Probabilistic analysis of the effects of climate change on groundwater recharge

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[1] Groundwater recharge is likely to be affected by climate change. In semiarid regions where groundwater resources are often critical, annual recharge rates are typically small and most recharge occurs episodically. Such episodic recharge is uncertain and difficult to predict. This paper analyzes the impacts of different climate predictions on diffuse episodic recharge at a low-relief semiarid rain-fed agricultural area. The analysis relies on a probabilistic approach that explicitly accounts for uncertainties in meteorological forcing and in soil and vegetation properties. An ensemble of recharge forecasts is generated from Monte Carlo simulations of a study site in the southern High Plains, United States. Soil and vegetation parameter realizations are conditioned on soil moisture and soil water chloride observations (Ng et al., 2009). A stochastic weather generator provides realizations of meteorological time series for climate alternatives from different general circulation models. For most climate alternatives, predicted changes in average recharge (spanning −75% to +35%) are larger than the corresponding changes in average precipitation (spanning −25% to +20%). This suggests that amplification of climate change impacts may occur in groundwater systems. Predictions also include varying changes in the frequency and magnitude of recharge events. The temporal distribution of precipitation change (over seasons and rain events) explains most of the variability in predictions of recharge totals and episodic occurrence. The ensemble recharge analysis presented in this study offers a systematic approach to investigating interactions between uncertainty and nonlinearities in episodic recharge.

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1. Introduction and Background

[2] The most recent Intergovernmental Panel on Climate Change (IPCC) report [*IPCC*, 2007] documents a growing consensus that the climate is changing due to increased atmospheric CO_2 from anthropogenic sources. However, the impacts of such change on terrestrial hydrologic systems remain uncertain. The impacts on groundwater resources in semiarid regions are particularly uncertain. Because groundwater is a major source of water supply for agricultural and domestic use, it is important to understand the possible connections between the climate and the recharge processes that replenish aquifers.

[3] In water-limited regions, climate change is likely to affect groundwater resources through changes in precipitation. Precipitation predictions provided by general circulation models (GCMs) vary significantly. Although these models generally agree that global average precipitation will increase with a warmer climate, there is much less agreement about regional changes [*IPCC*, 2007]. It is likely that climate change will affect precipitation intensity and timing as well as long-term totals. Higher-intensity rainfall is possible at all latitudes, and changes in precipitation are not expected to apply evenly over the seasons [*Trenberth et al.*, 2003]. Overall, local and regional effects of climate change on precipitation are highly uncertain.

[4] Groundwater is linked to precipitation through recharge at the water table. The amount of precipitation that escapes evapotranspiration (ET) and runoff and reaches the water table is influenced by a number of factors, including precipitation intensity and timing, meteorological variables such as temperature and humidity, topography, vegetation, and soil properties.

[5] Numerical models that consider all relevant physical factors can predict recharge from meteorological variables, but these predictions can be very sensitive to model assumptions and to errors in model inputs. This is especially true in semiarid regions, where recharge occurs infrequently during a few intense precipitation episodes [*Gee and Hillel*, 1988; *Allison et al.*, 1994]. Predictions of climate change impacts on groundwater resources must deal with two significant sources of uncertainty: (1) uncertainty about the nature of climate change (e.g., changes in precipitation and temperature) at local and regional scales and (2) uncertainty about the way recharge will respond to a given change in climate. The importance of both types of uncertainty implies

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the need for a probabilistic approach that explicitly recognizes the range of possible conditions that could occur.

[6] In recent years, a number of researchers have investigated the possible impacts of climate change on local groundwater systems. The study approaches and the predicted changes vary greatly across different settings and studies. *Rosenberg et al.* [1999] studied recharge changes in two major basins overlying the Ogallala aquifer under different GCM climate and CO_2 predictions and found decreases under all conditions due to increased ET. *Herrera-Pantoja and Hiscock* [2008] also predicted decreases in recharge in different locations in the United Kingdom due to higher ET, despite precipitation increases during the wet season. In contrast, *Kirshen* [2002] found recharge to a permeable Massachusetts aquifer to vary significantly depending on the climate scenario considered. Similarly, in a study of the Grand River basin in Michigan, *Croley and Luukkonen* [2003] found that the direction of recharge change depends on the climate scenario. *Serrat-Capdevila et al.* [2007] considered a comprehensive range of possible climates obtained from 17 GCM predictions for the San Pedro basin on the U.S.-Mexico border and showed that the average impact over the ensemble of these climates is a decrease in mountain front recharge.

[7] *Eckhardt and Ulbrich* [2003] predicted that changes in mean annual recharge will be small for a central European low mountain catchment, but intra-annual impacts will be more significant. *Jyrkama and Sykes* [2007] used a distributed watershed model to show both significant temporal and spatial recharge changes in a river watershed in Ontario. *Brouyère et al.* [2004] developed a hydrological model integrating soil, surface water, and groundwater components and showed that groundwater levels in a chalky aquifer in Belgium decrease under scenarios with increased winter rain and decreased summer rain. *Scibek and Allen* [2006] and *Scibek et al.* [2007] also used a combination of overland and subsurface modeling and showed that climate change impacts on groundwater levels in the Grand Forks area in Canada will be greatest where there is indirect recharge from rivers. *Tague et al.* [2008] similarly concluded that groundwater–surface water exchanges were important for predicting climate change impacts in mountainous regions in Oregon. For a river basin in the southern Great Plains, *Maxwell and Kollet* [2008] showed that shallow water tables of 2–5 m depth interact with the atmosphere, thus affecting recharge responses to climate change. Using a one-dimensional modeling approach, *Green et al.* [2007] implemented a Richards solver with a dynamic vegetation component to quantify how recharge changes in two different Australian climatic zones depend on nonlinear responses to soil and vegetation properties.

[8] In addition to climate and natural hydrological processes, socioeconomic changes may significantly affect recharge in many regions [*Holman*, 2006]. For example, *Loáiciga* [2003] presented a method that assesses the effects of both climate and population change on regional groundwater systems. In particular, he showed that population growth could be the overriding factor in inducing recharge change in a karst aquifer in Texas.

[9] Changes in climate are most often quantified in impact studies using change factors derived from GCM outputs. Each factor is computed for a particular meteorological variable at a particular time and space scale (e.g., a monthly value for each GCM grid cell) and represents the additive or multiplicative change from current to future GCM predictions. Some studies use change factors to scale historical meteorological data for hydrological investigations [e.g., *Kirshen*, 2002; *Croley and Luukkonen*, 2003; *Eckhardt and Ulbrich*, 2003; *Brouyère et al.*, 2004; *Serrat-Capdevila et al.*, 2007; *Maxwell and Kollet*, 2008; *Tague et al.*, 2008]. Others use change factors to calibrate stochastic weather generators [e.g., *Rosenberg et al.*, 1999; *Scibek and Allen*, 2006; *Green et al.*, 2007; *Herrera-Pantoja and Hiscock*, 2008]. These generators provide consistent synthetic time series for the meteorological inputs to hydrologic models. They are especially useful when long-term data are unavailable or do not have sufficient temporal detail to resolve critical events such as floods or recharge episodes. Many studies acknowledge uncertainty in future climate conditions by considering multiple climate forecasts. Studies that use stochastic weather generators also account for natural fluctuations in meteorological variables associated with a given climate.

[10] Uncertainties about the response of recharge to climate change depend on many factors, including topography, soil properties, and vegetation. Climate change impact studies typically use hydrologic models to study the aggregate effects of these factors. Such models cover a large range including empirical formulas, simple water balance calculations, multilayered distributed models, and detailed Richards' solvers. Some investigators have combined groundwater, overland flow, and unsaturated zone modeling to demonstrate the importance of groundwater–surface water interactions in certain settings [*Scibek et al.*, 2007; *Maxwell and Kollet*, 2008; *Tague et al.*, 2008]. The appropriate type of hydrological modeling depends on the dominant processes in a given study region. All models are susceptible to input uncertainties, questionable assumptions, and limited temporal or spatial resolution. However, past climate change studies do not generally consider uncertainty in the land surface and subsurface properties that control recharge (e.g., soil and vegetation factors) at a particular setting.

[11] Our objective in this study is to perform a comprehensive probabilistic analysis of the effects of climate change on groundwater recharge in a low-relief semiarid setting. We are particularly interested in recharge changes at rain-fed agricultural areas similar to those found in the southern High Plains (SHP), a topographically flat region spanning parts of Texas and New Mexico and overlying the southern portion of the Ogallala aquifer (Figure 1). In this work, we focus on one of the two SHP study sites considered by *Ng et al.* [2009]. The site is located in a rain-fed cotton area that currently produces an average diffuse recharge rate of about 40–65 mm/yr [*Ng et al.*, 2009]. Our emphasis on diffuse recharge is appropriate for our study site and is similar to *Green et al.*'s [2007] investigation of diffuse recharge in a Mediterranean climate zone of Australia.

[12] Although diffuse recharge dominates in our study area, other recharge conditions have been noted elsewhere in the region overlying the Ogallala aquifer, which also includes the central and northern High Plains. For example, the *Rosenberg et al.* [1999] study mentioned earlier considered two major water resource regions in the United States (the Missouri and Arkansas-White-Red river basins), which, compared with the SHP, experience cooler temperatures, include areas with greater precipitation, and

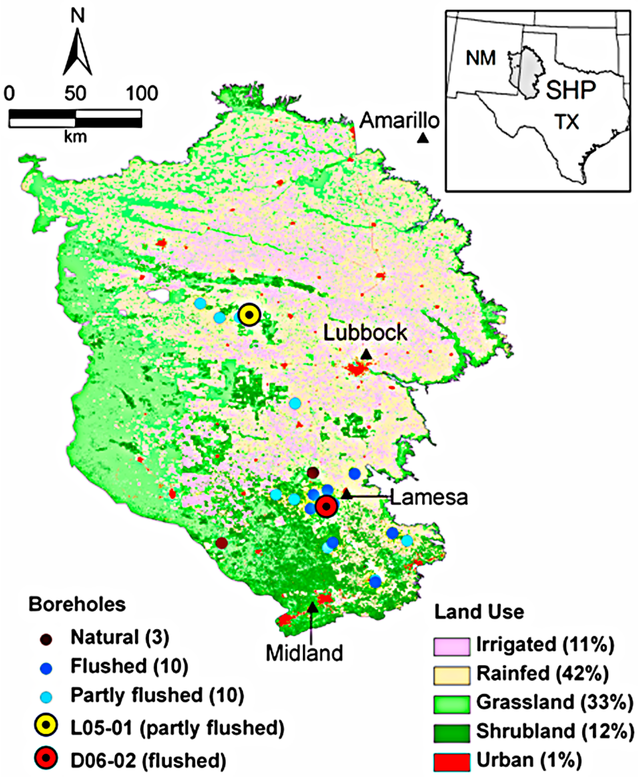

Figure 1. Southern High Plains (SHP) map [from *Ng et al.*, 2009, Figure 3]. Inset shows location of SHP in Texas and New Mexico. The data site used in this study are D06–02.

encompass more diverse terrain and elevations. The *Maxwell and Kollet* [2008] study also mentioned earlier focuses on a southern Great Plains river basin that is more humid and topography-driven than the SHP, which lacks perennial streams. These important differences in basin characteristics have a critical influence on the mechanisms that produce recharge (i.e., focused versus diffuse recharge). Differences in recharge mechanisms lead, in turn, to differences in the predicted effects of climate change. As a result, the *Rosenberg et al.* [1999] prediction of decreased recharge and the *Maxwell and Kollet* [2008] findings on groundwater level controls do not necessarily apply to the SHP region.

[13] In this recharge study, we explicitly account for uncertainties in soil and vegetation properties, in addition to uncertainties in meteorological variables and variability across different climate models for our SHP study site. Our approach is based on ensemble forecasting, a Monte Carlo procedure that generates a set of many equally likely outcomes rather than a single deterministic prediction. Ensemble forecasts provide a more informative description of the impacts of climate change than traditional deterministic forecasts.

[14] The aim of our climate change analysis is to examine sensitivity of recharge to climate change in a probabilistic framework rather than to generate absolute predictions of future recharge. In particular, we show how ensemble analysis can be used to improve understanding of the mechanisms responsible for changes in recharge. While previous climate change impact studies typically examine seasonal recharge patterns or longer-term dynamics, our analysis also assesses changes in the timing, frequency, and magnitude of infrequent recharge events over many years. This event-oriented focus is important in many low-relief semiarid settings, where diffuse recharge is often episodic. Because of the sensitivities to model errors in semiarid settings, proper consideration of uncertainties is paramount when evaluating episodic recharge.

[15] The ensemble forecasting procedure described in this paper accounts for different sources of uncertainty at the study site by combining data-conditioned realizations of soil and vegetation properties generated by *Ng et al.* [2009] with meteorological time series realizations generated with a stochastic weather generator for a range of GCM predictions. Recharge at the study site is simulated with a one-dimensional vertical Richards-based model. The results are used to provide valuable insights about the different ways that climate change may affect recharge.

[16] Section 2 of this paper provides background on the SHP region and our study site. Section 3 describes the one-dimensional diffuse recharge model used in this study and discusses its suitability for our study site. Section 4 presents our ensemble forecasting approach. Section 5 describes how we selected and incorporated GCM alternatives for our forecasting procedure. Section 6 summarizes ensemble forecasting results on episodic recharge at the southern High Plains study site, and section 7 presents some general conclusions based on our site-specific investigation.

2. Site Characteristics and History

[17] Our study site is located in the southern portion of the southern High Plains (SHP), a 75,500 km^2 region spanning parts of northern Texas and eastern New Mexico (Figure 1). The SHP has a semiarid climate, with about 75% of its 375–500 mm/yr precipitation falling during May through October. The region is topographically flat and internally drained through about 16,000 recharging playas, which cover about 1.4% of the total SHP area. Since major groundwater development, there are no longer perennial streams in the region, and remaining streams (called draws) have very low flows that typically last only several days or fewer [*Blandford et al.*, 2003]. The primary discharge mechanism is now irrigation pumpage. Mean clay content in the SHP ranges from 36% in the north to 23% in the south [*Scanlon et al.*, 2007]. The surface soils (upper 1.5 m) at the study site consist of sandy loam (mean clay content of 19%, silt 6%).

[18] Since the late 1800s to early 1900s, about 55% of the natural grassland and shrubland in the SHP has undergone agricultural development. About 42% of the region, including our study site, is rain-fed cropland and is dominated by continuous monoculture cotton production (1992 National Land Cover Data [*Vogelmann et al.*, 2001]). The current median water table depth is 25 m the southern part of the SHP and 63 m in the northern part. Under rain-fed agricultural regions in the SHP, the median water table depth is 30 m. The current water table depth at our study site is 10 m.

[19] Prior to land use change, recharge occurred nearly exclusively through playas [*Wood and Sanford*, 1995; *Scanlon and Goldsmith*, 1997]. A regional recharge estimate of 11 mm/yr based on groundwater chloride concentrations in the central High Plains was primarily attributed to playa

recharge by *Wood and Sanford* [1995]. Estimates of focused playa recharge based on tritium analyses range from 77 mm/yr to 120 mm/yr in the SHP [*Wood and Sanford*, 1995; *Scanlon and Goldsmith*, 1997]. Assuming an average value of about 100 mm/yr recharge through all playas (1.4% of SHP area), playas provide a regional average recharge rate of about 1.4 mm/yr (or a volumetric rate of 0.11 km^3/yr) to the SHP. Regional recharge rates of 0.1 mm/yr (0.08 km^3/yr) to 3 mm/yr (0.23 km^3/yr) have been used in groundwater modeling of predevelopment conditions in the SHP [*Luckey et al.*, 1986; *Blandford et al.*, 2003].

[20] Although most interplaya regions of the SHP under native vegetation experience negligible amounts of diffuse recharge [*Wood and Sanford*, 1995; *Scanlon and Goldsmith*, 1997], *Scanlon et al.* [2007] estimated new rates of 5–92 mm/yr (median 24 mm/yr) under rain-fed agricultural areas in the interplaya regions (away from playas). These results are based on unsaturated zone chloride balance calculations from 19 soil profiles (locations shown in Figure 1). Other than in the southeastern part, these higher percolation rates have not yet reached the water table in many parts of the SHP [*Scanlon et al.*, 2007], and they represent new recharge rates once equilibrium with the land use change is established. *Ng et al.* [2009] found new values of around 50 mm/yr recharge at our particular rain-fed study site. This value lies in the middle of the *Scanlon et al.* [2007] range. Extending this value to all SHP rain-fed agricultural areas (42% of the total SHP area) yields a new volumetric contribution of 1.6 km^3/yr in the SHP, compared with the 0.11 km^3/yr value from playas. This estimate suggests that on a regional scale, groundwater contribution from new diffuse recharge rates below rain-fed agriculture is greater than the playa contribution in the SHP.

[21] Groundwater level measurements further corroborate the dominance in the SHP of diffuse recharge under rain-fed cropland. Recharge estimates derived from observed water table rises in southeastern SHP following agricultural development [*Scanlon et al.*, 2005] correspond with recharge estimates from the unsaturated zone chloride data in rain-fed agricultural areas [*Scanlon et al.*, 2007]. This indicates that the major input to groundwater in rain-fed agricultural regions is areally distributed recharge through the unsaturated zone rather than focused recharge through playas caused by changes in runoff. Studying diffuse recharge in such areas is thus imperative for understanding groundwater impacts in the SHP.

[22] In this work, we examine future impacts on diffuse recharge in the SHP by investigating a study site in a rain-fed agricultural area in an interplaya location (away from playas) indicated in Figure 1. The change in land use (from grassland to cotton) that occurred at our study site around 1935 induced a soil moisture and chloride transient that was measured in an unsaturated zone soil profile at the site [*Scanlon et al.*, 2007]. *Ng et al.* [2009] used these profile data to generate conditional probability distributions for soil and vegetation properties and for subsurface moisture fluxes. These distributions provide the probabilistic information needed for the ensemble climate change analysis. The results generated by *Ng et al.* [2009] indicate that the site currently produces an average diffuse recharge rate of about 40–65 mm/yr. This recharge occurs episodically and exhibits significant interannual variability. Results shown later in this paper suggest that the relatively rare events that control groundwater recharge at our study site are sensitive to climate change.

3. Recharge Model

[23] In this study, we distinguish between percolation, the moisture flux at the bottom of the root zone, and recharge, the moisture flux at the water table. At our study site, the root zone is within the top 1.5 m of the soil profile [*Ng et al.*, 2009]. Although strong upward moisture fluxes may occur at 1.5 m under native grassland regions in the SHP [*Scanlon et al.*, 2003], the flux at this depth is almost always downward at the studied rain-fed cotton site [*Ng et al.*, 2009]. At this site, short-term percolation values fluctuate more than the deeper recharge values, but average annual values (averaged over the 71 years since land use change) at the two depths are similar (once the increased flux reaches the water table). For this reason, the terms "percolation" (moisture flux at 1.5 m depth) and "recharge" are used interchangeably when discussing annual averages. When discussing shorter-term weekly or monthly totals, we base our analysis on percolation simulations, which respond to surface forcing more quickly and dramatically than recharge. We base our analysis on these short-term percolation simulations because they provide the clearest picture of the physical mechanisms that relate climate change and episodic recharge. Surface signals are far more attenuated at greater depths, making it difficult to relate them to control factors.

[24] Moisture fluxes in this study, including percolation, are simulated with the Soil-Water-Atmosphere-Plant (SWAP) model version 3.0.3, a one-dimensional unsaturated zone model of soil moisture transport, solute transport, and vegetation [*van Dam et al.*, 2008]. Soil moisture is simulated in SWAP using a finite difference solution of the well-known Richards' equation. A Richards-based model is preferable over a multilayer bucket model in semiarid settings because fluxes can be small compared with precipitation.

[25] The one-dimensional vertical modeling approach used in this study is appropriate for simulating episodic diffuse recharge in semiarid, low-relief environments similar to our study site. Recent studies have shown that surface water dynamics can affect climate change impacts on recharge if there are significant groundwater and surface water interactions [*Scibek et al.*, 2007; *Tague et al.*, 2008]. However, these processes are not applicable at our study site, located in an interplaya, rain-fed agricultural area of the SHP with no perennial streams. As discussed in section 2, diffuse recharge through rain-fed agricultural areas like our study site is the dominant recharge process in the SHP.

[26] The water table depth at our study site is about 10 m, and more generally, the median water table depth in rain-fed agricultural areas of the SHP is 30 m. In regions where increased drainage rates have reached the water table (specifically the southeast), groundwater depths are less now than in the period before the introduction of widespread agriculture. However, there is evidence that these reduced groundwater depths are leading to increased irrigation pumpage in the region [*Scanlon et al.*, 2007], which may counter further depth declines in the future. *Maxwell and Kollet* [2008] showed for a river basin in the southern Great Plains that water tables within a 2–5 m "critical zone"

depth, located near river valleys, control evapotranspiration and thus potential recharge. With the deeper water table levels observed in the topographically flat SHP, it is reasonable to assume that the water table has little influence on the root zone there, and we apply the free gravity drainage condition in SWAP at the base of the 10 m profile for simulations of our study site. Although this choice for the lower boundary condition does not provide accurate simulations of the actual water table, it has little effect at the 1.5 m reference depth used to characterize percolation. As mentioned previously, percolation at this reference depth is used to examine short-term recharge mechanisms.

[27] Our one-dimensional vertical model domain is discretized such that the top layer is 2 cm thick, and thicknesses in lower layers increase by a 1.05 factor until a maximum 10 cm thickness is reached. SWAP implements the Richards' solver using the van Genuchten-Mualem soil moisture retention and unsaturated hydraulic conductivity functions [*van Genuchten*, 1980]. We use the nondynamic crop option, which requires the user to specify vegetation parameters over the growing season. SWAP computes potential evapotranspiration from daily meteorology using the Penman-Monteith equation [*Monteith*, 1981] and derives actual evapotranspiration with the empirical approach proposed by *Black et al.* [1969]. Daily actual evaporation and precipitation rates were applied for the surface boundary condition. The Richards solver uses a variable time step that cannot exceed 0.2 days. Ponding is allowed when infiltration limits are exceeded, and extra moisture is then removed from the model as runoff. Recharge analysis and model results for our site both indicate that surface runoff is very small compared with precipitation, with average annual amounts less than 1% in simulations.

[28] It should be noted that using precipitation data coarser than daily resolution may be inadequate for modeling recharge episodes. Subdaily meteorology provides more accurate simulations of episodic recharge and runoff, yet such fine-scale data are generally not available for the time periods considered in this study, nor are they available from GCM outputs. Largely on the basis of data availability, daily meteorological inputs were used for both the historical analysis of the site [*Ng et al.*, 2009] and the assessment of future climate change impacts described in this study. This is a nonideal but reasonable temporal resolution for obtaining informative results for the vegetated sandy loam surface conditions found at our study site.

[29] For our ensemble forecasting, uncertain SWAP model inputs are conditioned on soil moisture and chloride observations. These inputs include the six van Genuchten soil parameters; vegetation parameters such as maximum root depth, leaf area index, crop height, and minimal crop resistance; and the evaporation parameter required by the *Black et al.* [1969] evapotranspiration calculation. Observations had the greatest impact on the conditional input probability distributions for maximum root depth, certain shallow soil parameters, and the evaporation parameter. Further details on the parameter distribution estimates are given by *Ng* [2008].

[30] The one-dimensional vertical free gravity drainage modeling approach summarized above is effective for examining average annual diffuse recharge in settings such as the SHP. The implications of the conclusions presented for our study site extend to regions with similar diffuse recharge conditions. Other semiarid regions with similar properties include sandy regions in Senegal [*Gaye and Edmunds*, 1996] and parts of Australia [*Cook et al.*, 1989]. In river basins where topography is important, or in settings where feedback from a shallow water table occurs, it may be necessary to adopt a distributed modeling approach that accounts for lateral flow and for the effects of groundwater on surface infiltration and runoff [*Maxwell and Kollet*, 2008; *Scibek et al.*, 2007; *Tague et al.*, 2008]. However, it is important to note that the probabilistic framework we present is generally applicable. The simulation model that forms the basis for this approach should be chosen to be appropriate for the site of interest. Regardless of the model used, its inputs need to properly describe the conditions that produce recharge. For this reason the input realizations used in an ensemble forecast should be conditioned on observations, whenever possible.

4. Ensemble Forecasting Procedure

[31] Ensemble forecasting is a form of Monte Carlo simulation that reveals the range of possible outcomes that could occur in situations where uncertainty is significant. The basic idea is to perform a large number of model simulations, each based on a different sample (or realization) from the physically probable distribution of uncertain inputs. If the input samples are equiprobable, the results of these simulations can be viewed as equally likely alternative futures. The ensemble of simulated realizations can be used to construct probability densities and various statistical measures of variability. The ensemble forecasting procedure described in this paper accounts for multiple sources of uncertainty by combining conditional realizations of soil and vegetation properties generated by *Ng et al.* [2009] with realizations of meteorological time series.

[32] The effect of conditioning uncertain model inputs on soil moisture and soil water chloride measurements is demonstrated by the average annual recharge probability densities plotted in Figure 2, adapted from *Ng et al.* [2009, Figure 6]. These densities show the distribution of average annual recharge values over the 71 year historical period (from the time of land conversion until the observation time). The average annual recharge values were obtained by dividing the cumulative amount of percolation over the historical simulation period by the number of years simulated. The unconditional density in this figure was generated from about 30,000 equally weighted realizations obtained from SWAP model simulations. The soil and vegetation inputs for each of these simulations were obtained by sampling reasonable prior distributions. The conditional density shown in Figure 2 was obtained by using importance sampling to modify the equal weights of the unconditional realizations. Importance sampling assigns to each realization a weight that reflects the quality of its match to soil moisture and soil water chloride observations. Higher weights are given to realizations that are closer to observations.

[33] Figure 2 shows that conditioning of the average annual recharge probability density on soil moisture and soil water chloride observations at our study site shifts the density significantly toward increased recharge (negative fluxes are downward) while also reducing spread (or uncertainty). This shift brings the median of the average annual recharge density closer to the value independently

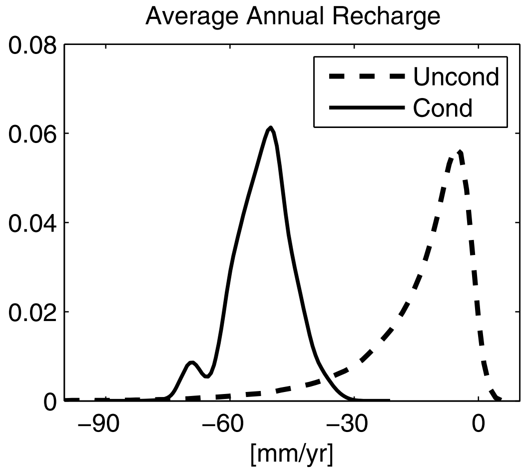

Figure 2. Probability densities of average annual recharge derived from Monte Carlo realizations of unconditional and conditional meteorological, soil, and vegetation properties (adapted from *Ng et al.* [2009, Figure 6]). Negative values represent downward moisture flux. Values are averaged over all years in the 71 year historical period analyzed by *Ng et al.* [2009]. The figure indicates that conditioning on site-specific observations can make a significant difference in recharge predictions.

identified from a steady state chloride mass balance analysis [*Ng et al.*, 2009]. The additional information provided by soil profile measurements clearly yields a narrower probability density.

[34] The ensemble forecasts for the climate change analysis presented in this paper are obtained from Monte Carlo simulations similar to those used by *Ng et al.* [2009] to obtain Figure 2. The primary addition to our earlier work is incorporation of uncertainty about the effects of climate change on meteorological variables. Figure 3 provides an overview of our climate change ensemble forecasting procedure. The primary inputs to this procedure are (1) samples of long-term (75 year) daily meteorological time series compatible with a specified IPCC GCM climate prediction and (2) samples from the conditional soil and vegetation property probability densities previously identified by *Ng et al.* [2009]. Each future climate condition predicted by a different IPCC GCM is referred to here as a "climate alternative." The meteorological time series samples for each climate alternative are produced by the LARS-WG v. 4.0 stochastic weather generator [*Semenov et al.*, 1998]. The soil, vegetation, and meteorological inputs are then used to simulate ensembles of future recharge values over a 75 year period for each climate alternative. Many years are simulated in order to include a reasonable number of infrequent recharge events in order to adequately characterize the episodic nature of recharge at the study site. The simulation period was chosen to facilitate comparisons with historical recharge estimates over a similar amount of time. It should be noted that our decision to use soil and vegetation parameters conditioned on recent observations in an analysis of climate change is justified only if there will be no major changes in soil or vegetation conditions in the future. The implications of this assumption are discussed later.

[35] As mentioned above, the importance sampling approach used by *Ng et al.* [2009] assigns different weights to different realizations of soil and vegetation properties. Because the meteorological time series samples produced by the weather generator are equally likely, it is convenient to also represent the other input distributions with equally weighted realizations. For this reason, we generate a new

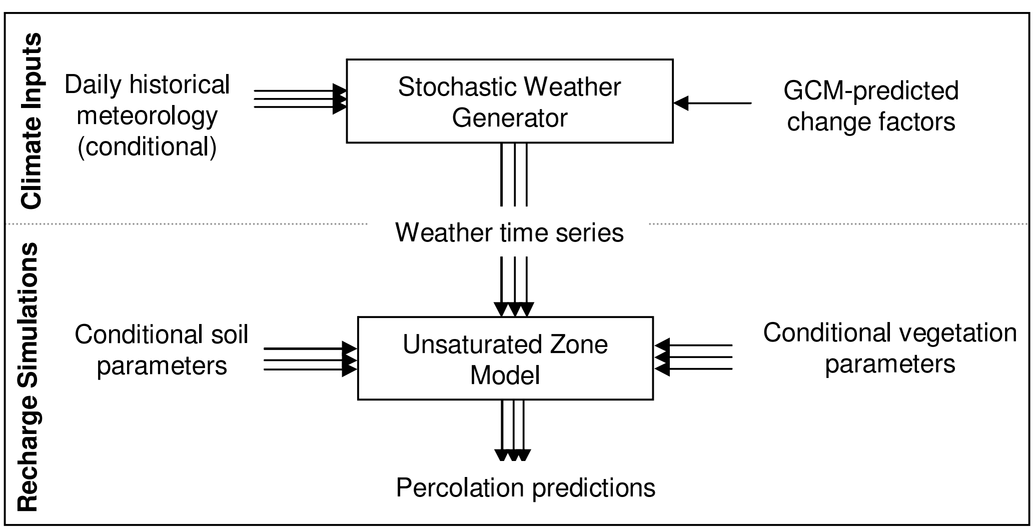

Figure 3. Diagram of the ensemble forecasting approach carried out for each general circulation model (GCM) climate alternative. An ensemble of percolation predictions is generated from multiple simulations of the Soil-Water-Atmosphere-Plant (SWAP) model using different inputs for each simulation (represented by the multiple arrows in diagram). Meteorological inputs (time series) are obtained from the LARS-WG weather generator. LARS-WG inputs are adjusted to account for differences in the GCM climate alternatives. Soil and vegetation parameter distributions and historical precipitation values are conditioned on soil moisture and chloride concentration observations. The final percolation ensemble incorporates natural meteorological variability as well as uncertainty from soil and vegetation parameters.

Table 1. List of All General Circulation Model Alternatives Considered

Alternative	GCM	GCM Sponsor/Country	Characteristic
Wet	ECHO-G	Meteorological Institute of University of Bonn, Meteorological Research Institute of the Korea Meteorological Administration (KMA), and Model and Data Group/Germany, Korea	wetter throughout most of the year
Intense	BCCR-BCM2.0	Bjerknes Centre for Climate Research/Norway	similar annual precipitation, higher intensity
Seasonal	CGCM3.1 (T47)	Canadian Centre for Climate Modeling and Analysis/Canada	similar annual precipitation, wetter summer and drier winter
All-dry	MIROC3.2 (medres)	Center for Climate System Research (University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)/Japan	all months drier
Driest	IPSL-CM4	Institut Pierre Simon Laplace/France	lowest annual precipitation

ensemble of equally likely conditional soil and vegetation inputs by resampling from the original realizations in proportion to the importance sampling weights, as described by *Arulampalam et al.* [2002]. The resampling works by including multiple copies of original realizations with high weights in the new ensemble. In contrast, few, if any, copies of original realizations with low weights are included. This produces a new ensemble of equally weighted realizations that has the same conditional probability distribution as the original weighted ensemble. In our application, about 150 of the more than 30,000 unconditional input realizations account for 97.5% of the total weight in the conditional distribution. Our ensemble forecasting analysis is based on an ensemble of 200 resampled equally likely samples composed, for the most part, of these high weight realizations. The resampled ensemble gives a representative cross section of the most likely model input combinations.

[36] The outputs of our ensemble forecasting analysis are daily LARS-WG time series of precipitation and SWAP simulations of potential ET (PET), actual ET (AET), soil moisture, and percolation. These time series are computed over the 75 year simulation period, for a specified climate alternative. The set of output time series obtained for a given set of randomly generated inputs constitutes one output realization. We compute, for each realization, time averages of monthly and annual total percolation. *Ng et al.* [2009] shows that under current land use and climate conditions, much of the recharge for our semiarid study site originates from a relatively small number of major events scattered over a 70–75 year period. In order to investigate the role of this episodic recharge phenomenon in the climate change context, we tally, for each realization, the total number of recharge events for a given event magnitude. A recharge event is defined in terms of the weekly total percolation time series. The beginning and end of each event occur at inflection points in the weekly percolation time series: The beginning is marked by a change from a negative to a positive weekly percolation second derivative, and the end is marked by a change from a positive to a negative second derivative, for negative (downward) percolation values. The event magnitude is defined as the peak weekly percolation value over the time window between the beginning and end of the event. In general, a percolation event will last more than 1 week. We characterize the ensemble of all realization averages, maxima, and event counts with probability densities and ensemble means, medians, and quartiles.

5. Climate Change Alternatives

[37] A number of GCMs have been developed to predict future climate conditions. These all generate results over coarser temporal and spatial resolutions than are needed to resolve episodic recharge at our study site. Sections 5.1–5.3 describe our approach for selecting GCM predictions and for putting these predictions in a form suitable for recharge analysis.

5.1. GCM Selection

[38] GCMs are coupled numerical models of the atmosphere, ocean, and land surface that simulate global conditions over grid cells of 2°–4° resolution. They are used to model changes in climate for different postulated CO_2 levels. In this study, we considered GCM outputs only for the SRES A1B scenario [*IPCC*, 2000], which is the midrange CO_2 emissions scenario most commonly used in the *IPCC* [2007] Fourth Assessment Report. We compare the climate predicted for the period 2080–2099 with the climate for the base case period 1980–1999, as is done in most of the *IPCC* [2007] Fourth Assessment Report summaries. GCM average monthly outputs simulated over the base case period agree reasonably well with observed 1980–1999 SHP average monthly data [*Ng*, 2008]. GCM matches to historical data tend to be poorer for temporal resolutions finer than 1 month [*Prudhomme et al.*, 2002].

[39] In order to focus our analysis, we consider climate predictions from five of the 25 GCMs participating in the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 3 (CMIP3) multimodel data set (see http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php). This data set includes outputs from the GCMs cited in the *IPCC* [2007] Fourth Assessment Report and is available online at http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php. Most models included in CMIP3 predict that future conditions are likely to be warmer in the SHP, but there are notable discrepancies in precipitation predictions [*Ng*, 2008]. The GCMs included in this study and listed in Table 1 were selected for the diversity of their precipitation predictions at our study site. As mentioned above, the aim of

our work is to examine the sensitivity of recharge to the climate changes simulated by different GCMs rather than to make absolute predictions. Our set of alternative GCMs includes two models with drier futures: IPSL-CM4 ("driest"), with the lowest annual rainfall, and MIROC3.2 (medres) ("all dry"), with decreased rainfall in all months. ECHO-G ("wet") has higher annual rainfall. Also included are two GCMs that give annual rainfall similar to current conditions: BCCR-BCM2.0 ("intense"), with more intense rainfall, and CGCM3.1(T47) ("seasonal"), with drier winters and wetter summers. All of these GCMs predict increased average daily maximum and minimum temperatures ($T_{\max}$ and $T_{\min}$) in almost every month.

5.2. Downscaling GCM Predictions With a Weather Generator

[40] Most GCM predictions are reported at 2°–4° spatial resolution and only at monthly or longer temporal resolutions. Finer temporal resolutions are available but are not considered very reliable [*Prudhomme et al.*, 2002]. For our study, we require higher resolution site-specific predictions at a daily resolution, in order to investigate the episodic events that yield recharge. A number of spatial and temporal downscaling techniques have been developed to generate higher-resolution meteorological predictions suitable for hydrologic analysis from GCM outputs (see the review by *Fowler et al.* [2007]). The most straightforward of these uses change factors, which represent the change from GCM outputs for the current climate to the GCM outputs for a future climate with a given emissions scenario. Downscaling is carried out by combining the change factors with observed fine-scale meteorological information. For spatial downscaling, it is common to assume that change factors computed at the scale of a GCM grid cell apply unmodified to all points within the cell. We implicitly follow this approach by applying the corresponding GCM grid cell output (representing hundreds of kilometers) directly to our study site (representing the point scale). We do this primarily because more complex alternatives have not been shown to give consistent results [e.g., *Scibek and Allen*, 2006].

[41] The simplest approach to temporal downscaling is to apply monthly GCM change factors directly to daily historical data, similar to the approach described above for spatial downscaling. This method has been adopted in a number of climate change and groundwater studies [*Kirshen*, 2002; *Eckhardt and Ulbrich*, 2003; *Croley and Luukkonen*, 2003; *Brouyère et al.*, 2004; *Serrat-Capdevila et al.*, 2007]. However, the *IPCC* [2007] Fourth Assessment Report warns that longer dry periods and higher-intensity precipitation events could occur when the total amount of rainfall decreases. These changes in the temporal distribution of rainfall could greatly affect recharge but cannot be generated by simply adjusting historical records with monthly change factors. Moreover, the approach cannot be used to generate the many independent realizations required in a 75 year ensemble forecasting analysis. Consequently, in this study, we use a stochastic weather generator to simulate the daily meteorological time series needed to generate ensemble predictions of episodic recharge.

[42] Particular care must be taken in choosing a generator that can properly simulate the rain events that lead to episodic recharge [*Ng*, 2008]. The review by *Wilks and Wilby* [1999] describes the two main classes of stochastic weather generators: (1) those that model precipitation occurrence as a Markov process and (2) those that explicitly model spell lengths (number of consecutive rainy days and number of consecutive dry days). Because first-order Markov processes tend to under-simulate long dry spells [*Wilks and Wilby*, 1999], they are less attractive for analyses of episodic recharge. As a result, we use the spell-length generator LARS-WG v. 4.0 [*Semenov et al.*, 1998]. This weather generator performs well over a range of different climate conditions [*Semenov et al.*, 1998; *Semenov*, 2008], and it has been adopted in a number of other climate change studies [e.g., *Semenov and Barrow*, 1997: *Scibek and Allen*, 2006; *Semenov*, 2007]. It also appears to be able to satisfactorily simulate extreme daily precipitation rates [*Semenov*, 2008], which is crucial for modeling episodic recharge [*Ng*, 2008].

[43] Using historical data for calibration, LARS-WG can generate daily time series realizations of precipitation, maximum and minimum air temperature ($T_{\max}$ and $T_{\min}$), and solar radiation. Monthly change factors derived from GCM outputs for future and base case periods are applied to LARS-WG to generate time series compatible with a changed climate. Note that the change factors for the mean wet and dry spell lengths, which implicitly determine mean monthly precipitation intensity, must be derived from daily GCM outputs. In this study, we define monthly precipitation intensity to be the total monthly precipitation divided by the number of rainy days.

[44] The SWAP model used in our study requires two meteorological variables not generated by LARS-WG: vapor pressure and wind speed. Because relative humidity is not expected to change with rising temperatures [*Allen and Ingram*, 2002], changes in vapor pressure were indirectly introduced through $T_{\min}$. Monthly multiplicative change factors calculated from GCM outputs of wind speed were applied to historical wind speed values. In addition, solar radiation outputs were slightly altered to better match calibration data. Further details are provided by *Ng* [2008].

5.3. Predicting the Effects of Climate Change on Recharge

[45] For this study, we use LARS-WG to generate, for each GCM climate alternative plus the base case, 200 realizations of meteorological time series of 75 years length. As mentioned earlier, using a long analysis period is important for characterizing infrequent episodic recharge events in semiarid environments. The base case is simulated with LARS-WG in order to compare with the historical analysis of *Ng et al.* [2009]. Climate alternative analyses are compared with this LARS-WG simulated base case for consistency.

[46] In our study, the weather generator is provided with the conditional precipitation ensemble generated by *Ng et al.* [2009] rather than the historically observed precipitation series, which was recorded at a station in Lamesa, Texas, about 15 km from our study site. The conditioned precipitation realizations reflect additional information provided by field measurements of soil moisture and chloride. The conditioning procedure assumes that the timing of each historical rainfall events is known perfectly (to within 1 day), and thus the conditional precipitation realizations differ from one another only with respect to the magnitude of rainfall

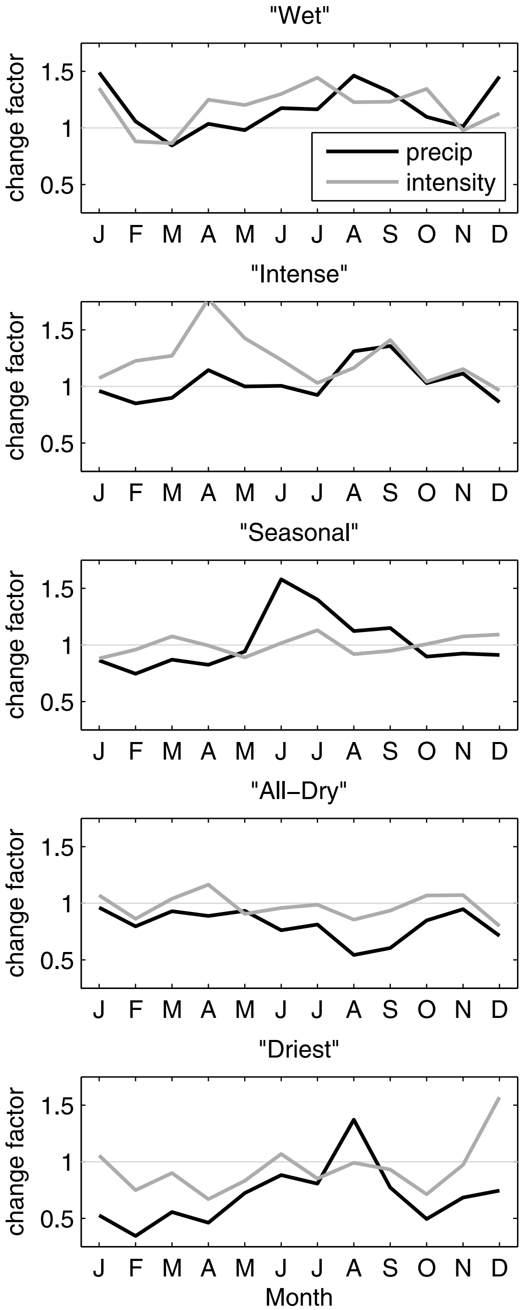

Figure 4. Effective multiplicative change factors derived from the monthly LARS-WG precipitation and monthly precipitation intensity for the five GCM alternatives and base case considered in this study. Precipitation intensity is total monthly precipitation divided by number of rainy days in the month. Monthly values for each realization in the ensemble are averaged over all years in the 75 year simulation period. Effective change factors match reasonably well with GCM-derived change factors.

during rainy days. The conditioned realizations provide a more realistic description of uncertainty than a single deterministic time series. *Ng et al.* [2009] found recharge simulations to be relatively insensitive to uncertainty in other meteorological variables.

[47] The base case meteorological realizations are generated from LARS-WG parameters fit to the *Ng et al.* [2009] conditional precipitation ensemble and to a single historical time series for all other meteorological variables. Meteorological realizations for the five GCM alternatives are derived from the same conditional precipitation ensemble and historical time series as the base case, modified by the corresponding GCM change factors. Together with the conditional soil and vegetation realizations generated by *Ng et al.* [2009], these LARS-WG meteorological realizations make up the uncertain inputs used in the SWAP model to analyze recharge mechanisms under future climate conditions. The recharge simulations are initialized with the final conditions from the historical simulations performed by *Ng et al.* [2009], in 2006. For the base case and each of the five climate alternatives, SWAP is used to derive 200 realizations of percolation, soil moisture, crop AET (defined as AET during the growing season), and total AET (defined as AET throughout the year) over the 75 year simulation period.

[48] For validation purposes, it is useful to evaluate effective climate change factors from the LARS-WG outputs. For each climate alternative, a multiplicative change factor is determined, where a LARS-WG climate alterative realization is used for the numerator and the corresponding LARS-WG base case realization is used for the denominator. The ensemble mean of change factors over all realization pairs is then the effective multiplicative change factor for the alternative. Because the weather generator supplies the weather time series actually used to evaluate recharge, these effective change factors implicitly define the alternative climates considered in our study. Figure 4 shows the effective LARS-WG multiplicative change factors for average monthly precipitation and average monthly precipitation intensity. The effective change factors are reasonably close to the change factors obtained from the GCMs that are used to calibrate LARS-WG.

[49] The change factor plots in Figure 4 clearly show the distinctive seasonal patterns associated with each of the five GCM alternatives. Note the broadly higher values for the "wet" alternative, the distinct peaks for the "intense" and "seasonal" alternatives, and the broadly lower values for the "all-dry" and "driest" alternatives. The impacts of these different climate alternatives are discussed in section 6.

6. Results and Discussion

6.1. Validation of the Weather and Recharge Simulations

[50] We chose LARS-WG for our ensemble forecasting analysis because it has features that are well suited for predictions of episodic recharge at a semiarid site. However, it is important to emphasize that weather generators are constructed to match only certain statistics, making it unlikely that they can accurately simulate all the characteristics of real weather. For example, LARS-WG and many other weather generators are known to underestimate interannual variability [*Semenov et al.*, 1998; *Wilks and Wilby*, 1999]. However, *Gurdak et al.* [2007] identified signatures of both the Pacific Decadal Oscillation (10–25 years) and El Niño–Southern Oscillation (ENSO) (2–6 years) in historical groundwater levels in the High Plains. Also, *Ng et al.* [2009] showed it was likely that unusually wet years produced disproportionately large contributions of recharge at our study site. Although weather generators may not capture all the subtleties of real weather, they should at least

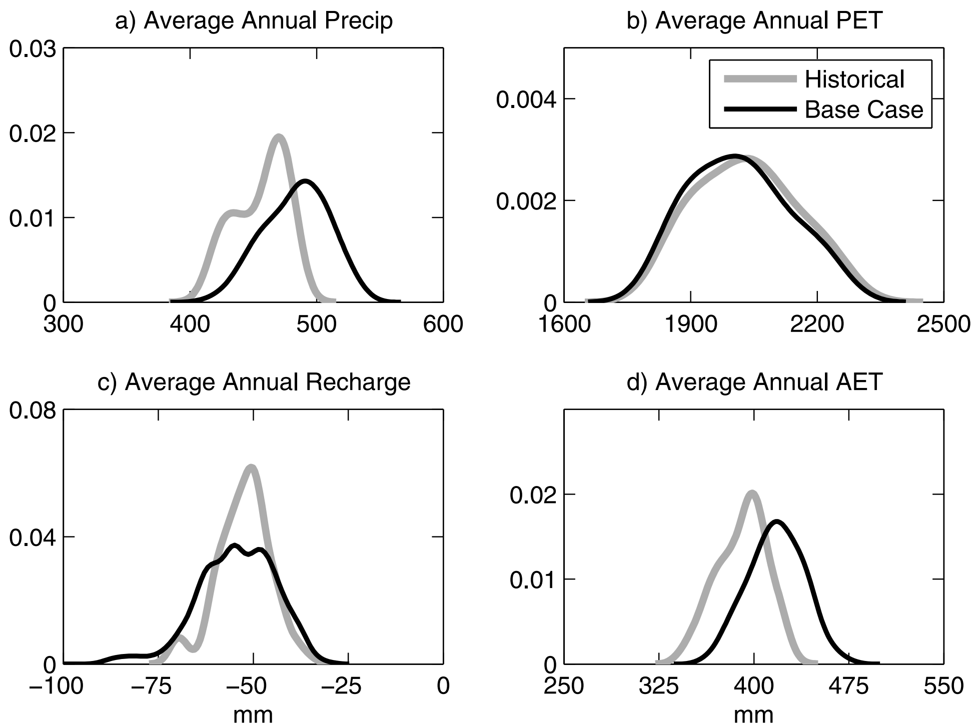

Figure 5. Historical and simulated base case probability densities constructed from realizations of (a) average annual precipitation and (b) average annual potential evapotranspiration (PET). Average annual values for each realization in the ensemble are averaged over all years in either the 71 year historical period (historical) or the 75 year LARS-WG simulation period (base case). Historical realizations are derived from the conditional time series described by *Ng et al.* [2009]. Simulated realizations are derived from the LARS-WG base case time series. Probability densities of (c) average annual recharge and (d) average annual actual evapotranspiration (AET), averaged over all years in the historical or LARS-WG simulation periods. Recharge and AET realizations for both historical and simulated cases are derived from the SWAP model. The bias in the LARS-WG precipitation probability density does not significantly affect recharge, although it has an effect on AET.

reproduce those features that are most important for the application of interest. It is thus important to check that the percolation time series derived from the weather generator with no climate change (base case simulations) included has statistical properties that are similar to those observed during the historical period.

[51] Figures 5a and 5b compare historical and simulated base case probability densities of average annual precipitation and average annual PET. The average annual values are averaged over all simulations years. The realizations used to construct the historical probability densities were derived from the 71 year conditional time series described by *Ng et al.* [2009]. The realizations used to construct the simulated "base case" densities were derived from 75 year time series produced by LARS-WG (using inputs set to reproduce historical statistics). Ensemble spread in the historical average annual precipitation originates from uncertainty in precipitation intensities during rainy days, as discussed earlier. Ensemble spread in the historical average annual PET originates from uncertainty in vegetation parameters used in the Penman-Monteith equation [*Monteith*, 1981]. It is apparent that LARS-WG is able to adequately reproduce the PET distribution. However, its precipitation distribution is biased to the high side.

[52] Comparisons of historical and simulated probability densities for average annual recharge and average annual AET in Figures 5c and 5d reveal the implications of these precipitation discrepancies. Note that conditional soil and vegetation property realizations from *Ng et al.* [2009] are used in both the historical and simulated base cases. Figure 5 indicates that average annual recharge derived from LARS-WG meteorological forcing compares favorably with average annual recharge estimated from historical data, even though LARS-WG average annual precipitation is somewhat biased. Most of the excess rain generated by LARS-WG seems to go to the high LARS-WG AET amounts, despite the similar PET. Because the excess LARS-WG rainfall has little impact on recharge, it apparently lacks the distinctive features (i.e., timing, intensity, etc.) needed to produce the episodic events that yield recharge at the study site. Figure 5 also shows greater spread in the LARS-WG recharge probability density. This reflects the greater sources of randomness in the LARS-WG precipitation series (i.e., random rainfall times).

[53] Figure 6 provides some indication of the performance of LARS-WG in simulating interannual variability over a multiyear period. It compares the ensemble quartiles of the maximum monthly precipitation values for the historical and LARS-WG time series. For each realization, the maximum values of monthly precipitation are taken are all simulation years. Because the LARS-WG base case time series are generated to have the same monthly precipitation as the

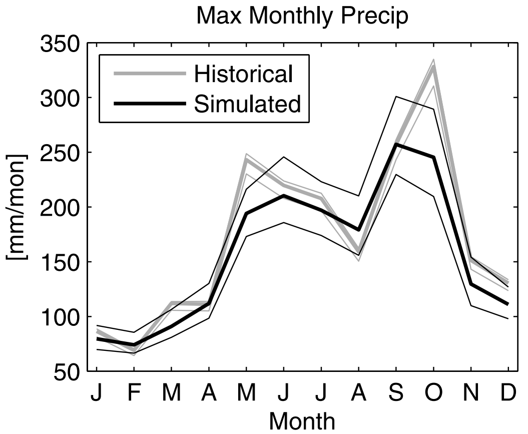

Figure 6. Ensemble median (bold curves) and first and third quartiles (thin curves) of the maximum monthly precipitation probability density. Monthly maxima for each realization in the ensemble are taken over all years in either the 71 year historical period or the 75 year LARS-WG simulation period. Historical realizations are derived from the conditional time series described by *Ng et al.* [2009]. Simulated realizations are derived from LARS-WG base case daily time series. Note that LARS-WG under simulates high-rainfall events in late spring and fall.

historical series, higher maximum monthly precipitation in one series indicates greater monthly precipitation extremes for that series over the other. Although LARS-WG does not explicitly include interannual variations, it generates year-to-year deviations due to its stochastic nature. It is apparent from Figure 6 that high rainfall periods observed in the late spring and early fall are underestimated by the weather generator.

[54] Because *Ng et al.* [2009] showed that high precipitation events have an important impact on recharge during these seasons, the LARS-WG under-simulation of maximum monthly precipitation could lead to under-predictions of recharge. To further investigate this, we show in Figure 7 the ensemble quartiles of the number of recharge events (as defined earlier) during the simulation period with peak weekly percolation greater than the value specified on the horizontal axis. Figure 7 indicates that there were typically only a few events with percolation magnitudes greater than 30 mm/week. Higher magnitude percolation events occur over short time periods, often lasting less than a few weeks (not shown here). As expected from its underestimation of extreme monthly rains, high recharge events are less frequent with the base case LARS-WG weather series. However, LARS-WG appears to compensate for missed high-intensity rainfall by slightly over-simulating the number of low rainfall events. This leads to greater prediction of lower-magnitude recharge events, which collectively make a significant recharge contribution. Consequently, although LARS-WG may underestimate the number of large recharge events at the study site, it provides an estimate of total recharge over the historical period that is consistent with available observations.

[55] The recharge compensation observed with LARS-WG for our site is fortuitous but cannot be relied upon in general. The analysis presented here suggests that recharge estimates derived from stochastic weather generators may be less reliable when long-term recharge totals depend strongly on a small number of episodic events which are difficult to reproduce. A likely example is a very arid site with low-conductivity soils. In such cases, weather generators that underestimate seasonal and interannual precipitation variability may also underestimate long-term recharge [*Ng*, 2008].

6.2. Recharge Predictions

[56] The percolation predictions generated by our ensemble analysis take the form of multiyear time series, each corresponding to a particular random combination of precipitation forcing, soil properties, and vegetation parameters. Comparisons in Figure 8 of two typical realizations obtained for the "wet" and "all dry" alternatives show that percolation is episodic, exhibiting distinct peaks after some, but not all, major rainfall events. It is also apparent that the two climate alternatives give qualitatively different results, with the "wet" alternative exhibiting more peaks of higher intensity. Although these percolation peaks are damped and delayed by the time they reach the water table, the water they carry eventually becomes recharge. Each percolation peak represents a significant contribution to total recharge.

[57] We examine in section 6.2.1 the average annual recharge obtained for our five climate alternatives and then consider in section 6.2.2 the mechanisms responsible for differences among these alternatives. We focus on ensemble statistics such as ensemble means, medians, quartiles, and event counts because these give a good overview of the aggregate response of all the realizations generated by our ensemble forecasting procedure.

6.2.1. Long-Term Average Results

[58] Figures 9 and 10 summarize the ensemble forecast results obtained for the five different alternative GCM pre-

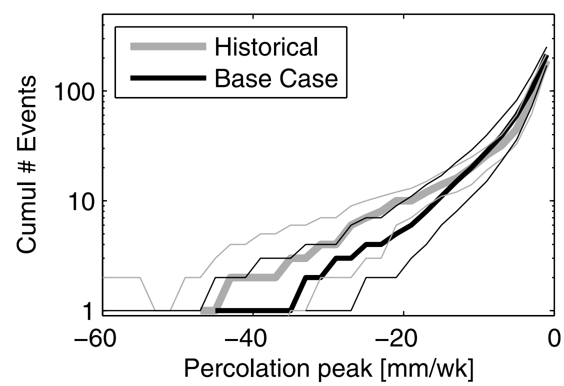

Figure 7. Ensemble median and first and third ensemble quartiles of the number of recharge events with a magnitude greater than the value specified on the horizontal axis, counted over either the 71 year historical period or the 75 year LARS-WG simulation period. A recharge event is defined by two successive inflection points in the weekly percolation time series. The event magnitude is the highest weekly percolation value during the event time window. Historical realizations are derived from the conditional time series described by *Ng et al.* [2009]. Simulated realizations are derived from the LARS-WG base case time series. As discussed in the text, LARS-WG under-simulation of infrequent high-recharge events does not significantly affect overall recharge amounts.

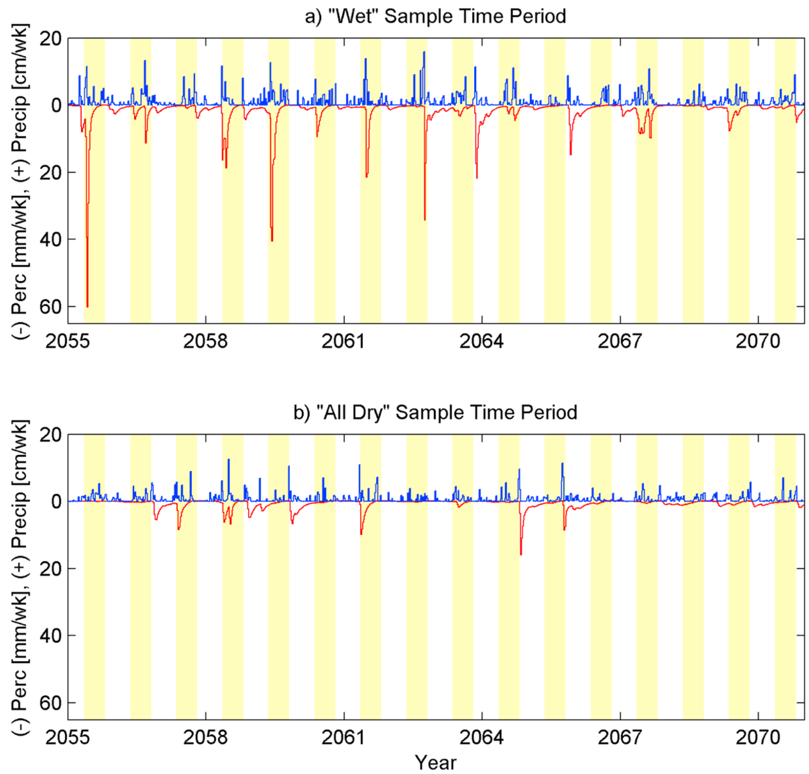

Figure 8. Examples of typical weekly time series realizations for (a) “wet” alternative and (b) “all dry” alternative. Weekly total precipitation is shown in blue above the horizontal line, and weekly total percolation is shown in red below the horizontal line. Growing seasons are shaded in yellow. The frequency, timing, and magnitude of episodic recharge events differ for the GCM alternatives.

dictions considered in our study. Figure 9 compares probability densities. Figure 10 compares percent changes, relative to the simulated base case, in the ensemble means of several average annual fluxes, also for each of the five alternatives. In Figures 9 and 10, the average annual value for each realization in the ensemble is taken over all years in the 75 year LARS-WG simulation period.

[59] The shapes of the probability densities shown in Figure 9 differ significantly. The base case recharge density is fairly symmetric, but the “intense” and “seasonal” distributions are skewed (in different directions). Recharge uncertainty is generally less for the drier alternatives. Although wetter (drier) meteorological conditions generally yield more (less) recharge, it is apparent from Figure 10 that average annual recharge does not scale in a simple, proportional way with average annual precipitation. For most of the cases examined, relative changes in recharge are more pronounced than relative changes in rainfall. The “seasonal” alternative is notable since the precipitation and recharge changes have different signs (precipitation increases while recharge decreases). For the alternatives with agreeing signs, changes in recharge are about 1.5 to more than 3.5 times greater than changes in precipitation.

[60] Average annual PET, which represents energy demand, increases for all the climate change alternatives, due to the higher study site temperatures predicted by all of the GCMs. However, changes in the average annual crop AET do not appear to be correlated with changes in average annual PET. Precipitation change is generally a better predictor of change in both crop and total AET. This confirms that the study site is moisture rather than energy limited, a condition that marginalizes the effects of climate-induced temperature changes. Although average annual AET closely follows average annual precipitation, it is important to note that relatively small differences have a significant effect on recharge. These effects can be better understood if we examine finer-scale temporal variations in seasonal precipitation, which have a significant influence on the partitioning of water between ET and recharge.

6.2.2. Detailed Analysis of Alternatives

[61] Figure 11 shows the seasonal variation in the ensemble mean of the monthly total percolation for each alternative, while Figure 12 shows the ensemble median of the number of recharge events with a peak weekly percolation magnitude greater than the value specified on the horizontal axis. Figure 13 gives a seasonal assessment of the number of recharge events that focuses on differences between the base case and the “intense” alternative. Taken together, Figures 11–13 provide insights about the mechanisms that control recharge for different types of climate change. The details are discussed for each alternative in the following paragraphs.

6.2.2.1. “Wet” Alternative: Wetter Throughout Most of the Year

[62] The “wet” climate alternative represents the wettest end of the spectrum of GCM predictions considered in our study. Average annual precipitation increases by about 20% above the base case, with the largest monthly increases occurring during the rainy June–October period and the dry December–January season (Figure 4). The ensemble mean

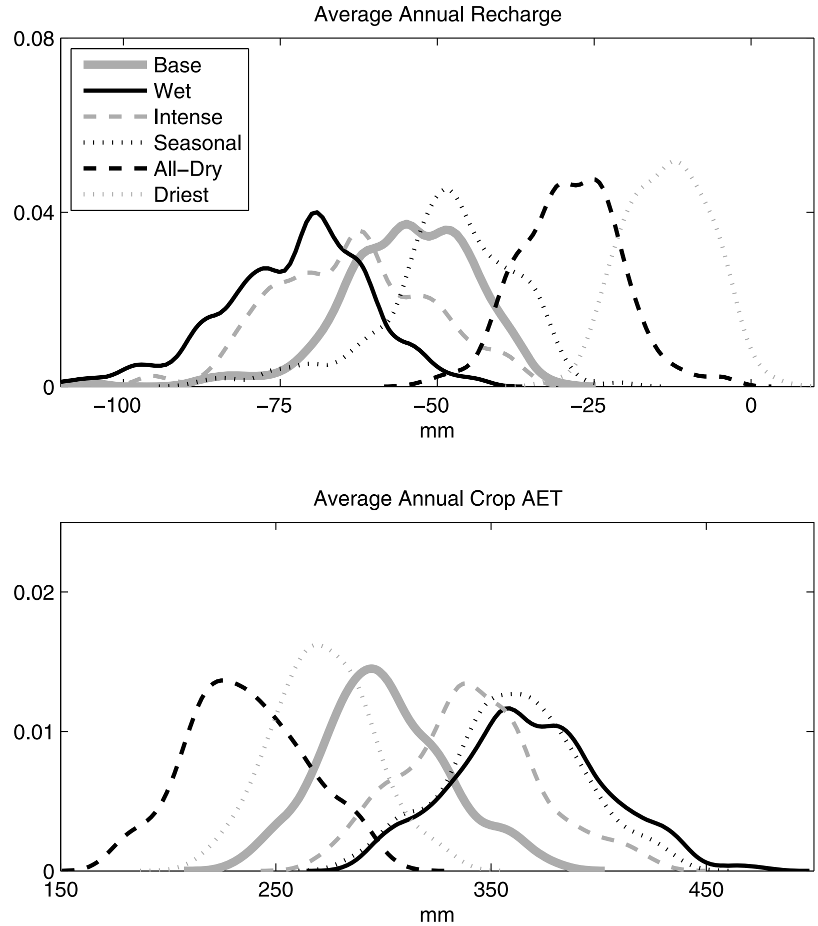

Figure 9. Probability densities constructed from realizations of average annual recharge and average annual crop AET, for the base case and for each of the five GCM climate alternatives. Average annual values for each realization in the ensemble are averaged over all years in the 75 year LARS-WG simulation period. Realizations used to construct the probability densities are derived from the LARS-WG time series.

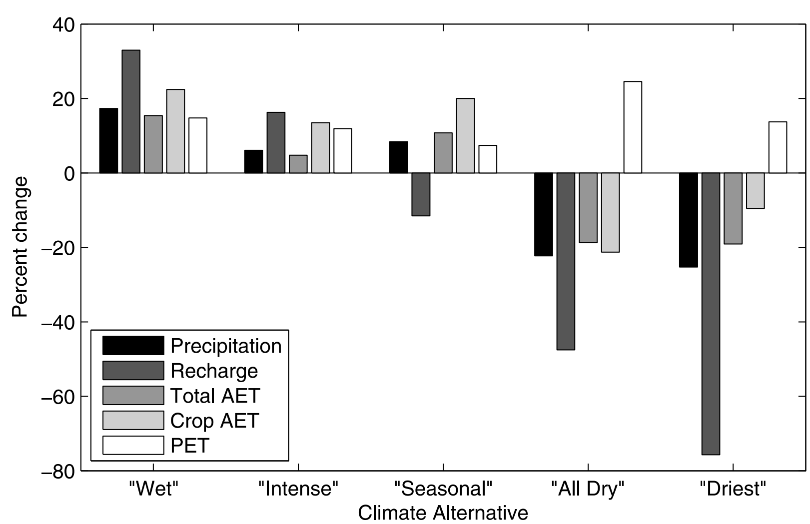

Figure 10. Percent changes, relative to the base case, in the ensemble means of several average annual fluxes, for each of the five alternatives. Average annual flux values for each realization in the ensemble are averaged over all years in the 75 year LARS-WG simulation period. Realizations are derived from LARS-WG time series. Changes in total AET and recharge generally follow changes in precipitation rather than PET.

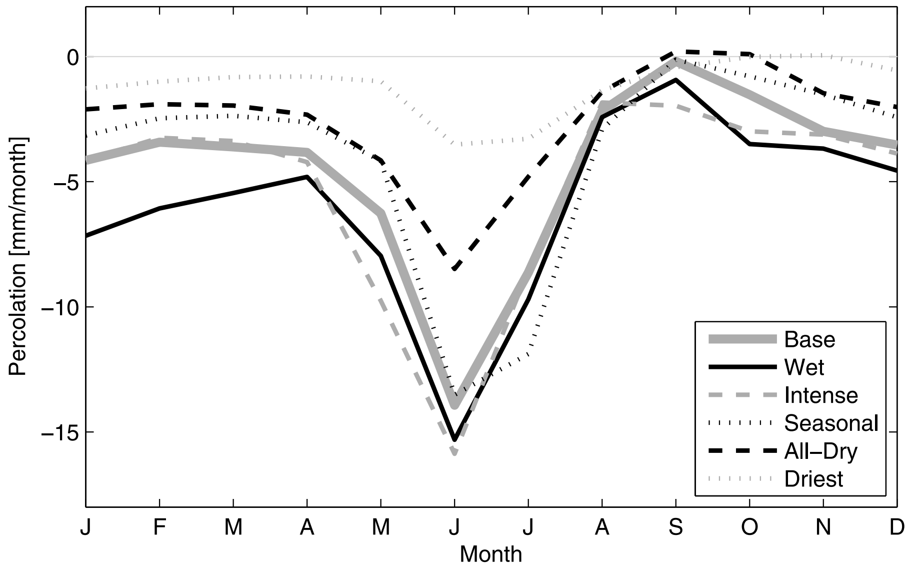

Figure 11. Ensemble mean of monthly percolation for each of the five alternatives. Monthly percolation values for each realization in the ensemble are averaged over all years in the 75 year LARS-WG simulation period. Realizations are derived from LARS-WG time series.

of the "wet" average daily rainfall intensity increases relative to the base case in almost all months except February–May (Figure 4). These changes give an increase in monthly downward percolation (over the base case) for every month except August (Figure 11). Although the greatest precipitation increase (total amount and intensity) for the "wet" alternative occurs in the late summer, much of this precipitation increase appears to be taken up by crops, which are mature by this time. In fact, average annual crop AET for the "wet" alternative increases more than average annual precipitation. This result could be a benefit for cotton production in the region. Notable increases in May–June downward percolation occur despite largely unchanged spring monthly mean precipitation values (compare Figures 5 and 12). These increases appear to result from a combination of increased rainfall intensity and increased antecedent moisture from wetter winters.

[63] The incidence of high-magnitude recharge events, with magnitudes of 20 mm/week or greater, doubled from about five times in 75 years for the base case to about 10 times for the "wet" climate (Figure 12). This increase in the number of significant events reflects increases in both total rainfall and rainfall intensity.

6.2.2.2. "Intense" Alternative: Similar Annual Precipitation, Higher Intensity

[64] The "intense" alternative predicts that average annual precipitation will remain close to the present-day value, with wetter totals in the late summer roughly balanced by drier

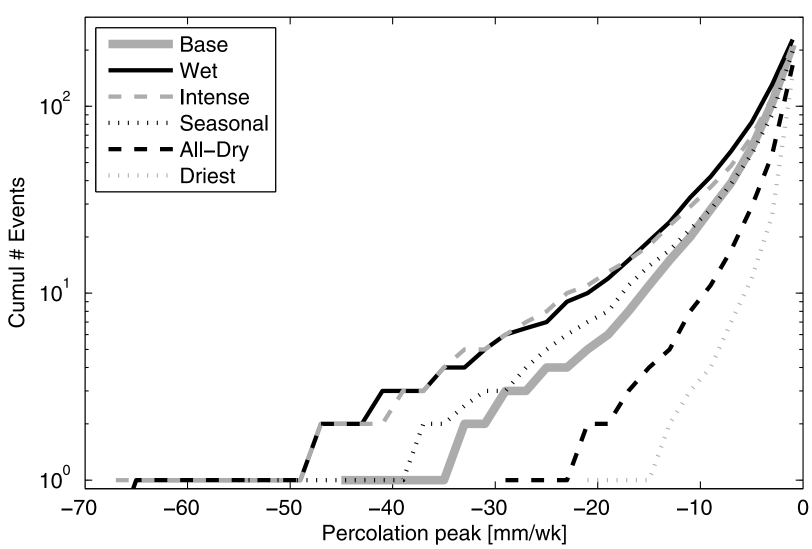

Figure 12. Ensemble median of the number of events with a weekly percolation magnitude greater than the value specified on the horizontal axis for the five climate alternatives. Events for each realization in the ensemble are counted over the entire 75 year simulation period. Realizations are derived from the LARS-WG base case time series.

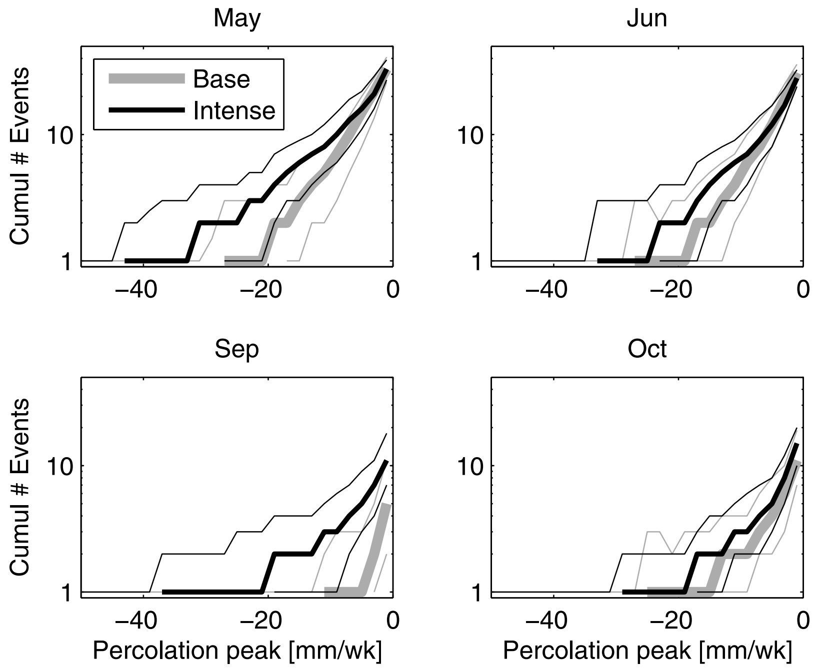

Figure 13. Ensemble median and first and third ensemble quartiles for number of events with a weekly percolation magnitude greater than the value specified on the horizontal axis during the indicated month. Events for each realization in the ensemble are counted over the entire 75 year simulation period. Gray curves show the base case, while black curves show the "intense" alternative. Realizations are derived from the LARS-WG base case time series. Recharge events occur significantly more often in May and September under the "intense" alternative.

winters. The key feature of the "intense" alternative is the increase in daily rainfall intensity. Precipitation intensity increases in both the spring and the fall, while total spring precipitation remains about the same as the base case (Figure 4).

[65] Monthly downward percolation for the "intense" alternative increases most, relative to the base case, in the spring (Figure 11). It actually decreases slightly during the winter. However, the average annual recharge increases by nearly 20% even though the average annual precipitation increases only about 10% (Figure 10). The timing of the more intense storms that occur with the "intense" alternative appears to have a substantial impact on recharge.

[66] Changes in precipitation intensity experienced in the "intense" alternative are likely to result in more high-magnitude recharge events during both May and September (Figure 13). There is also an increase in the total number of recharge events over a broad range of magnitudes during the fall, when total precipitation is expected to increase in addition to precipitation intensity. Because rainfall totals in the winter and spring months do not increase significantly, late spring antecedent moisture levels are about the same as for the base case. This implies that the predicted increase in spring downward percolation is caused almost exclusively by higher rain intensity.

[67] Although the "wet" alternative provides a wetter climate overall, the "intense" alternative generates nearly as many high-magnitude recharge events (Figure 12). This demonstrates that changes in spring rain (including intensity) have a disproportionate impact on recharge. The "intense" alternative yields a smaller increase in predicted crop AET (only about 10% higher than the base case) than the "wet" alternative (Figure 12).

6.2.2.3. "Seasonal" Alternative: Similar Annual Precipitation, Wetter Summer and Drier Winter

[68] Like the "intense" alternative, the "seasonal" alternative predicts average annual precipitation close to base case conditions. Average monthly precipitation decreases in the winter but increases throughout the summer. A significant increase in June rainfall yields an increase in July downward percolation. This happens even though the intensity of June rainfall is essentially the same as the base case. Additional late summer rains are mostly taken up by ET. As a result, the net change in average annual recharge is a 10% decrease, which is in the opposite direction of the approximately 10% increase in average annual rainfall. This implies that increased July downward percolation, relative to the base case, is insufficient to compensate for the decrease experienced during the rest of the year (Figure 11).

[69] Although total summer rainfall amounts are similar for the "wet" and "seasonal" alternatives, the earlier concentration of summer rain before maximum rooting in the "seasonal" alternative suggests that there should be more percolation and less crop AET for this option (Figure 4). Instead, it seems that dry antecedent conditions following drier winters limit summer percolation for the "seasonal" alternative. These results suggest that recharge events are controlled by a complex mix of factors which must align in particular ways to yield significant long-term recharge.

6.2.2.4. "All Dry" Alternative: All Months Drier

[70] The "all dry" alternative predicts a drier future than the base case, with lower precipitation in every month. As

might be expected, downward percolation decreases throughout the year for this alternative. Although small amounts of downward percolation still occur in winter, September and October have barely any recharge. The greatly decreased summer rains also limit root water uptake. *Ng et al.* [2009] suggest that recharge uncertainty scales with precipitation, with lowest uncertainty during dry periods. This observation is supported by the smallest spread in recharge values for the "all dry" and "driest" alternatives, which have the lowest average annual recharge (Figure 9).

[71] The "all dry" alternative is too dry to experience any high-intensity recharge events (Figure 12). Most events that occur with this alternative have percolation magnitudes less than 20 mm/week, and the total number of events of any size is about 25% less than the base case. An approximate 20% drop in rainfall gives a 50% drop in recharge and about a 20% drop in crop AET for the "all dry" alternative (Figure 10). Because rain-fed cotton is already near the limit of economical feasibility under current semiarid conditions [*Howell et al.*, 2004], such a reduction in water supply would likely end rain-fed cotton cultivation at the study site.

6.2.2.5. "Driest" Alternative: Lowest Annual Precipitation

[72] The "driest" alternative gives the least precipitation and recharge of all the climate alternatives investigated in our study. It differs from the "all dry" scenario in predicting a much wetter August and much drier winter (Figure 4). Average monthly downward percolation for the "driest" alternative decreases relative to the base case for every month except September, and winter percolation falls almost to zero (Figure 11). Because of the high August rains, September percolation is close to the base case value, which is quite small. No increase in downward percolation occurs in response to the August rains, because of dry antecedent soil moisture conditions and crop AET demands. There is a substantial drop in intense episodic recharge for the "driest" alternative (Figure 12). In fact, there are barely any events with percolation magnitudes greater than 10 mm/week.

[73] The role of ET is apparent from Figure 10, which indicates that the decrease of approximately 10% in crop AET is smaller than the 25% drop in precipitation and much less than the drop of about 75% in recharge. Crops are taking up a larger fraction of annual rainfall, especially during August when excess rain is available, and leaving little moisture to generate recharge. This suggests that rain-fed cotton may remain possible, even though average annual rainfall is lower than in the "all dry" alternative.

[74] The "driest" alternative provides a particularly dramatic example of the amplification of climate change impacts. This amplification of a small decrease in average annual rainfall into a much larger decrease in average annual recharge may seem counterintuitive at first, but is readily explained by considering how the timing of precipitation interacts with crop water demands and antecedent moisture conditions.

7. Summary and Conclusions

[75] This paper presents a probabilistic approach for analyzing the impacts of climate change on diffuse episodic recharge in semiarid climates. The objective is to use the approach to provide insight into how climate changes might affect the mechanisms that control diffuse recharge in such environments. It is useful to discern patterns in the infrequent episodic events that dominate semiarid recharge by looking at an ensemble of many time series of relatively long duration. In an ensemble analysis covering a long forecast period, most conditions that generate recharge will be encountered sufficiently often to provide quantitative descriptions of mechanisms and to support probabilistic assessments.

[76] Our approach relies on an ensemble forecasting technique that accounts for uncertainty in soil and vegetation properties as well as uncertainty in the meteorological variables associated with climate predictions. The analysis focuses on changes in percolation at the bottom of the root zone between a base period and a forecast period. Examining percolation at this depth makes it possible to resolve the individual short duration events that contribute most of the recharge in semiarid regions. We consider five alternative future climates predicted by five representative GCMs selected from *IPCC* [2007]. Realizations of percolation and other hydrologic fluxes are obtained from repeated simulations of the SWAP unsaturated zone flow and solute transport model [*van Dam et al.*, 2008]. These flux realizations depend on realizations of uncertain meteorological inputs and uncertain soil and vegetation properties, which are the primary inputs to SWAP. The meteorological realizations for the base case (no climate change) and for each of the five climate change alternatives are 75 year daily time series produced with the LARS-WG weather generator [*Semenov et al.*, 1998]. The soil and vegetation property realizations are obtained from the importance sampling procedure described by *Ng et al.* [2009]. These property realizations are conditioned on observations of soil moisture and chloride concentration at the study site.

[77] Weather generators provide meteorological realizations with higher temporal resolution than can be obtained directly from climate models. This is important for accurate simulation of transient precipitation and recharge events. Generators are also more convenient for ensemble analyses than a single record. The LARS-WG parameters for the base case (no climate change) were adjusted to obtain a good statistical match to the conditional precipitation ensemble generated by *Ng et al.* [2009] and to historical observations for other meteorological variables. For each of the five climate change alternatives, the generator parameters were modified from the base case values using climate change factors derived from GCM outputs.

[78] Meteorological time series obtained from weather generators, such as LARS-WG, may underestimate the occurrence of rare and intense recharge events that account for a significant fraction of total recharge in dry environments. Although validation tests indicate that LARS-WG gives a reasonable description of episodic recharge at our SHP study site over the 75 year forecast period, it is likely that more reliable results could be obtained if the weather generator incorporated a more accurate description of interannual variability. Some researchers have introduced information on interannual variability in weather generator simulations of current climate conditions by using sea surface temperature and pressure [*Katz and Parlange*, 1993; *Wilby et al.*, 2002]. It may be useful to also incorporate such indices in simulations of future climate alternatives.

[79] Results from our ensemble analysis of five climate alternatives at a semiarid study site in the U.S. southern

High Plains indicate that precipitation changes have a greater impact on recharge than temperature changes. The possible precipitation changes represented by our five GCM alternatives vary from drier to wetter, with changes in predicted average annual rainfall spanning a range of -25% to +20%, relative to the present climate. These alternatives give a range in average annual recharge that is even greater, from -75% to +35% relative to present conditions. For most alternatives, changes in average annual recharge are greater than the corresponding changes in average annual precipitation. These results can be explained by considering the role of episodic recharge events. Such events can have a critical impact on the replenishment of groundwater resources and the mobilization of contaminants in the subsurface environment.

[80] Our simulations show that one of the most important factors affecting episodic recharge is the timing of high-rainfall periods. If these periods occur in the winter or spring, when PET is lower and crops have not fully emerged, a significant fraction of rainfall is likely to result in recharge. Furthermore, if these rains occur with great intensity, they are likely to produce higher-magnitude recharge events. Alternatively, if rainfall occurs during summer, when plant root systems are mature, soil moisture is low, and PET is high, it is much more difficult for infiltrating water to pass below the root zone and result in recharge. These findings show that GCM predictions of average annual precipitation changes do not provide adequate information on likely climate change impacts because they lack the seasonal and transient features that control episodic recharge. Overall, impacts on recharge will be determined by a complex mix of climate and land-surface factors.

[81] The significant range in our recharge results reflects the considerable uncertainty in the amount and timing of rainfall across the five climate alternatives, and the uncertainty in terrestrial conditions that will filter changes in climate. We believe that our recharge results give a realistic view of the current level of uncertainty about the local and regional impacts of climate change. At this point, it seems more appropriate to try to define the range of possibilities than to make specific predictions. Ensemble forecasting studies such as the one described here are a step in that direction.

[82] Although our unsaturated zone model provides useful information about recharge mechanisms, it relies on a very simple description of vegetation dynamics. It is likely that a more physically based dynamic vegetation model could provide additional insights [*Green et al.*, 2007]. In particular, other studies have shown that higher temperatures could shorten the growing season [*Rosenzweig*, 1990] and that CO_2 fertilization effects could impact root water uptake [*Allen et al.*, 1996]. These effects are not included in SWAP's static vegetation model, which prespecifies crop development independent of atmospheric conditions.

[83] Our emphasis on diffuse recharge in low-relief regions greatly simplifies our analysis by allowing the use of a one-dimensional unsaturated zone model. However, in many areas, topographically focused recharge is an important, and often primary, contributor to recharge. The ensemble-based methods used here can be extended to incorporate lateral moisture movement. However, doing this with the Richards'-based description of unsaturated flow used in SWAP would be very computationally demanding for large ensembles. The ensemble forecasting procedure used here consisted of 200 model runs for 75 years, and the parameter estimates from *Ng et al.* [2009] used 30,000 simulations. It is possible that the insights provided here about diffuse recharge could be used to develop simpler unsaturated zone models that account for the influence of topography while remaining computationally feasible for large ensemble runs. We believe that the advantages of a long-duration ensemble-based analysis of episodic recharge make it worthwhile to develop models appropriate for ensemble forecasting.

[84] The ensemble forecasting analysis presented here illustrates the advantage of combining data assimilation techniques, which enable us to incorporate relevant field observations, with a stochastic weather generator, which enables us to generate realistic short-term rain events, and general circulation models, which enable us to consider different climate change alternatives. This integrated ensemble-based approach to climate change analysis provides a systematic way to extract the maximum amount of information from limited data while properly accounting for uncertainty. In this respect, we hope that our study provides a basis for continuing research on the connections between climate change and groundwater resources.

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