S_{y_{sat}}$ at the various observation wells range from 0.20 at well-1 to 0.24 at well-4 (red symbols in Figure 3.12), while the theoretical curve (red line) predicts a range in mean $S_{y_{sat}}$ of ~0.15 to 0.28, with the highest specific yield occurring at a water table depth of $D_{WT} = 0.2$ m (Figure 3.12b). The overall range in $S_{y_{sat}}$ values predicted from equation (17) (i.e., including the temporal variability) is roughly 0.05 – 0.55, which encompasses the majority of the 5-day values present in the field observations (Figure 3.7d). The range and mean values of specific yield noted here are also comparable to values reported in the literature for other shallow water table environments [e.g., Loheide et al., 2005; Shah and Ross, 2009; Logsdon et al., 2010].

Similar to some of the earlier studies discussed above – but specifically in terms of the spatial variability – Figure 3.12b predicts a maximum in specific yield at intermediate water table depths ($D_{WT} = 0 – 0.3$ m), with $S_{y_{sat}}$ decreasing as the seasonal mean water table rises or falls beyond that level (Figure 3.12). This “turnover” point is shallower than in previous studies but likely reflects the fact that the mean water table itself is very shallow at this field site, as well as the fact that we have introduced a new metric to account for saturated conditions. The use of “saturated” specific yield, in fact, prevents $S_{y_{sat}}$ from being forced to zero as the water table approaches the surface (in contrast to depth-compensated specific yield). This is due to the fact that the water “yield” – in the case of $S_{y_{sat}}$ – is explicitly defined as the amount of water consumed (i.e., through
transpiration), rather than the change in soil water storage. And transpiration does not
generally decline as the water table rises toward (or even above) the surface. Rather, $ET_G$
typically increases in response to augmented plant water use from both groundwater and
the vadose zone [as suggested by the results of Figure 3.12 and previous studies such as
Shah and Ross, 2009]. It should also be noted that the use of piezometers to measure
hydraulic head at fixed depths below the water table (rather than screened across the
water table) precludes the observation of pore space-induced “enhanced” diurnal
fluctuations in water table depth as the groundwater reaches the surface. This is in
contrast to the response of the depth-compensated specific yield curve, which is strongly
influenced by this factor [e.g., Loheide et al., 2005]. Thus, $Sy_{sat}$ does not asymptote to
zero as $D_{WT}$ decreases to zero, but instead attains its maximum value as the water table
approaches the surface (i.e., the blue line in Figure 3.12b). And in the case of temporal
variations (as noted above), this “turnover” point does not even exist, since $Sy_{sat}$ increases
monotonically as $D_{WT}'$ decreases (even in instances of standing water; Figure 3.12a).
Clearly, this increase in saturated specific yield as the water table reaches the surface is
one of the most important distinctions between $Sy_{sat}$ and other formulations of specific
yield.

To summarize the behavior predicted by equation (17), and illustrated in Figure 3.12,
we find that $Sy_{sat}$ is affected by both spatial and (especially) temporal variations in water
table depth. In general, the saturated specific yield increases as water table depth
approaches the surface. Similar to Shah and Ross [2009], we primarily attribute this
increase to enhanced water availability and plant water use from within the vadose zone.
Related to this is the fact that the distance between the water table and the depth at which
the head fluctuations are measured actually increases as the water table rises. This would likely lead to reductions in diurnal amplitude, despite similar (or larger) rates of overall groundwater water use by roots within the overlying saturated zone (which thickens as the vadose zone thins). Although these are likely to be two contributing factors, they cannot provide a complete explanation, since temporal $S_{\text{ysat}}$ anomalies continue to increase even as the vadose zone disappears completely (at specific observation wells) and as the water table elevation subsequently rises above the land surface (albeit with an associated reduced variability in $S_{\text{ysat}}$, Figure 3.12a). We suspect that some of this behavior may be explained by the fact that a vadose zone always exists near the edges of the wetland, and so the areal extent of the saturated zone simply expands as the water table rises above the surface (i.e., enhancing rates of $ET_G$ for the wetland as a whole, while simultaneously showing little change in the amplitude of diurnal head fluctuations measured at piezometers in regions of deep water). If this is the case, it highlights the importance of utilizing multiple observation wells (i.e., across a gradient of saturated-to-unsaturated conditions) when obtaining spatially representative $ET_G$ estimates for wetland systems (particularly those with standing surface water).

Finally, as described above, Figure 3.12b has shown that $S_{\text{ysat}}$ tends to maximize for locations (i.e., wells) that have a seasonal-mean $\bar{D}_{\text{wT}}$ that is at (or just below) the ground surface. We have noted that this makes sense in terms of enhanced contributions to $ET_G$ from both groundwater and the vadose zone, and that other previous studies have shown similar behavior [e.g., Shah and Ross, 2009]. However, the fact that $S_{\text{ysat}}$ “turns over” and thereby decreases as one moves to locations with an even higher seasonal-mean water table (i.e., $\bar{D}_{\text{wT}}$ above ground), is somewhat puzzling. Although this “turnover” behavior
is similar to other studies, most previous investigations have used different formulations of $S_y$, and one might actually expect $S_{ysat}$ to simply asymptote to a final, “standing-water” value once you reach wells that have been deployed in (and beyond) saturated conditions. In other words, since $ET_G$ is likely occurring at the potential rate at all sites with $D_{wt} < 0$, why would the amplitude of diurnal head fluctuations actually increase (for the same $ET_G$) as one moves to wells in deeper standing water? Although a number of explanations are possible (e.g., differences in groundwater recovery, lateral flow, soil texture, or organic material), we offer one suggestion here that is related to a logistical consideration of piezometer deployment in conditions of standing water. Although well-1 and well-2 (for example) are, indeed, slightly “deeper” relative to the mean water table (as compared to the other three wells), their screen depths are, in fact, notably shallower than the other three wells when measured relative to the soil surface (due to the trade-off between surface elevation and standing water depth). Thus, the piezometers located in standing water are actually sampling a shallower (and likely denser) portion of the $P. australis$ root system, which could result in greater head fluctuations due to preferential plant water consumption from shallower roots. The wells in the unsaturated zone, on the other hand, are also screened below the water table, but at a depth (~2.5-m depth below the soil surface), where deeper roots would extract correspondingly less groundwater for the same rate of $ET_G$ (i.e., higher $S_{ysat}$). Other factors, of course, may also be playing a role in the observed “maximum” in $S_{ysat}$ (Figure 3.12), but the explanation offered here reiterates the important distinction between hydraulic head and depth-to-water-table – a distinction which is not only necessary for applying the diurnal fluctuation method in saturated
conditions, but which also highlights the potentially important influence of piezometer depth on the resulting observations (and, hence, estimates of \( S_{y_{sat}} \)).

**SUMMARY AND CONCLUSIONS**

Water table hydrographs are useful tools for assessing rates of evapotranspiration from groundwater (\( ET_G \)), as often occurs in shallow water table environments with phreatophytic plants. However, the widely known White method that is used for estimating daily \( ET_G \) (from diurnal fluctuations in water table depth) is associated with numerous uncertainties. Some of these uncertainties relate to temporal resolution – as well as errors in estimating groundwater recovery – while others relate to the estimation of specific yield (especially in conditions with shallow, varying water table depths). In this study, we developed a new “Fourier method” for estimating \( ET_G \) more accurately [based on previous work by Czikowsky and Fitzjarrald, 2004], and this method applies a repeating, 24-hr sine function over a de-trended, multi-day moving window to measure diurnal fluctuations in water table. Due to the de-trending process, a daily-varying scaling factor was introduced to recover the “true” diurnal amplitude and arrive at reasonable estimates of both specific yield and \( ET_G \). This scaling factor, which averages around 1.9, is dependent on the shape and duration of the hourly transpiration curve and can be easily estimated from observations of incoming solar radiation or approximate clear-sky values. We also defined a new metric for applying the concept of specific yield to saturated conditions, and the response of this “saturated specific yield” (\( S_{y_{sat}} \)) to variations in water table depth was explored. The new methods and concepts – along with the White method – were applied and tested at a (predominantly) saturated riparian wetland site in south-central Nebraska (USA) using independent energy balance measurements of \( ET_G \) (to
estimate \( S_{\text{sat}} \)). Diurnal fluctuations in water table were measured across a gradient of five observation wells (from saturated to unsaturated conditions) during the 2009 growing season. Importantly, due to the prevalence of standing water and saturated soil at the field site, the piezometers were not screened across the water table, but rather were used to measure hydraulic head at specific, shallow depths (i.e., to calculate an approximate “depth-to-water-table” that is similar to previous studies, but with differences in interpretation that are generally non trivial). The conclusions from this study are summarized below.

Comparison of the White and Fourier methods with observed daily to 7-day mean \( ET_G \) values shows that the Fourier method performs considerably better than the White method, regardless of the size of the moving window that is applied. On daily timescales, the error in estimated \( ET_G \) was reduced from \( r^2 = 0.14 \) and RMSE = 2.7 mm (White method) to \( r^2 = 0.47 \) and RMSE = 1.8 mm (Fourier method). Applying a 3-day moving average to the White method improved the results considerably (\( r^2 = 0.39 \) and RMSE = 1.7 mm), but still did not match the accuracy of using a 3-day Fourier window (\( r^2 = 0.62 \) and RMSE = 1.2 mm). We found that – for this particular location and climate – a 5-day moving window provided the best results when using the Fourier method to estimate \( ET_G \). It would be appropriate to test different window sizes when applying the Fourier method to other study sites and climatic regions.

Temporal variations in saturated specific yield, \( S_{\text{sat}} \), were found to follow an inverse, exponential relationship with depth-to-groundwater (at all five observation wells), with a stronger (weaker) response at wells located in unsaturated (saturated) conditions. This inverse relationship – while similar to some studies – is contrary to most previous
investigations of the dependency of $Sy$ on variations in water table. However, this is primarily due to the fact that conventional definitions of specific yield relate changes in $Sy$ to changes in soil water storage, which is identically zero under continuously saturated conditions. Instead, $Sy_{sat}$ is defined in terms of the actual plant water use (i.e., transpiration), regardless of the change in soil water content. This leads to higher values of saturated specific yield as the water table rises – even for piezometer locations where the water table is already above the surface. We hypothesize that this overall increase in $Sy_{sat}$ with water table elevation is related to at least three factors: 1) greater contribution to transpiration from water within the vadose zone (as has been suggested in previous studies), 2) greater contribution from groundwater within the thicker and shallower saturated zone above the screen depth of the piezometers (i.e., despite similar, or reduced hydraulic head fluctuations at depth), and 3) higher aerially-averaged $ET_G$ rates due to thinner unsaturated zones along the edge of the wetland (i.e., despite limited impacts on hydraulic head fluctuations at the “saturated” wells).

In addition to temporal changes, $Sy_{sat}$ was found to vary spatially according to the seasonal-mean depth-to-water-table at each observation well ($\overline{D}_{WT}$). To help describe this behavior, the empirical, exponential relationships noted above (which had been derived separately for each well) were combined into a more general functional form. The results of this analysis revealed that – unlike the temporal variability – $Sy_{sat}$ did not vary monotonically with $\overline{D}_{WT}$. Rather, a “peak” in $Sy_{sat}$ was noted in locations with shallow water tables ($\overline{D}_{WT} = 0–0.3$ m), where mean $Sy_{sat}$ values maximized at $\approx 0.24$ (with a much broader temporal range of $\approx 0.12–0.56$). Locations with higher or lower seasonal-mean water tables, however, were associated with lower values of $Sy_{sat}$ ($\approx 25–40\%$ lower for a
±0.6 m deviation in $\bar{D}_{wt}$). The drop in saturated specific yield with increasing $\bar{D}_{wt}$ can likely be attributed to some of the same mechanisms noted above for the temporal variability. Decreasing $S_{y_{sat}}$ in regions of increasingly higher standing water, on the other hand, requires an altogether different (and competing) explanation. We hypothesize here that this behavior may, in fact, be related to piezometer depth and associated measurements of hydraulic head (as opposed to true “water table depth”). Observation wells in deep, standing water tended to be deployed at shallower depths (relative to the soil surface), implying that they were also located higher in the root zone. Since shallow roots tend to preferentially withdraw a greater fraction of the total plant water use, larger diurnal variations in hydraulic head would likely be observed at shallower piezometer depths (for the same rate of $ET_G$). This, in turn, would result in lower estimates of $S_{y_{sat}}$ in regions of deeper water. Although it is difficult to verify the precise mechanism involved, it is clear that the effect is strong enough to contribute to the observed “peak” in specific yield at intermediate values of $\bar{D}_{wt}$.

The “Fourier method” presented here is a step toward increasing the accuracy of $ET_G$ estimates from diurnal water table fluctuations. Similarly, the concept of “saturated specific yield” provides a means for expanding the application of these methods to saturated environments. Both issues highlight the value of utilizing multiple observation wells across a gradient of water table depths, as well as the attention that must be paid to the measurement of hydraulic head (and associated well depth, root distribution, etc.). Additional studies should be performed, however, to test these methods and ideas in other regions and under different environmental conditions (soil type, vegetation, climate, etc.). The empirical nature of the present study also highlights the need for model
investigations to more clearly elucidate the physical mechanisms for some of the observed behavior, such as the dependency of $S_{Y_{sat}}$ on water table depth. Finally, we note the continued need for coupled models which provide an integrated assessment of the interactions between groundwater, surface water, and the land-atmosphere fluxes of mass and energy.
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Figure 3.1. Hourly water table elevation observed at well-4 (relative to the land surface) for a 4-day sample period (August 21-24, 2009), along with daily calculations of diurnal amplitude based on a) the White method (equation 4) and b) the Fourier method (equation 7). For the White method, $s$ represents the absolute change in water table (i.e., the distance between the horizontal black lines) over a full 24-hr period, beginning and ending at midnight. The slope of the red line (i.e., $r_{gw}$) denotes the hourly rate of groundwater recovery, which is assumed to be constant and is calculated using a linear fit to the five hourly data points between midnight and 4:00 A.M. The equation for $ET_G$ uses “+s” (”−s”) in instances where the water table falls (rises) during the 24-hr period. For the example using the Fourier method (panel b), a centered, 3-day moving window was applied (midpoint shown by red dot). Window sizes used in this study vary from one to seven days. A numerical curve-fitting routine was used to determine the black trend line $(D + A \cdot t)$, along with the other empirical parameters, $B$ and $E$. 

\[ Z_{\tau}(t) = D + A \cdot t + B \sin \left( \frac{2\pi (t+E)}{24} \right) \]
Figure 3.2. Sample calculations of the “scaling factor,” $k$ (Equation 8), for two idealized scenarios using a repeating, 12-hour square wave (left panels) and a theoretical clear-sky solar radiation curve (right panels). a) and b) show the hourly $ET_G$ rate for four consecutive days, with each curve scaled to produce 6 mm of daily total $ET_G$. c) and d) show the hourly cumulative $ET_G$ loss, while e) and f) represent the hypothetical water table elevation (multiplied by specific yield), assuming a constant groundwater recovery.
rate of \( r = 0.2 \text{ mm hr}^{-1} \) (see Equation 6). g) and h) show the final, de-trended time series of water table elevation (multiplied by specific yield).

Figure 3.3. Daily observed shortwave radiation, \( SW_{obs} \) (right axis; gray bars), and daily scaling factors for the Fourier method, \( k-SW_{obs} \) (solid black line) and \( k-SW_{clr} \) (dotted line), which were estimated from accumulated hourly values of observed solar radiation and theoretical clear sky values, respectively. Dashed line represents a 3\textsuperscript{rd}-order polynomial fit to \( k-SW_{obs} \).
Figure 3.4. Map showing the study area (black rectangle) in south-central Nebraska, as well as the wetland land cover and locations of the meteorological station, LAS transmitter and receiver, and five groundwater wells.
Figure 3.5. Water table hydrographs from five observation wells during the 2009 growing season (see Figure 4). Inset figure (lower left) shows a comparison of the well-2 hydrograph with nearby surface water level measurements during mid-September. Gray shaded areas show dates which were excluded from the $ET_G$ estimation procedure due to precipitation events. Note that negative values along the y-axis represent water table measurements that are above ground level.
Figure 3.6. 3-day running mean observations of total wetland ET (solid black line) for the 2009 growing season, based on energy balance measurements from Lenters et al. (2011). Also shown are estimates of transpiration ($ET_G$; solid gray line), open-water evaporation ($E_{ow}$; dotted line), and evaporation from surface water under the canopy ($E_{cw}$; dashed line). All units are in W m$^{-2}$ (left axis) and mm day$^{-1}$ (right axis), and $E_{ow}$ and $E_{cw}$ have not been multiplied by their respective fractional areas ($f_{ow}$ and $f_{cw}$).
Figure 3.7. Estimates of saturated specific yield ($S_{ysat}$) vs. depth-to-water-table (measured as hydraulic head at five observation wells; $D_{WT} = -h_{WT}$). a) shows $S_{ysat}$ based on the standard, daily White method (Equation 4), while b), c), d), and e) show $S_{ysat}$ using the Fourier method (Equation 8) with 1-, 3-, 5-, and 7-day moving windows, respectively.

Figure 3.8. Empirical coefficients, $a$ and $b$ (from Equation 16 and the 5-day Fourier method; Figure 7d), as a function of the seasonal-mean depth-to-water-table, $\bar{D}_{WT}$, at each of the five observation wells. Also shown are linear and exponential fits (solid and dashed lines) to $b$ (triangles) and $a$ (circles), respectively.
Figure 3.9. Comparison of observed $ET_G$ values (from energy balance measurements; x-axis) with both of the diurnal water table fluctuation methods (y-axis). a) and b) show the daily and 3-day running mean White method, respectively, while c), d), e), and f) show the Fourier method using 1-, 3-, 5-, and 7-day moving windows, respectively. Red squares (and summary statistics) represent the average $ET_G$ from all 5 wells, while the gray dots denote $ET_G$ values from individual wells.
Figure 3.10. Same as Figure 3.9e, but using the more general empirical relationship for \( S_y_{sat} \) (Equation 17), rather than applying individual regression coefficients to each of the five observation wells.
Figure 3.11. Time series of 5-day running mean $ET_G$ observations from the energy balance method (solid black line) for the 2009 growing season, as well as $ET_G$ estimates from both the 5-day Fourier method (solid red line) and the daily White method (solid blue line; averaged to a 5-day running mean for consistency). For comparison purposes, we also show $ET_G$ from the 5-day Fourier method using Equation 17 (dashed red line).
Figure 3.12. Schematic showing the dependency of saturated specific yield, $S_{y_{sat}}$, on variations in: (a) depth-to-water-table, $D_{WT}$, and (b) seasonal-mean depth-to-water-table, $\overline{D}_{WT}$, based on empirical relationships derived from the 5-day Fourier method and data collected at the wetland field site (Figures 7d and 8; Equations 15b and 17). Dashed black curves denote lines of constant $\overline{D}_{WT}$ (with values given in m), while dotted black curves denote 5-day temporal anomalies in water table depth ($D_{WT}' = D_{WT} - \overline{D}_{WT}$; ranging over ±0.3 m). Solid black, blue, and red curves represent the zero line, land surface, and mean
$S_{Y_{sat}}$, respectively, while red symbols denote the seasonal-mean $S_{Y_{sat}}$ measured at each of the five observations wells (Figure 4). Gray shaded areas show the approximate regions which fall outside the bounds of the observed variations in water table depth at the study site.


**Introductory Statement for Chapter 4**

In Chapters 2 and 3, the interrelationship between ET and groundwater was investigated in detail, but mostly from the perspective of observations and model simulations at a single field site in south-central Nebraska. External climatic controls on ET and its interaction with groundwater were not explicitly examined, nor were the impacts of regional variations in climate, soil type, and vegetation. In the following chapter, a broader perspective is gained by investigating the impact of spatial and temporal (i.e., interannual) variations in climate on ET, as well as the role of vegetation type, soil texture, and groundwater depth. A distributed land surface / ecosystem model is used to simulate the surface water balance across a broad spatial domain, thereby incorporating the strong climatic gradients that exist across the state of Nebraska and surrounding regions. In addition, a new approach is proposed to quantify the interdependencies of climatic variables (e.g., radiation, temperature, relative humidity, and precipitation) from historical observations. This use of co-varying climatic variables allows one to examine more realistic scenarios and water balance sensitivities to interannual climate forcing. Two interannual climate scenarios are examined by increasing/decreasing precipitation by a factor of 1.5 while also changing other coupled variables accordingly (i.e., solar radiation, air temperature, and relative humidity). Chapter 4 complements the former two chapters by evaluating the effects of climatic and environmental factors on ET across a broad spatial region, including the effects of groundwater, soil type, and vegetation cover.
CHAPTER 4: SENSITIVITY OF EVAPOTRANSPIRATION TO VARIATIONS IN CLIMATE, VEGETATION, AND DEPTH-TO-GROUNDWATER IN THE CENTRAL U.S.

ABSTRACT

The sensitivity of evapotranspiration (ET) to climate forcing (e.g., solar radiation, precipitation, temperature) and other environmental factors (e.g., soil, vegetation, groundwater) plays an important role in water transfer within the soil-vegetation-atmosphere system. However, little is known about the combined impact of these coupled drivers on ET. In this study, we investigated the sensitivity of summer ET to interannual variations in precipitation, air temperature, relative humidity, solar radiation, and groundwater depth at a wetland field site in south-central Nebraska using a land surface / terrestrial ecosystem model known as Agro-IBIS (Integrated Biosphere Simulator). Both the individual and combined impacts of climate forcing on ET were analyzed using two interannual climate variation scenarios, in which precipitation was increased (and decreased) by a factor of 1.5. To account for interdependencies in co-varying climatic quantities, changes in solar radiation, relative humidity, and air temperature were also accounted for in these two scenarios. These interdependencies were determined from observed, historical climate variability in the central U.S. using 60 years of gridded, high-resolution, summer (June–August) climate observations over the state of Nebraska and surrounding regions. Simple statistical techniques were used to determine the most representative co-variation between interannual precipitation anomalies and corresponding anomalies in other climatic variables. ET was also separated into transpiration and surface evaporation to examine the individual responses of each
component to climate variability. The results show that transpiration and evaporation respond to external drivers in substantially different ways. While transpiration is most sensitive to variations in precipitation and radiation, surface evaporation is most sensitive to air temperature and groundwater depth. We also compared the ET response to climate variability for both “natural” vegetation and the invasive species *Phragmites australis* (applied uniformly over the central U.S.). The results show that interannual climate variability affects ET (and other water balance components) in significantly different ways in water- and energy-limited regions of the central U.S. For example, in areas that are not generally water-limited (e.g., eastern Nebraska), increased precipitation leads to a decline in ET due to decreases in available energy (i.e., solar radiation and air temperature), as well as to increases in relative humidity. It is also found that land cover type and soil texture play important roles in determining summertime ET rates. *P. australis*, for example, is found to have higher ET rates than natural vegetation in regions with abundant summer precipitation, but lower rates in water-limited regions. Regardless of vegetation type, ET is found to be less sensitive to variations in climate in areas where coarse soil texture is the dominant soil type (e.g., sand).

**INTRODUCTION**

Evapotranspiration (ET) is an important land surface process in earth’s climate system and is controlled by a variety of environmental factors, including moisture availability (e.g., precipitation and shallow groundwater), and available energy (e.g., solar radiation and air temperature). These factors are generally considered to be the main external drivers of ET (Hobbins et al. 2008; Teuling et al. 2009). They are coupled to each other and can vary across seasonal, interannual, and decadal timescales (Ryu et al.
Although it is generally expected that a warming climate would lead to increases in ET, there are other important feedbacks and environmental factors that play significant roles in determining ET. To investigate the sensitivity of ET to climate variability, a number of studies have examined the effects of individual climatic forcings, and across a variety of scales and ecosystems (Goyal, 2004; Gong et al., 2006; vanHeerwaarden et al., 2010). Although each climatic variable has a distinct effect on ET (as shown in the previous studies), these “separate” forcings – in nature – are always coupled to one another. Therefore, more realistic investigations of the impact of climate variability on ET should account for co-variations in the climate forcing factors. However, relatively little attention has been paid to the effects of interdependent climate variables on ET and other components of the land surface water balance.

Previous studies of the impact of climatic drivers on ET have primarily used indirect methods to infer ET response (such as measurements of runoff, pan evaporation, or soil moisture). For example, Gedney et al. (2006) examined the changes in observed runoff to various climatic and environmental factors and concluded that declining trends in ET are the primary cause for observed increases in runoff. Roderick and Farquhar (2002) investigated pan evaporation trends and found that these trends can be explained by the changes in sunlight and interdependencies among global solar irradiance, diurnal temperature range, and atmospheric humidity. Robbock and Li (2006) examined summer soil moisture trends over Ukraine and Russia and found that ET plays a significant role in the increasing soil moisture trends observed during a 30-year period (1960’s to 1990’s), in conjunction with corresponding variations in solar radiation and CO₂.
Other studies have obtained direct ET estimates (from calculations or simulations) to examine trends and associated external climatic factors. For example, Teuling et al., (2009) analyzed observed global radiation and precipitation data to investigate regional ET trends and found that ET is primarily controlled by radiation in energy-limited (i.e., humid) regions and by precipitation in water-limited (i.e., arid) regions. Wang et al. (2010) found similar results on the basis of a modified Penman-Monteith method, which was used in conjunction with remote sensing and meteorological stations to estimate ET. Ryu et al. (2008) studied interannual variability of ET using six years of observations from an eddy covariance tower in California and examined the sensitivity to various factors (such as soil moisture and radiation). They found that ET is negatively scaled with radiation, precipitation limits ET in water-limited periods and ET is positively scaled with radiation, potential ET limits ET in energy-limited periods.

Compared to studies that have examined the impacts of climate on the surface energy and water balance, less attention has been paid to the effects of groundwater. However, an increasing number of studies in recent years have begun to focus on gaining a better understanding of the water and energy balance in regions with significant groundwater contributions (such as wetlands and riparian zones). For instance, Maxwell and co-workers (Maxwell and Miller, 2005; Kollet and Maxwell, 2008) found that incorporating groundwater into land surface models leads to more realistic surface energy and water balances. Yeh and Eltahir (2005) showed that without proper representation of the effect of groundwater in the soil zone, the surface water balance in the state of Illinois (where the water table is shallow) could not be closed. Soylu et al. (2011) examined the
sensitivities of ET in land surface models to the existence of groundwater by comparing the response to various soil types, soil hydraulic parameters, groundwater depths, and model solution techniques, and they found that ET-groundwater interactions are primarily sensitive to the choice of soil hydraulic parameters. Unlike these previous modeling efforts, Nosetto et al. (2009) examined the interaction between crop productivity and groundwater depth over a sandy landscape. They found that crop yield (and transpiration) was maximized when groundwater depths were within an optimum range (between roughly 1 and 2 m). When the water table depth was outside this optimum range, a sharp decline in crop yield was observed.

In addition to the impacts of variations in climate and groundwater, land cover change – such as the invasion of non-native vegetation – can also have important effects on ET rates. However, the impacts of non-native species on water quantity and quality are poorly understood (Hooper et al., 2005). *P. australis* is one of the primary invasive plant species targeted for removal in recent years over the central U.S. The state of Nebraska, for example, began removing this species along the riparian corridors of the main river systems in 2007, with the goal of reducing riparian ET loss along the rivers (as well as to aid in restoring the native ecosystem). Therefore, understanding the impacts of non-native vegetation species (and its removal) on the surface energy and water balance is of critical importance to many regions in the central U.S.

In the current study, we analyzed the sensitivity of ET to interannual changes in external climatic drivers (i.e., precipitation, temperature, solar radiation, and relative humidity), as well as the effects of other environmental controlling factors such as groundwater depth, vegetation type, and soil texture. The main objective is to examine
the relative impacts of each of these external controls on ET rates. In the process of identifying appropriate scenarios for examining interannual climate variability, we also quantified the interdependencies among the various climatic forcing factors (using a high-resolution, 60-year climate dataset for the central U.S.). A land surface hydrologic/ecosystem model was used to investigate the sensitivity of ET (and other water balance components) to the various drivers, and the model was validated using observations from a wetland field site in south-central Nebraska.

In the next section, following a description of study area, we provide a brief discussion of the land surface model and describe how it was adapted for use in shallow groundwater environments. This is followed by an evaluation of the model through comparisons with observations at the wetland field site, which is dominated by an invasive variety of *P. australis*. The methods section also describes how the model was used to examine the sensitivity of ET to various external drivers, including a discussion of the interdependency among regional climatic variables within the state of Nebraska and surrounding regions, as well as the impact of various land cover types. Finally, in the results and discussion section, we present the model simulation results, and the various factors controlling ET are discussed in detail.

**STUDY AREA**

We used meteorological data from a wetland field site, which is located south central Nebraska (USA) (as explained in detail in former chapters), to compare the simulation results against field observations of ET for the growing season of 2009 for a single cell to evaluate the model performance for *P. australis*. On the other hand, the study domain for
regional simulations covers the central US including the state of Nebraska and northern part of Kansas (38.75°, 43.75°N; -104.25°, - 95.25°W). Although the entire region receives most of its precipitation from April through October, Eastern and western halves of the study area represent significant differences climatically. The eastern half has a “humid continental climate” and the western half has a “semi-arid climate” (according to Köppen scheme). While the eastern half receives 4 mm day⁻¹ mean summer precipitation, the western half receives only 1.5 mm day⁻¹. Climatic differences in these two sub-regions lead different limitations for ET. In the west with a limited supply of soil water, availability of water, not the energy, dominates changes in ET. Therefore, the western half of the study area can be considered as a “water-limited” environment. On the other hand, in the east with higher water availability, ET converges its potential rate. In this case the available energy mainly limits ET and thus the eastern half of the study area can be considered as an “energy-limited” environment.

The study area shows flat topography. The elevation slopes downward gradually from west (about 1700 m above sea level – ASL) to east (about 250 m ASL). Dominant soil type in the area is loam, silt and sandy soils. Notably, the north central part of the study domain is dominated by sand, where Sandhills is located. Sandhills is an unusual region that includes native grassland on grass-stabilized sand dunes covering about 47,000 km². Low water holding capacity of sand texture easily transmits precipitation from the surface to deep drainage, which leads lower soil moisture availability for ET regardless of the climatic settings of the area. Thus, the area produces significant recharge for the Ogallala aquifer, which is one of the world’s largest aquifers covering 450,000 km².
METHODS

Model Description

We used the Integrated Biosphere Simulator (IBIS) land surface/ecosystem model (Foley et al. 1996; Kucharik et al. 2000) to evaluate the sensitivities of ET to interannual climate variability, water table depth, and changes in land cover. IBIS is a dynamic global vegetation model that simulates the land surface energy, water, and carbon balance, as well as vegetation dynamics and phenology and canopy physiology (Foley et al., 1996; Kucharik et al., 2000; Lenters et al., 2000; Li et al., 2005). The model has been evaluated at various temporal and spatial scales in numerous climatic regions, and it has been shown to accurately simulate land surface hydrologic and ecosystem processes. For example, Lenters et al. (2000), Kucharik et al. (2000), and Vano et al. (2006) evaluated the IBIS-simulated water balance and associated river discharge and found that hydrological processes can be simulated reasonably with IBIS. Twine and Kucharik (2008) evaluated the simulated plant phenology by comparing the model results with satellite information of greenness. Kucharik (2003) used Agro-IBIS (a modified version of the original IBIS model that incorporates agricultural systems) to simulate crop yield over the central U.S. and found consistent spatial pattern between observed and simulated crop yields.

The land surface module of IBIS is based primarily on the land surface transfer scheme of Thompson and Pollard (1996a and 1996b), which simulates the energy, water, carbon, and momentum balance of the soil-vegetation-atmosphere system (Foley, et al., 1996). Total ET from the land surface is simulated as the sum of soil evaporation, canopy
transpiration, and evaporation from canopy interception (Pollard and Thompson, 1995). Evaporation rates are calculated using a standard mass transfer / resistance approach, which utilizes vapor pressure deficit, temperature, soil water availability, and stomatal and canopy conductance (Campbell and Norman, 1998). Transpiration rates are calculated independently for each plant functional type by also taking into account leaf area index (LAI) and various plant-specific physiological parameters.

IBIS uses a multi-layer soil model to simulate temperature and soil moisture. Vertical water movement between soil layers is calculated using Richards’ equation. IBIS has 11 soil layers extending to the depth of 2.5 m, as well as three snow layers and two vegetation canopy layers (upper and lower). IBIS does not explicitly represent water table dynamics. Instead, the lower boundary condition is allowed to vary from 100% free drainage to zero flux (or anywhere in between, based on an empirical coefficient ranging from 0 to 1). In this study, the representation of groundwater as a lower boundary condition is necessary to simulate the groundwater contribution to surface ET. Similar to adjustments made by Yeh and Eltahir (2005) to incorporate groundwater into IBIS, we changed the bottom flux boundary condition to a fixed soil moisture boundary condition by forcibly saturating the soil layers below the top of the capillary fringe.

Agro-IBIS uses CONUS dataset as spatial soil texture distribution, which is based on USDA State Soil Geographic Database. Although the grid size of original dataset is 1 km x 1 km, Agro-IBIS uses an aggregated version of this dataset into 5-minute spatial resolution (approximately 8 km). Also, natural vegetation dataset was derived from the International Geosphere Biosphere Programme’s 1 km DISCover land cover dataset (Loveland and Belward 1997; Twine et al. 2004) in Agro-IBIS.
Model Simulations and Interdependencies of Climate Forcings

Two sets of simulations were designed to examine the model sensitivities to external ET drivers in single grid cell runs. In the first set of simulations, the effects of climatic drivers (i.e., precipitation, solar radiation, air temperature) on ET, T, E and SM were examined separately. In the second set of simulations, we examined the impact of groundwater on ET, T, E and SM with respect to radiation, temperature and precipitation by plotting depth to water table versus these climatic drivers. To examine the results of single-cell simulations, the simulation results were visualized by plotting 2-dimensional surface plots using the ArcGIS Geostatistical Analyst, which provides a comprehensive set of tools to visualize, analyze and understand spatial distribution of observed sample points.

To determine the relative dependencies of climate forcings, first, we produced maps showing annual summer means of climate variables and then slopes of linear regressions, correlation coefficient and significance for each variable against precipitation (i.e. radiation, maximum temperature and diurnal temperature range) to obtain the relative magnitudes of changes for each climate forcing. While these maps provide insights about relative dependencies of climate forcings for spatially distributed individual cells, the general relationship of the climate forcings over the entire studied region requires more detailed comparisons. Therefore, scatter plots were created using annual anomalies from 60 years long term summer mean assigned to every 5 minute by 5 minute cell over the entire study area to obtain general variations of climate variable pairs. Linear regressions obtained from these scatter plots were not convenient for the purpose of quantification of the climatic variables inter-dependences due to the overly dispersed nature of these plots.
(each plot includes about 399,000 data point – 61 by 109 grid points for 60 years). To understand the general tendencies and accumulation zones of the majority of the data points, color maps were created. Color maps basically separate these scatter plots into small grids cells and assign a color for each grid cell based on the number of sample point falls into that specific grid cell. We created 70 by 70 grid mesh size for each scatter plots. The main advantage of these color maps is that they clearly show where the majority of the observation points were located and their general slope tendencies, which are difficult to understand from scatter plots. To gain better understanding on the interdependencies of the climate variables, we also created different color maps showing the co-variations of 3 climate variables in a single figure. The only difference of this 3-variable color maps is that they show the mean value of a third variable of all sample points located in the same grid cell instead of showing the number of sample that fall into the corresponding cell.

In regional simulations, we performed two sets of IBIS simulations to assess the interannual combined effect of regional variations of climate forcings and vegetation types on ET over the central US. The impact of interannual climate variability was determined by changing precipitation by a factor of 1.5 with co-varying changes in radiation, $T_{\text{max}}$, $T_{\text{min}}$, and relative humidity. The effects of land cover, soil texture and interannual climate variations on ET were evaluated separately by showing the deviations of simulated ET, soil moisture and surface runoff from the control runs (simulations using observed climate inputs).
RESULTS AND DISCUSSIONS

Model Evaluation

We first evaluate IBIS simulated ET against observed ET collected from a field site located at a riparian wetland in the semi-arid region of south-central Nebraska (USA). IBIS requires hourly meteorological inputs including air temperature, relative humidity, incoming solar radiation, precipitation, and wind speed. To collect these meteorological input data, a tower was installed in the wetland during 2009 summer season. Dense and tall *P. australis* community was the dominant vegetation type in the wetland, which maximum height was observed as about 4.2 meters in July 2009 and there was standing water in the wetland during the observation period.

In its standard version, IBIS does not include a specific plant functional type for *P. australis*. However, *P. australis* is very similar to corn in terms of plant architecture and transpirative response to the external climate forcings. Therefore, we selected plant type as corn and applied some minor modifications to simulate the *P. australis* during the summer of 2009. The modifications include adjustment for harvest date and LAI decline function to prevent the model transpiration shut off during the studied period. These modifications were especially necessary for the simulations that we tested the sensitivities of climatic drivers on ET as will be explained in the method section. In our analysis, the time period of interest was summer months. However, simulations with elevated ambient temperatures caused early transpiration shut off in corn because the crop reaches its maximum maturity level as early as in the mid-August. To circumvent
this unwanted model constrain, we modified the harvest date and canceled LAI decline function in corn crop type.

To assess the model sensitivity to groundwater, we first provided a control run assuming free drainage bottom boundary conditions (i.e., no groundwater influence). Subsequently, we replaced the lower boundary condition of the model with zero depth to groundwater (i.e., water table is on the ground surface) to simulate wetland conditions. Figure 4.1 shows that simulated ET significantly improved when groundwater was used as lower boundary. Moreover, the model results presented in Figure 4.1 suggest that using corn with minor modifications can satisfactorily simulate the latent heat flux of *P. australis*.

**Influence of External Climate Drivers on ET**

IBIS calculates total ET by summing plant transpiration (T), surface evaporation (E) and intercepted water evaporation. Responses of T and E to the environmental factors are different than each other; therefore we separated the components of ET into E and T (intercepted E was ignored) to better understand the sensitivities of each component on climatic drivers (i.e., precipitation, solar radiation, air temperature) and depth to water table. We used the wetland field site simulation, which input data was collected in 2009 growing season, as a control run and deviate climatic drivers. However, we did not force the model to keep soil layers saturated. Instead, we used free drainage bottom boundary conditions in the control run to avoid any soil moisture effect on the simulated ET responses to the climatic drivers. Two sets of simulations were designed to examine the model ET sensitivities. In the first set of simulations, the effects of climatic drivers to
model results were examined through 2 dimensional surface color plots. In these set of plots, we changed observed precipitation, air temperature and solar radiation (incoming shortwave) independently in the ranges of ±30%, ± 3°C and ±15% respectively.

In order to examine the results of single-cell simulations, the results were visualized by plotting 2-dimensional surface plots using the ArcGIS Geostatistical Analyst, which provides a comprehensive set of tools to visualize, analyze and understand spatial distribution of observed sample points. Ordinary Kriging geostatistical model was used in visualization of both sets of simulations. Mathematically, the goodness of the geostatistical model for spatial interpolation was determined by root mean square error, root mean standardized error, and average standard error of each of the surface plots (Tables 4.1 and 4.2). Higher accuracy in surface interpolations can be determined by the fact that if root mean square error value is smaller, if root mean standardized error is close to 1, and if average standard error is close to root mean square error (Jonston et al. 2001).

Results of the first set of IBIS model runs in single grid cell were presented in Figure 4.2, which shows the simulated ET, T, E and SM deviations from the control run (i.e., observed climate inputs from the wetland site and free drainage bottom boundary condition) in separate plots. Figure 4.2 shows that while T is most sensitive to precipitation and radiation changes; evaporation is highly sensitive to temperature changes.

Transpiration increases as radiation and precipitation increases, however T reaches its maximum value when temperature anomaly is in the range of +0.5 to +1.5 °C (optimum
temperature range) under the observed radiation and 30% elevated precipitation conditions. Outside of this temperature range T slightly decreases (Figure 4.2-a2). Also note that as moisture availability decreases (precipitation in Figure 4.2-a2), the optimum temperature range, shifts toward more negative values. Similar shift is also observed in simulated LAI values (Figure 4.3). There are various environmental factors including leaf temperature and soil moisture availability that might limit T through limiting photosynthetic rate of the plant. In elevated precipitation case, even though soil water stress factor has no significant effect on plant photosynthesis, model simulates relatively lower photosynthesis rate, which constrains the plant growth and results in low transpiration. Photosynthetic rate of C4 plants such as corn-like vegetation is determined from three potential capacities to fix carbon in IBIS (Collatz et al, 1992; Foley et al, 1996; Kucharik et al, 2000). These are light-limited rate, Rubisco-limited rate, and $\text{CO}_2$-limited rate of photosynthesis. Rubisco-limited rate of photosynthesis is function of temperature. Photosynthesis rate increases until an optimum leaf temperature then after this point is reached photosynthesis rate starts to decline (Eq. 5B in Collatz et al 1992). The optimum leaf temperature for corn is 41°C (Figure 4.4). However, in our field site, observed air temperature range is between 10 and 35°C during the summer months, which indicates that the temperature is lower than the optimum leaf temperature even in simulations with elevated temperature. The main reason, which causes decline in T as temperature increases might be the increasing trend in E. Evaporation increases results in decline in leaf temperatures, which negatively affects photosynthesis rate of the plant. Decline in photosynthesis rate also enhances E through declining LAI, which causes
more solar radiation to reach the ground and also causes higher air-soil transfer coefficients due to increasing wind speed at the ground level (Figure 4.2-a3 and c3).

In the second set of simulations, we examined the effect of groundwater on ET, T, E and SM with respect to radiation, temperature and precipitation by plotting depth to water table versus these ET drivers. In these plots “depth to water table” notation represents the top of capillary zone, not the actual water table depth. We did not correct this value due to the fact that the reported capillary thicknesses associate with large uncertainties and we used only silt loam soil texture for all single grid cell simulations.

Second set of IBIS model simulation results were presented in Figure 4.5, which is similar to Figure 4.2 but the main emphasis here was to indicate the sensitivities of ET, T, E and SM on groundwater. Figure 4.5 indicates that T is substantially sensitive to radiation and temperature. However depth to water table and T do not show a linear relationship. Transpiration reaches its maximum value where the water table is about 100cm depth, which is optimum depth to water table providing the higher transpiration rate (Figure 4.5-a2 - b2) and LAI (Figure 4.3) in these simulations. Above this optimum groundwater depth, soil water availability is the main stress factor limiting T. However below the optimum depth, evaporation from the ground increases significantly and contributes decline in leaf temperature, which constrains T as groundwater getting closer to the surface. Another interesting point worth to mention here is that the effect of groundwater on E. As depth to water table is higher than about 80 cm, E becomes even lower than the control run simulated E (Figure 4.4-a3, b3, c3). The lower E values can be attributed to the higher LAI (Figure 4.3.c), because higher LAI cause both lower solar
radiation reaching the ground due to increasing attenuation and lower the air-soil transfer coefficients due to decreasing wind speed at the ground level.

The results imply that groundwater depth is located between 0.9 and 1.3 m from the surface results in both higher T and LAI. Assuming that the thickness of capillary fringe is 0.35 m based on reported values (Mausbach, 1992) for the silt loam that we used as the soil type in our single grid cell simulations, actual optimum groundwater depth range becomes 1.25 m – 1.65 m, which conforms well to the findings of Nosetto et al. (2009). They found the optimum groundwater depth range, where crop yields were highest, is between 1.4 – 2.4 m for corn. However they attributed the decrease in grain yield with shallow groundwater to the effect of waterlogging, root anoxia and salinity, our results show that it can also be attributed to change in leaf temperature due to higher E.

Both 2-D surface plots in Figure 4.2 and 4.5 associate with some errors due to the applied geostatistical methods, which errors were shown in Table 4.1 and 4.2 respectively. Even though evaporation plots shows the lowest accuracy in both figures, the errors are generally insignificant.

_Determination of Interdependencies of Climate Variables_

Although each of the climate forcing has a distinct effect on ET, these forcings are coupled to each other. Therefore, these forcings has a combined impact on ET. To give a reliable indication of change in ET, relative dependencies of climate forcings to each other needs to be determined. To analyze the co-variations of climate forcings, we utilized 60 years daily climate data (1948 – 2007) including radiation, minimum and maximum air temperature and precipitation in 5-minute spatial resolution (~8 km) over
the entire US. While precipitation and air temperature data were prepared by using available meteorological station observations across the US, solar radiation data is based on National Center for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) reanalysis estimations (Kalnay, et al 1996). We focused on a domain in the central US covering the state of Nebraska and northern part of Kansas (38.75° - 43.75°N, 104.25° - 95.25°W) for the further analysis with our climate datasets.

In order to determine the inter-dependencies of climate variables, we analyzed summer means of a climate dataset, which covers 60 years (1948 – 2007) of daily temperature, precipitation, radiation, and relative humidity observations. Figure 4.6 shows 60 years long term summer average spatial distributions of these variables over the entire US. While higher summer precipitation was observed over East - Southeast US, very limited or no summer precipitation occurs over Western US. Solar radiation follows an inverse distribution pattern with the precipitation distribution due to cloud covers over the US as expected. Higher daily maximum temperature ($T_{max}$) observed south southwestern states with relatively lower altitudes such as southern Arizona California’s Central valley and Texas, and lower $T_{max}$ observed generally in mountainous regions and Northern US. Higher diurnal temperature range (DTR), which is the difference between daily maximum and minimum temperature, is observed over the western US and relatively lower DTR is observed over eastern US.

As a first step toward determination of co-variations of climate forcings, correlation coefficient maps, slope of linear regression maps and significance maps were created for each of the forcing pairs. Figure 4.7.a shows the percent increase on radiation for every 10% increase in precipitation. Western US shows lower magnitude of radiation change in
response to precipitation change and higher anti-correlation, while east shows higher magnitude of change but lower anti-correlation or statistically not any significant correlation at all (e.g., Tennessee, Kentucky and Illinois). Figure 4.7.b indicates that every 10% increase in precipitation causes 0.5°C or less decrease in $T_{\text{max}}$ over the US. The relationship between $T_{\text{max}}$ and precipitation is generally significant over the entire studied region except small patches such as north of Minnesota. Figure 4.7.c shows a strong anti-correlation between DTR and precipitation over the entire region. A higher magnitude of change in DTR is observed over dry western US up to 0.3°C decrease for 10% increase of precipitation. Figure 4.7.d shows the most extensive coverage of statistically meaningless relationship over most of the eastern US between $T_{\text{max}}$ and radiation. However western US show significant correlation except central California and $T_{\text{max}}$ increases up 7°C for every 10% increase in radiation over mountainous regions.

The strong anti-correlation between precipitation, $T_{\text{max}}$ and DTR during the warm season has also been found in previous studies (Karl et al. 1993; Dai et al. 1997, 1999; Zhou et al. 2009). The reason for this anti-correlation has been attributed to reduction of incoming solar radiation by cloud cover and increase in surface latent heat release by surface wetness due to precipitation and soil moisture (Dai et al, 1999; Roderick and Farquhar, 2002; Portmann et al, 2009), while nighttime $T_{\text{min}}$ is controlled by net longwave radiation, which cloud cover prevents long wave radiation escapes through trapping the radiation and re-emitting back towards the earth.

The maps in Figure 4.6 and 4.7 showed that climate forcings varies significantly depending on geographic locations and altitude. Therefore quantification of inter-dependencies of climate variables for entire dataset would associate with significant
uncertainties. Instead, we limited our analysis to a smaller domain over central US including state of Nebraska, part of Northern Kansas and small portion of South Dakota, where variations of mean climate forcings and linear regression slopes are relatively little and statistically significant in all climate pair relationships (Figure 4.7). Long term summer average spatial distributions of precipitation, radiation, DTR, $T_{\text{max}}$ and $T_{\text{min}}$ over selected domain were given in Figure 4.8, which indicates that average summer precipitation over Nebraska gradually declines from about 4 mm/day in the east to 1.5 mm/day in the west. Also solar radiation distribution map shows a similar but inverse gradual pattern from 333 Wm$^{-2}$ in western to 305 Wm$^{-2}$ in eastern Nebraska. Maximum temperature and DTR shows variations across the domain but the ranges of these variations are significantly less than the ranges of variations over the entire US.

To simulate the combined impact of interannual variations of climatic forcings on ET, first, scatter plots (Figure 4.9) were used to provide a general relationship between each climatic variable pairs. While DTR versus precipitation anomaly plot shows the highest correlation and the least dispersion, radiation versus precipitation plot shows the worst correlation and the highest dispersion. The correlation coefficients of all plots except precipitation versus radiation were higher than 0.5, but regression lines still represent limited portion of sample sizes. Moreover, general boundaries of the scattered data may be clearly delineated in Figure 4.9, however the densities of the sample population is not very clear due to excessive number of data (~399,000 data point). The sample population densities might be important in terms of understanding the general slope tendencies of majority of the sample points to be able to fit a line more objectively than scatter plot trend line. Therefore, color maps showing the sample population densities of variable
pairs were created (Figure 4.10). These color maps indicate that slope of each linear regression of a climate variable against precipitation are slightly different depending on whether the precipitation anomaly is negative or positive.

To quantify the inter-relationships between climate variable pairs for the studied domain, wind rose diagrams were used. Originally, these diagrams are used to show the relative frequency of directions from where the wind is coming from. However, in our analysis, we used these diagrams for the purpose of determining the direction of general tendencies of co-variations of climate forcing pairs. We took zero anomalies of each variable pairs as origin of the wind rose diagram and assigned a corresponding angle value of each observation point depending on its location. One of the main advantages of using the wind rose diagrams over linear regression is that they can detect different slopes depending on whether the anomalies are negative or positive. Wind rose diagrams provide an objective way to create trend lines that represent the majority of the sample points. The right panel of Figure 4.10 shows the trend lines for each climate variable against precipitation. These plots suggest that if precipitation decreases 10% from its long-term average value, radiation increases about 1.6%. However if precipitation increases the same rate, radiation decreases by about a 1.6 times higher than its response to decreasing precipitation (2.5%). The reason might be the fact that radiation decreases with increasing cloud cover however this does not necessarily cause more precipitation. Even small increase in precipitation could largely impact radiation due to increasing cloud cover. Similarly, $T_{max}$ responses to negative precipitation anomaly by 1.35 times higher than positive precipitation anomaly because of the fact that decreasing precipitation associated with lower cloud cover, which cause $T_{max}$ to increase with a faster
rate. Also, DTR responses to precipitation anomaly change 1.8 times higher when the anomaly becomes negative than it becomes positive. The main reason might be that decreases in cloud cover (negative precipitation anomaly) enhances incident sunlight, which increases the maximum day time temperature and reduces the net loss of long-wave irradiance from the surface at night, which decreases the minimum night time temperature. On the other hand, relative humidity response to negative and positive precipitation anomaly is almost the same as expected. Based on the analysis that we showed in Figure 4.10, we prepared Table 4.3, which indicates two interannual climate variability scenarios with changing precipitation by a factor of ±1.5. These scenarios are used in regional model simulations to examine the sensitivity of ET to interannual climate variability.

Moreover, Figure 4.11 showing the color maps with three variables provides not only better understanding for the interdependencies of climate variables in terms of their sensitivities to each other but also evidences to assure the reliability of the dataset that we used in this study. For example, left panels of Figure 4.11.a, b, c, and d shows that $T_{\text{max}}$, DTR, and relative humidity are sensitive to both radiation and precipitation, however $T_{\text{max}}$ and relative humidity associates with higher uncertainty than DTR due to their more scattered color pattern. On the other hand, color maps showed on right panel of Figure 4.11 have lower uncertainties in sensitivities among variables due to proper color layering.
We performed two sets of IBIS simulations to assess the interannual combined effect of regional variations of climate forcings and vegetation types on ET over the central US (38.75° - 43.75°N, 104.25° - 95.25°W). The natural vegetation cover and *P. australis* cover were evaluated in response to the impact of interannual climate variability in the first and second simulation sets respectively. The model was run using 5-minute spatial resolution (~8 km) using hourly time steps after a spinup of 10 years that allowed model to reach equilibrium for both cases separately. We selected 1990 as our control year for both simulation sets because 1990 shows not only relatively small climate anomalies, but also it was not preceded by a series of anomalous years (Figure 4.12).

First, we run the model without changing any input variables (control run) after 10 years of model spin up period by using natural vegetation as a land surface cover, and then run the same simulation but using *P. australis* as land cover. Figure 4.13 shows input precipitation, incident solar radiation and simulated ET for both land cover type. The figure indicates that the east and west of the model domain are very different than each other climatically. While east of the studied area received about 4 mm day⁻¹ precipitation and about 13.1 mm day⁻¹ water equivalent of incident solar radiation, west part of the studied area received about 1.5 mm day⁻¹ precipitation and 13.9 mm day⁻¹ water equivalent of incident solar radiation. Water and energy availability in this two regions are quite different than each other.

These different climatic conditions lead different simulation results in east and west. For example, IBIS generated higher total runoff (surface and sub-surface drainage) and soil moistures in east than that in west (Figure 4.14). However, the model results, in
north-central part of the domain, where Sandhills is located, show a distinctive pattern. Sandhills is a region that includes native grassland on grass-stabilized sand dunes. Low water holding capacity of sand easily transmits precipitated water to the bottom, which cause lower soil moisture and higher subsurface drainage (Figure 4.14). Considering the distinctive characteristics of specific regions in the studied domain that mentioned above, we separated the domain into 3 sub-regions where climate and soil textures are relatively homogeneous, namely east, northwest (NW) and southwest (SW). Basically, we separated energy-limited east and water-limited west (dividing longitude is 97W) and then we further separated west into 2 sub-regions, which are SW and NW (dividing latitude is 41N), mainly because of distinctive characteristics of Sandhills. Table 4.4 shows general characteristics of each sub-region.

While the impact of soil textures on water and energy balances is clear in Figure 4.14, where relatively low soil moisture and high drainage were generated in Sandhills, the effect of land cover has also significant influence on water and energy balances. The simulation using \textit{P. australis} as land cover generated less runoff and soil moisture mainly due to its higher ET rates (Figure 4.14). Figure 4.15 also compares \textit{P. australis} and natural vegetation land cover simulations through showing net solar radiation and potential ET calculated from Priestley-Taylor method (Priestley and Taylor, 1972), where ground heat flux was assumed as 10\% of net solar radiation and Priestley-Taylor alpha coefficient was taken as 1.26. Generating different net solar radiations of IBIS depending on the vegetation type could be attributed to direct (due to its leaf structure) and indirect (due to altering soil moisture) effects of vegetation type on land surface albedo. Figure 4.15 also implies that while \textit{P. australis} causes higher potential ET values in water-
limited region (west of the domain), natural vegetation consisting of mixed grassland and limited distribution of savanna (on south west corner of the study domain) lead higher potential ET in energy-limited east. Potential ET is mainly determined by net solar radiation in simulations rather than relative humidity, which is same for both simulations.

To better understand the fraction of atmospheric demand that is used for ET, we provided a map showing the spatial distribution of actual ET to potential ET ratio (ETa/ETp) (Figure 4.16). This ratio actually represents the energy- and water-limited regions. Figure 4.16 clearly shows the distinction between that energy-limited east, where the ETa/ETp ratio is about 0.55 and water-limited west, where the ratio is about 0.38 (Table 4.5). However, these mean ratios are different in two land cover simulations. The simulation using P. australis as land cover shows higher difference between the ETa/ETp ratio values in east and west (i.e., the ETa/ETp ratio of P. australis simulation is higher in east and lower in west than that of natural vegetation simulation), which is mainly because of the fact that ETp in P. australis simulation is higher and ETa is lower in the west (especially SW) and ETp is lower and ETa is higher in the east (Table 4.5). Even though, land cover plays an important role in determining the magnitude of ETa/ETp ratios, soil moisture also affects it, for example ETa/ETp ratio stays the same in NW sub-region (Sandhills) in both simulations (Table 4.5). This suggests that regardless of vegetation type, ET does not change significantly in areas where coarse soil texture is the dominant type.

We performed two sets of IBIS simulations by applying two interannual climate variation scenarios, where change in each of climate forcings were shown in Table 4.3 for both scenarios. We tested the responses of natural vegetation and P. australis to
interannual climate variations based on these scenarios. Simulation results show that natural vegetation and *P. australis* responses to climate variations are significantly different than each other. For example in water-limited NW and SW, the impact of increased precipitation scenario on ETa for *P. australis* is more dramatic than that of natural vegetation (up to 50% increase in ETa; Figure 4.17a, c). Table 4.6 also shows that *P. australis* increases its ETa about 3 times higher than that of natural vegetation simulation. On the other hand, in energy-limited east, increased precipitation scenario has negative effect on ETa, where it decreased up to 25%. Simulated runoff (Figure 4.18a and c) and soil moisture (Figure 4.19.a and c) was also affected positively in entire domain with increasing precipitation scenario. However, in the scenario of decreased precipitation, the response of ETa did not show an inverse relationship with the simulation results of the first scenario. Rather, ETa decreased overall of the study area and the differences in ETa for both vegetation covers are not very different than each other (on the order of 5-10%; Figure 4.17b, d). Also, runoff and soil moisture shows insignificant differences for both land cover simulations under decreased precipitation scenario (Figures 4.18 and 4.19).

The responses of both vegetation covers to interannual climate scenarios in energy-limited east are worth to mention here. Simulation results showed that both increased and decreased precipitation climate scenarios resulted in reduced ETa especially in natural vegetation land cover (Table 4.6). The main reason for ETa reduction is that increasing precipitation scenario actually decreases the available energy through decreasing radiation by 12.4% (Table 4.3). Therefore, decreasing energy in an energy-limited area leads lower ETa values. On the other hand, decreasing precipitation by 33% leads lower
available water for plant use. Even though enhanced radiation input was used in this scenario (5.3%), water scarcity causes stress in vegetation and leads lower ETa values. These results imply that changing the coupled input climate variables accordingly in energy and water balance simulations could lead significantly different results, rather than changing one variable at a time in interannual climate variation studies.

SUMMARY AND CONCLUSIONS

Understanding the sensitivities of ET to interannual climate variability and water table depths can be crucial in terms of quantifying water transfers in soil-vegetation-atmosphere system. However, there are few previous studies focused on combined impacts of these coupled variables on ET. Here, we used a land surface/ecosystem model to investigate sensitivities of ET to climate variations, land cover and depth to groundwater over the central US. First, we simulated ET from a P. australis community located in a wetland study site in south central Nebraska and compared model results with observations calculated from energy balance equation. Model results were satisfactorily close to the observations. Using this result as our control simulation, we examined the effects of precipitation, radiation and temperature on ET using a single grid cell. We analyzed the responses of ET, its components and soil moisture relative to the control run to understand model sensitivities on each climate variables. Results showed that simulated changes in T are mainly controlled by precipitation and radiation. However, simulated E changes are mainly controlled by temperature. It was found that increasing E provides negative feedback to T by reducing canopy leaf temperature and soil moisture plays very important role to partitioning of E and T for given climate conditions.
Moreover, we investigated the effect of groundwater on ET by keeping the various soil layers saturated to mimic constant water table. Results showed that E is the most sensitive variable to groundwater depth changes and when groundwater table is about 1 – 2 m deep, E yields even lower values than the control simulations, in which free drainage lower boundary condition was applied. As groundwater depth is getting shallower than 1 m, a sharp increase in E was observed. On the other hand, T reaches its maximum value when water table depth is about 1 m. Sharp increase in E on shallow groundwater depths reduces T.

Single grid cell simulation results were used to explain ET responses to interannual climate forcings variations. However, climate variables are coupled to each other and they have a combined effect on ET. To obtain their combined effect on ET, we analyzed interdependencies of climate variables over central US by using 60-year period 5-minute spatial resolution climate dataset. We developed a new methodology to obtain relative changes of climate variables by utilizing wind rose diagrams. After quantifying the interdependencies of these variables, we used 2 interannual climate variation scenarios through changing precipitation by a factor of 1.5. Results suggested that while increasing precipitation by a factor of 1.5 (+50%) causes about 12.4% decrease in radiation, 2.6 °C decrease in $T_{\text{max}}$, 1.6 °C decrease in $T_{\text{min}}$, and 16% increase in relative humidity; decreasing precipitation by a factor of 1.5 (-33%) causes 5.3% increase radiation, 2.3°C increase in $T_{\text{max}}$, 1.1°C increase in $T_{\text{min}}$, and 9.9% decrease in relative humidity over the central US during summer periods.

The interannual climate variation scenarios were applied to simulations using natural vegetation and $P. australis$ as land covers over the central US. We evaluated results in
three distinctive sub-regions, which are east, northwest and southwest. East is an energy-limited region including Elkhorn, Lower Platte, Missouri, and Nemaha river basins. Northwest and southwest are water-limited regions. While Sandhills represented by northwest; Republican and Middle Platte River basins are located in southwest sub-region. Results suggested that ET responses are significantly different in water-limited west and energy-limited east of the studied area and land cover and soil types play important roles in controlling ET along with climate forcing. For example, *P. australis* responses to increased precipitation scenario as increasing its ET three times higher than the natural vegetation cover in water-limited west. However, when the same scenario applied to energy-limited east, simulated ET decreased in both land cover types but more extensively in natural land cover.

In addition to Teuling et al., (2009)’s results, who argued that ET is controlled by radiation in energy-limited regions and by precipitation in water-limited regions, in this study, we showed the interdependencies of climate forcings also need to be considered. That is to say, change in precipitation associate with change in radiation, temperature, and relative humidity and all these changes have a combined effect on ET. Our results also showed that land cover and soil texture are important factors need to be considered in ET sensitivities studies.
REFERENCES


Table 4.1. Prediction errors of ordinary Kriging interpolation method in ArcGIS Geostatistical Analyst for the surface plots showed in Figure 4.2.

<table>
<thead>
<tr>
<th></th>
<th>Root Mean Square Error</th>
<th>Root Mean Square Standardized Error</th>
<th>Average Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prec. vs. Temp.</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total ET</td>
<td>0.34</td>
<td>0.43</td>
<td>0.84</td>
</tr>
<tr>
<td>Transpiration</td>
<td>1.02</td>
<td>1.08</td>
<td>1.06</td>
</tr>
<tr>
<td>Evaporation</td>
<td>2.13</td>
<td>1.03</td>
<td>2.12</td>
</tr>
<tr>
<td>Soil Moisture</td>
<td>2.11</td>
<td>1.15</td>
<td>1.78</td>
</tr>
<tr>
<td><strong>Prec. vs. Rad.</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total ET</td>
<td>0.62</td>
<td>0.65</td>
<td>0.89</td>
</tr>
<tr>
<td>Transpiration</td>
<td>1.93</td>
<td>1.64</td>
<td>1.18</td>
</tr>
<tr>
<td>Evaporation</td>
<td>3.66</td>
<td>0.96</td>
<td>3.83</td>
</tr>
<tr>
<td>Soil Moisture</td>
<td>2.04</td>
<td>1.10</td>
<td>1.84</td>
</tr>
<tr>
<td><strong>Rad. vs. Temp.</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total ET</td>
<td>0.42</td>
<td>1.47</td>
<td>0.30</td>
</tr>
<tr>
<td>Transpiration</td>
<td>1.43</td>
<td>1.30</td>
<td>1.12</td>
</tr>
<tr>
<td>Evaporation</td>
<td>3.01</td>
<td>1.01</td>
<td>3.01</td>
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<tr>
<td>Soil Moisture</td>
<td>1.62</td>
<td>3.22</td>
<td>0.37</td>
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Table 4.2. Same as Table 4.1. except for surface plots showed in Figure 4.5.

<table>
<thead>
<tr>
<th></th>
<th>Root Mean Square Error</th>
<th>Root Mean Square Standardized Error</th>
<th>Average Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Precipitation</strong></td>
<td></td>
<td></td>
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<tr>
<td>Total ET</td>
<td>0.65</td>
<td>0.44</td>
<td>1.43</td>
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<tr>
<td>Transpiration</td>
<td>1.97</td>
<td>0.69</td>
<td>2.82</td>
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<tr>
<td>Evaporation</td>
<td>8.12</td>
<td>0.56</td>
<td>14.46</td>
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<td>Soil Moisture</td>
<td>3.48</td>
<td>0.35</td>
<td>10.02</td>
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<tr>
<td><strong>Radiation</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Total ET</td>
<td>0.43</td>
<td>0.55</td>
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<td>Transpiration</td>
<td>1.10</td>
<td>1.00</td>
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<td>Soil Moisture</td>
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<td>0.40</td>
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<td><strong>Temperature</strong></td>
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<td></td>
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<td>Total ET</td>
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<td>Transpiration</td>
<td>1.85</td>
<td>0.65</td>
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<td>Soil Moisture</td>
<td>6.29</td>
<td>0.51</td>
<td>12.42</td>
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</table>
Table 4.3. Interannual precipitation change scenarios (factors of ±1.5) and co-variations of each climate forcings as shown in Figure 4.10.

<table>
<thead>
<tr>
<th>Precipitation change (%)</th>
<th>Radiation change (%)</th>
<th>$T_{\text{max}}$ change ($^\circ$C)</th>
<th>$T_{\text{min}}$ change ($^\circ$C)</th>
<th>Relative Humidity change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>50.00</td>
<td>-12.37</td>
<td>-2.56</td>
<td>-1.58</td>
<td>+16.00</td>
</tr>
<tr>
<td>-33.00</td>
<td>5.34</td>
<td>2.31</td>
<td>1.11</td>
<td>-9.90</td>
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</table>
Table 4.4. Characteristics of each sub-region, where east and west divided by longitude 98W and NW and SW divided by latitude 41N.

<table>
<thead>
<tr>
<th></th>
<th>East</th>
<th>Northwest (NW)</th>
<th>Southwest (SW)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy - water limitation</strong></td>
<td>Energy-limited</td>
<td>Water-limited</td>
<td>Water-limited</td>
</tr>
<tr>
<td><strong>Dominant soil type</strong></td>
<td>Silt, loam</td>
<td>Sand</td>
<td>Loam, loamy sand</td>
</tr>
<tr>
<td><strong>Natural land cover types</strong></td>
<td>Grassland and savanna</td>
<td>Grassland</td>
<td>Grassland</td>
</tr>
<tr>
<td><strong>Water basins</strong></td>
<td>Elkhorn, Lower Platte, Missouri, Nemaha</td>
<td>Loup, Niobrara (Sandhills)</td>
<td>Republican, Middle Platte</td>
</tr>
</tbody>
</table>
Table 4.5. Actual and potential ET for the three distinctive regions for summer 1990. While actual ET is from IBIS simulations, potential ET is calculated from Priestley-Taylor method.

<table>
<thead>
<tr>
<th>mm/day</th>
<th>P. australis</th>
<th>Native vegetation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Potential ET</td>
<td>Actual ET</td>
</tr>
<tr>
<td><strong>SW</strong></td>
<td>8.65</td>
<td>3.31</td>
</tr>
<tr>
<td><strong>NW</strong></td>
<td>9.02</td>
<td>3.20</td>
</tr>
<tr>
<td><strong>East</strong></td>
<td>8.50</td>
<td>4.92</td>
</tr>
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</table>
Table 4.6. Changes of ET, total runoff, volumetric water content, and precipitation for both *P. australis* and natural vegetation from control simulations when 2 coupled interannual climate scenarios, which were given in Table 4.3, were applied for 3 sub-regions (as defined in Table 4.3) both as percent and as absolute amount (values in parenthesis).

<table>
<thead>
<tr>
<th>Region</th>
<th>% (mm/day)</th>
<th>Increasing Precip.</th>
<th>Decreasing Precip.</th>
<th>Increasing Precip.</th>
<th>Decreasing Precip.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>P. australis</strong></td>
<td></td>
<td></td>
<td><strong>Native Veg.</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ET</td>
<td>21.87 (0.72)</td>
<td>-26.74 (-0.89)</td>
<td>6.57 (0.21)</td>
<td>-19.17 (-0.61)</td>
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<tr>
<td></td>
<td>Runoff</td>
<td>370.01 (0.93)</td>
<td>-60.71 (-0.15)</td>
<td>414.42 (2.32)</td>
<td>-67.86 (-0.38)</td>
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<tr>
<td></td>
<td>VWC</td>
<td>27.92 (0.08)</td>
<td>-13.66 (-0.04)</td>
<td>37.19 (0.12)</td>
<td>-20.16 (-0.06)</td>
</tr>
<tr>
<td>South West</td>
<td>ET</td>
<td>33.56 (1.07)</td>
<td>-34.15 (-1.09)</td>
<td>13.83 (0.48)</td>
<td>-26.92 (-0.93)</td>
</tr>
<tr>
<td></td>
<td>Runoff</td>
<td>236.45 (0.16)</td>
<td>-37.17 (-0.03)</td>
<td>399.99 (0.48)</td>
<td>-48.00 (-0.06)</td>
</tr>
<tr>
<td></td>
<td>VWC</td>
<td>33.49 (0.11)</td>
<td>-13.35 (-0.04)</td>
<td>40.03 (0.14)</td>
<td>-19.64 (-0.07)</td>
</tr>
<tr>
<td>North West</td>
<td>ET</td>
<td>2.14 (0.11)</td>
<td>-25.93 (-1.28)</td>
<td>-6.46 (-0.29)</td>
<td>-18.61 (-0.85)</td>
</tr>
<tr>
<td></td>
<td>Runoff</td>
<td>629.82 (1.41)</td>
<td>-53.34 (-0.12)</td>
<td>536.76 (2.92)</td>
<td>-68.62 (-0.37)</td>
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<tr>
<td></td>
<td>VWC</td>
<td>34.64 (0.17)</td>
<td>-17.05 (-0.08)</td>
<td>27.00 (0.15)</td>
<td>-19.01 (-0.11)</td>
</tr>
<tr>
<td>East</td>
<td><strong>Rainfall</strong></td>
<td>50 (1.66)</td>
<td>-33 (-1.10)</td>
<td>50 (1.66)</td>
<td>-33 (-1.10)</td>
</tr>
</tbody>
</table>
Figure 4.1. Three-day moving average of observed and simulated with and without representing groundwater as a lower boundary daily evapotranspirations of the wetland field site.
Figure 4.2. Color maps showing the effect of climate forcings on ET components and soil moisture under free drainage lower boundary condition. Left panel shows precipitation vs. temperature, middle panel shows precipitation vs. radiation and the right
panel shows radiation vs. temperature plots. Rows indicate percent changes in total ET, transpiration, evaporation and volumetric water content respectively from top to bottom relative to the simulation with the observed climate inputs collected from the wetland study site.
Figure 4.3. LAI responses of the simulated corn-like vegetation to the changes of each individual climate variable. a) represents LAI responses to the percent change in radiation, B) represents LAI responses to the percent change in precipitation, C) represents LAI responses to the change in temperature.
Figure 4.4. Temperature dependency of rubisco capacity (Vmax) under no water stress for corn crop in IBIS.
Figure 4.5. Similar to Figure 4.3 but each climate variable is plotted against depth to water table. Percent changes in variables are given relative to the simulation with the observed climate inputs collected from the wetland study site under free drainage lower boundary condition.
Figure 4.6. Long term summer average spatial distributions of precipitation, radiation, DTR, $T_{\text{max}}$ and $T_{\text{min}}$ across the US.
Figure 4.7. Co-variations of observed climatic forcings for 60 years of summer mean over the continental US. Each panels shows spatial distribution of three maps including slope of linear regression, statistical significance and correlation coefficient of a) radiation vs. precipitation; b) $T_{\text{max}}$ vs. precipitation; c) DTR vs. precipitation and d) $T_{\text{max}}$ vs. radiation
Figure 4.8. Long term summer average spatial distributions of precipitation, radiation, DTR, $T_{\text{max}}$ and $T_{\text{min}}$ over central US
Figure 4.9. Scatter plots of climatic forcings over the domain covering the state of Nebraska. Each point indicate individual 5-minute resolution raster cell for an individual year. Each plot includes approximately 400,000 data point covering over entire Nebraska domain for 60 year time period. DTR anomaly indicates the difference between maximum temperature ($T_{\text{max}}$) and minimum temperature ($T_{\text{min}}$).
Figure 4.10. Color maps (right panel) showing sample densities of scatter plots, wind rose diagrams (middle panel) showing the angles of most populated directions from the origin (no anomaly point) and scatter plots (right panel) showing both linear regression trend lines (black lines) and wind rose diagrams calculated angles (red lines). Relationships between radiation, $T_{\text{max}}$, DTR and relative humidity against precipitation are given here from top to the bottom respectively.
Figure 4.11. Similar to the right column of Figure 4.11 but color maps showing relationships among 3 climate variables.
Figure 4.12. Time series of summer period averaged a) radiation, precipitation and b) daily maximum and minimum temperatures for central US (38.75° - 43.75°N, 104.25° - 95.25°W)
Figure 4.13. Observed precipitation (a), incident solar radiation (b), and simulated actual ET for *P. australis* (c) and natural vegetation (d) during 1990-summer period control runs (all units are mm/day).
Figure 4.14. Control simulation results (using observed climate inputs for 1990) including total runoff (a and b) and volumetric water content (c and d). Left panels show simulation results of *P. australis* and right panels show that of natural vegetation.
Figure 4.15. Simulated net solar radiations (top figures) and potential ETs calculated from Priestley – Taylor method (lower figures). Figures on left and right show *P. australis* and native vegetation.
Figure 4.16. The spatial distribution of the ratio of actual ET (IBIS simulated) to potential ET (calculated from Priestley Taylor method) for *P. australis* (a) and natural vegetation (b).
Figure 4.17. Percent deviations of simulated ET from the control simulations, which uses the observed input climate forcing for the year 1990 for two interannual climate scenarios including increased and decreased precipitation by a factor of 1.5 (radiation, $T_{\text{min}}$, $T_{\text{max}}$, relative humidity have been modified accordingly as shown in Table 4.3. a) and b) show percent ET deviation of *P. australis* for increased and decreased precipitation scenarios respectively c) and d) show percent ET deviation of natural land cover for increased and decreased precipitation scenarios respectively from control runs.
Figure 4.18. Same as Figure 4.17 but showing difference of simulated total runoffs (including surface runoff and drainage) from control runs.
Figure 4.19. Same as Figure 4.17 but showing deviation of simulated volumetric water content (VWC) for the top 10 cm of the soil zone.
CHAPTER 5: SUMMARY AND CONCLUSIONS

Evapotranspiration (ET) is an important process that is controlled by many environmental and climatic factors. Partitioning of available energy into ET (latent heat flux) and sensible heat flux at the land surface affects earth’s climate and weather systems. There has been great effort to understand the nature of controlling mechanisms and interactions between ET and other earth system processes. The controlling factors of ET can be grouped into two primary categories, namely moisture availability (e.g., soil moisture) and energy availability (e.g., solar radiation). Precipitation and groundwater exfiltration in shallow water table environments are the two main contributors to soil moisture, which is a key factor in most land surface hydrological processes such as ET and runoff. Air temperature and relative humidity are also key factors for ET in terms of controlling the atmosphere’s “drying power” (i.e., vapor pressure deficit).

The overall goals of this study were to quantify the impact of groundwater and climatic forcings on the land surface water and energy balance, as well as the sensitivities of various techniques for estimating ET (both empirical and modeled) when the water table is close to the surface. We performed several analyses to quantify these impacts and sensitivities. First, groundwater and ET interactions were examined in detail in Chapters 2 and 3. In Chapter 2, we investigated the role of different numerical model parameterizations in quantifying the impact of groundwater on root zone soil moisture and ET, as well as model sensitivity to soil texture and water table depth, by using models with varying complexities. The influence of groundwater on ET was simulated using various static lower boundary conditions (i.e., groundwater level was fixed at various prescribed depths). It was found that the parameterization of soil hydraulic
properties is the most important factor for ET modeling studies in shallow groundwater environments. These parameters determine the thickness of the critical zone (i.e., the zone of strongest influence of water table on surface ET) and play a more significant role than node spacing, soil texture, and even model selection.

In Chapter 3, we analyzed the effect of ET on groundwater level using observed diurnal water table fluctuations from a wetland field site. It has been previously shown that the magnitude of diurnal water table variations due to plant water consumption is mainly dependent on specific yield, soil type, groundwater depth, vegetation type, and solar radiation, as well as other climate variables (e.g., temperature, wind speed, and relative humidity), and that ET estimation from diurnal water level fluctuations provides a cost effective and efficient solution (albeit with some drawbacks). Here, we developed a new Fourier-based method to estimate groundwater ET with a greater accuracy than existing methods, and we explored the role of specific yield in using diurnal water table fluctuation methods for estimating ET in saturated environments (including conditions of standing water). It was found that specific yield estimates at the study site varies significantly in space and time, responding strongly (and inversely) to temporal variations in water table depth. Spatial variations in specific yield are weaker, but more complex, showing an increase in specific yield as groundwater nears the surface, then declining thereafter as one moves into regions of standing water.

Finally, in Chapter 4 we used a land surface / terrestrial ecosystem model to investigate the sensitivity of ET to interannual climate variability, land cover type, and water table depth over the central U.S. In this part of the study, the effects of air temperature, solar radiation, relative humidity, and precipitation on the land surface water
balance were investigated both separately and in concert (i.e., using observed covariances determined from historical climate data). The combined impact of climate forcing interdependencies on ET were simulated using two interannual climate scenarios, in which precipitation was increased (and decreased) by a factor of 1.5 (in conjunction with corresponding variations in radiation, temperature, and relative humidity). When ET is broken down into its two primary components, it is found that the relative responses of transpiration and surface evaporation to external environmental drivers are substantially different. While transpiration is most sensitive to precipitation and radiation, evaporation is most sensitive to temperature and groundwater depth. Moreover, the regional simulations show that interannual climate variability affects ET significantly different in water- and energy-limited regions. Also, land cover type and soil texture play important roles in determining ET rates, especially in hot and dry years.

In conclusion, our findings provide insight into the interactions between groundwater and ET, as well as the impacts of interannual climate variability and land cover type on these interactions. The land surface and atmosphere form a coupled system, and each of the variables investigated here have important feedbacks on each other. We consider precipitation and groundwater capillary flux as the primary suppliers of moisture to the vadose zone. However, in heavily irrigated basins (such as the Frenchman Creek watershed, discussed in Chapter 1), irrigation supplies a significant amount of moisture to the soil zone at the cost of declining groundwater tables and streamflow during the growing season (which, in turn, has an impact on the surface energy and water balance). Although examining such impacts is beyond the scope of this study, it would be
interesting in future studies to examine the effects of irrigation on historical ET trends in various river basins of the central U.S. and other heavily irrigated regions of the world.