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RESEARCH ARTICLE

Irrigation variability and climate change affect derived distributions of simulated water recharge and nitrate leaching

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ABSTRACT

Irrigation ('blue') water has high value as municipalities seek water security under growing populations and projected climates, but spatial variability makes estimating return flows to groundwater challenging. We demonstrate a framework for simulating spatially variable infiltration and derived distributions of return flows using an agricultural and vadose zone model to simulate recharge and nitrate leaching under irrigated corn in semi-arid northeastern Colorado, USA. Derived distributions indicated increased historical recharge (2–42%) as the spatial variability of applied irrigation increased. Projected climate in 2050 increased recharge above historical rates by up to 58%, but climatic effects decreased with increasing irrigation variability.

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Irrigation efficiency; spatial variability; groundwater; Colorado

Introduction and motivation

Water rights, policy and emergent water markets call for improved estimates of agricultural water budgets. In Colorado, USA, water law considers historical return flows to streams and groundwater part of regional water resources which must be quantified before selling water rights. Such return flows are challenging to estimate due to spatial variability of applied irrigation water caused by inefficiency of in-field irrigation application. Irrigation field research has been conducted to evaluate crop water production functions in the semi-arid eastern plains of Colorado, USA (Saseendran, Ahuja, Nielsen, Trout, & Ma, 2008; Trout & DeJonge, 2017). Such studies are important for assessment of the water footprint and optimal use of water resources. Eastern Colorado from the Continental Divide of the Rocky Mountains to the eastern plains is a system in which water flows from pristine alpine conditions with streamflow dominated by spring snowmelt, through an urban and suburban corridor with growing water demands, to agricultural landscapes where crop production is enabled or greatly enhanced by irrigation ('blue' water consumption). Agriculture is the main water user, but cities are buying water rights for potential use upstream, because the water source is primarily coming from the mountains. Buyers (cities and industry) and sellers (agricultural producers) both need to know the value of water in this semi-arid

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environment, and producers need to evaluate scenarios for optimizing reduced irrigation water use.

In the context of this special issue, blue water refers to irrigation water supplies from surface water and groundwater. In Colorado, surface water is typically diverted from rivers into canals ('ditches') managed by ditch companies that provide water to multiple users (Waskom, Marx, Wolfe, & Wallace 2014). Groundwater pumping is limited to regional aquifers (other than part of the Ogallala Aquifer in the southeast of Colorado). Interactions between direct precipitation ('green' water), which is highly variable, and evapotranspiration (ET) demand of a crop determine the net demand for blue water. Excess irrigation or precipitation may cause return flows to surface water and eventually to groundwater, augmenting or recharging blue water supplies. Soil water in the root zone (also called 'green water storage' by some) is actually supplied by both blue and green waters. In practice, disaggregating blue and green water can be complex and highly uncertain.

Projected climate change and variability further complicate the assessment, and require computer simulations to extend available field data and predict complex interactions in agricultural systems (e.g., Lauffenburger, Gurdak, Hobza, Woodward, & Wolf, 2018). The present study builds upon the work by Islam et al. (2012b) who simulated potential effects of climate change on corn production driven by historical (1950–1999) and projected climates centred at 2050 (2035–65) and 2080 (2065–95) using an agricultural systems and vadose zone model named the Root Zone Water Quality Model (RZWQM2) (Ma et al., 2012a). However, they did not explore irrigation effects on deep percolation of water and nitrate leaching beneath the root zone. Previous work also has not considered irrigation (in)efficiency in terms of its impact on the in-field spatial variability of irrigation, which drives subsequent variability of water and nutrient fluxes, including surface runoff (considered negligible in field research), recharge and leaching of N beneath the root zone.

Agricultural system models have been used extensively for studying the impacts of climate change on crop production. In this regard, the USDA-ARS Root Zone Water Quality Model (RZWQM2) (Ahuja, Rojas, Hanson, Shaffer, & Ma, 2000) linked with the DSSAT suite of crop models (Jones et al., 2003), has been used widely to simulate the effects of both Free Air-CO_2 eneriched Experiments (FACE) and Global Climate Model (GCM) projected temperatures and rainfall on diverse field crops and crop rotations under various rainfed (green water), irrigated (primarily blue water) and N fertilizer application levels in the Great Plains of the USA (Islam, Ahuja, Garcia, Ma, & Saseendran, 2012a, 2012b; Ko et al., 2010, 2012).

The objectives of this simulation study were to:

(1) Propose a framework for estimating the derived distributions of simulated fluxes from specified distributions of spatially variable irrigation.
(2) Quantify non-linear flux responses to variable irrigation amounts using the previously calibrated agricultural systems and vadose zone model, RZWQM2.
(3) Explore potential effects of climate change on the averages of the above derived distributions of fluxes.

Methods and study location

The framework for exploring potential impacts of irrigation efficiency and climate change is applied to continuous corn (maize; *Zea mays L.*) based on experiments at the Limited Irrigation Research Farm (LIRF) in eastern Colorado, USA (Trout & DeJonge, 2017). Islam et al. (2012a, 2012b) used RZWQM2 to simulate maize grain yield and water use efficiency assuming uniform spatial irrigation at full evapotranspiration (ET) demand and for five levels of deficit irrigation under historical and projected climates. The current simulations build upon their study using the previously calibrated model parameters (Ma et al., 2012b), as described below.

Study location: limited irrigation research farm, Colorado, USA

The LIRF field site is located near Greeley, Colorado, USA (Figure 1) just north of the confluence of the Cache la Poudre and South Platte Rivers. A detailed site description and data for maize crop water productivity are available for the years 2008–2011 (Trout & Bausch, 2017). During this period, maize was grown in a four-year rotation with winter wheat, sunflower and pinto bean, where maize was in a different block of treatment plots each year. Six irrigation treatments ranged from 40–100% of the estimated crop water requirement or full evapotranspiration (ET) demand. Experiments were designed to minimize other management treatment effects, including

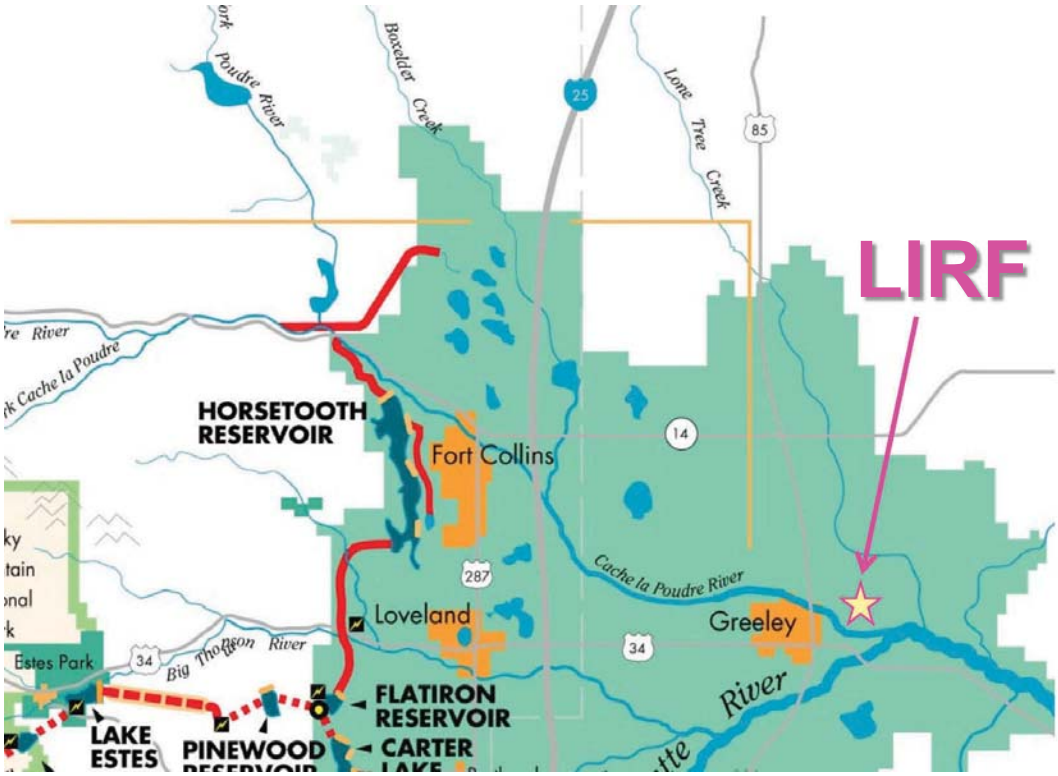

Figure 1. The Limited Irrigation Research Farm (LIRF) study site (star symbol) near Greeley, Colorado, USA. Green shaded area indicates the general extent of irrigated agriculture.

Source: Northern Water, used with permission.

seeding rate, emergence and nutrient stress. Actual conditions varied somewhat among irrigation treatments (Trout & Bausch, 2017), but effects on maize production and water use were considered minor compared with the irrigation treatment effects (Gleason et al., 2017; Trout & DeJonge, 2017).

Irrigation events were applied every 4–7 days in the field based on soil water deficits and forecasted precipitation in order to target the six treatment levels. Each treatment was replicated four times, and average seasonal irrigation amounts ranged from 126 to 427 mm of water applied. As described below, simulated irrigation events did not match the experimental rates exactly, but were designed to mimic the treatments using weekly applications based on computed ET demand. No interactions between plots (9-m wide) were assumed in all LIRF experimental and simulation results to date. Surface runoff from one plot to another is rarely observed and considered to be insignificant in the water balance. Canopy-level atmospheric conditions are likely affected by advection of air from off-site and between plots, but atmospheric variables are considered to be uniform across the LIRF experimental plots.

Newer experiments at LIRF (2012- present) were modified to optimize water used based on growth stages (unpublished data). These treatments and effects of timing allocations were not simulated here, but have been investigated in terms of maize physiological responses to water stress (DeJonge, Taghvaeian, Trout, & Comas, 2015; Gleason et al., 2017).

Agricultural systems simulations using RZWQM2

We built this study upon previous simulations (Islam et al., 2012b), where RZWQM2 was calibrated to field grain yield, biomass, leaf area index and soil water content in the root zone for three growing seasons (2008–2010). Ma et al. (2012b) documented details of the calibration procedure, which showed excellent agreement between simulated and field-estimated transpiration, as well as simulated versus experimental irrigation amounts. Evaluations of these and other simulated variables and system components provide a relatively high level of confidence in the calibrated model's responses to irrigation. Surface runoff, however, was neither measured nor tested in the model evaluations. Thus we are less confident in the simulated runoff volumes, but expect that runoff comprises a minor part of the total water balance.

Application of a vertical (one-dimensional) model like RZWQM2 may be problematic when used to explore fully three-dimensional processes. One-dimensionality assumes minimal lateral interactions between processes that would bias the representative values of each subarea. Significant surface runoff under high irrigation rates or extreme precipitation events could violate this assumption, so such events should be checked in simulation results. Again, surface runoff is not measured and is considered negligible in the experiments.

The RZWQM2 is a process-oriented cropping system model developed for simulating the impacts of tillage, residue cover, water, fertilizers, pesticides, and crop management practices on carbon, nitrogen, and water dynamics by integrating the physical, chemical and biological processes in the soil-water-crop-air system (Ahuja et al., 2000). In addition to a generic crop model that can be parameterized to simulate specific crops, the model contains the CSM (Cropping System Models) crop modules of DSSAT

v4.6 for simulation of specific crops (Ma, Hoogenboom, Ahuja, Ascough, & Saseendran, 2006). Studies verifying the capabilities of RZWQM2 for explaining and managing dryland cropping systems in the Great Plains have been reported (Saseendran et al., 2008, 2015). Cameira et al. (2005, 2007) evaluated the capabilities of RZWQM to simulate crop development, water balance terms, and fate of nitrogen in field soil-crop environment. They concluded that model accuracies were acceptable in practical applications for complex and spatially variable field conditions.

The nutrient model simulates nitrogen cycling in the soil (Ma et al., 2012a). Processes include mineralization and immobilization of N based upon C:N ratios, aerobic decay of organic matter to ammonium (NH_4), aerobic nitrification of NH_4 to nitrate (NO_3), and anaerobic denitrification of NO_3 to gaseous forms (N_2 and N_2O). Soil water content, temperature, pH and microbial pools affect these processes and rates of transformation.

The model interface for RZWQM2 provides automated tools to simulate management practices including irrigation scheduling. The present simulations implemented the ET deficit method with 7 days minimum between irrigation events and 100% of the potential ET specified for the base simulation. This is defined as the 100% ET demand irrigation level, which averaged 533 mm y^{-1} for the historical period and 474 mm y^{-1} for the 2050 projected climate scenario (Islam et al., 2012b). Other levels are simply scaled by a factor (e.g., 1.4 for 140% ET Demand) applied to all irrigation events. This is appropriate for simulating a distribution of various rates on the same application dates (i.e., in-field variability).

The historical meteorological data inputs spanned 50 years (1 January 1950 – 31 December 1999) for these simulations. To remove artificial effects of initial conditions, model runs were repeated four times, saving the final state after each run and using the simulated state variables as initial conditions for the subsequent run. The model domain was 3 m deep with a unit gradient (gravity drainage) bottom boundary condition. Nutrient inputs included three forms of N applications (NO_3, NH_4 and Urea-N) applied at the experimental rates and timing each year totalling 150 kg-N ha^{-1} y^{-1}.

Daily model output included actual ET, surface runoff, recharge ('deep drainage' in RZWQM2) and N leached at 3-m depth. Here, deep percolation is considered pre-groundwater recharge without estimating a time lag, which could be substantial for a deep water table. Long-term average recharge to groundwater would be the same, but N loads could change with denitrification and other N-cycle processes above the water table.

Irrigation efficiency and derived distributions of flux variability

Irrigation efficiency within a field is related to the uniformity of irrigation application and soils, whereas whole-system irrigation efficiency also considers off-field conveyance and storage losses. Factors within a field include spatial variability of applied water (via furrows, sprinklers or drip lines) and soil infiltrability causing lateral redistribution of applied water. In these simulations, soils were assumed to be uniform in the horizontal dimensions, making irrigation uniformity the only effective factor. Field-scale irrigation efficiency or 'application efficiency' (Clemmens, Allen, & Burt, 2008) is defined as,

$$AE = \frac{100\%\ ET\ demand}{Irrigation\ water\ applied} \tag{1}$$

where 100% ET demand is the computed PET (mm d^{-1}) minus precipitation (mm d^{-1}). These fluxes and the areal average irrigation water applied (mm d^{-1}) are integrated over the growing season to get the average *AE*. On a daily basis, the change in soil-water storage should be subtracted from the denominator, but on a seasonal basis, the change in storage is assumed to be much smaller than the depth of irrigation water applied. This assumption is appropriate for well-irrigated crops, not for dryland or very limited average irrigation.

Clemmens et al. (2008) discussed various aspects of irrigation efficiency related to water conservation. They provided illustrations (Clemmens et al., 2008; Figures 2 and 3) of the relationships between the distributions of water applied and portion of area exceeding the full crop water demand for distributions with different spatial coefficients of variation. They used nonlinear, symmetric (e.g., Gaussian) distributions, but the spatial distributions could be anything from linear (uniform distribution) to highly skewed (e.g., log-normal).

If the spatial distribution of irrigation water applied is known or otherwise specified, one needs a transfer function to convert the distribution of annual irrigation water applied to a distribution of output fluxes (e.g., deep percolation). Because the transfer function $g(x)$ can be highly nonlinear, RZWQM2 was used to compute output fluxes y for discrete values of annual irrigation application amount x, which were then interpolated to obtain a continuous function for $y = g(x)$.

Figure 2 is a schematic illustration (after Benjamin & Cornell, 1970) of an output distribution or probability density function $f_Y(y)$ derived from an input distribution $f_X(x)$ and a nonlinear transfer function $y = g(x)$. The equal areas represent

$$f_Y(y)\ dy = f_X(x)\ dx \tag{2}$$

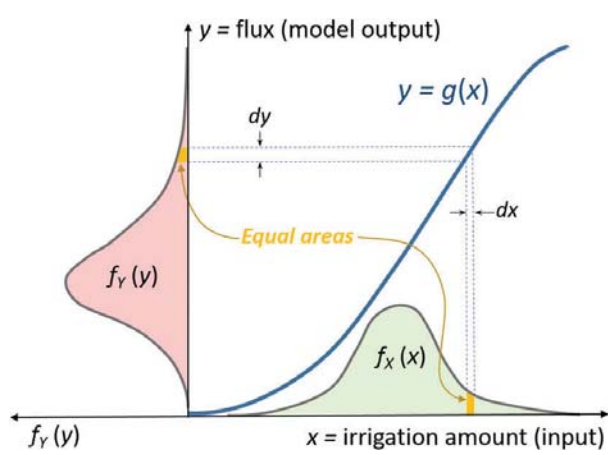

Figure 2. Conceptual diagram of a derived distribution (after Benjamin & Cornell, 1970, Fig. 2.3.4), where $f_Y(y)$ is derived from $f_X(\mathbf{x})$ given $y = g(x)$. Here, x is irrigation amount (or fraction of full ET), y is the average RZWQM2 output (deep percolation, N leached, or surface runoff), and the continuous function $g(x)$ is interpolated from discrete simulations (see results below in Figure 5).

The schematic distributions are bell shaped, but here we assume that $f_X(x)$ follows a simple uniform distribution, meaning $f_X(x) = (x_{\max} - x_{\min})^{-1}$ for all x within this finite range, and the mean irrigation water applied is $(x_{\max} + x_{\min})/2$. Also, we let $g(x)$ be a polynomial function, because this continuous analytical function fit the discrete model results very well. The derived distribution approach would work for any specified input distribution (enforcing $x \geq 0$) and any interpolated transfer function $y \sim g(x)$ fitted to the RZWQM2 output fluxes.

In the present simulations, the mean value of irrigation water applied meets 1.4 times the computed ET demand, and the range is allowed to vary (Table 1). This assumption is based on common irrigation practices that avoid under-watering large parts of a field, leading to higher field-average irrigation amounts. This differs from the field experiment at LIRF, which avoided over-irrigation and targeted deficit irrigation rates as low as 40% of full ET demand. In our simulations, irrigation rates varied from 30% to 250% of full ET demand for the highest variability case, such that $0.3 \leq x \leq 2.5$ in the interpolated the transfer function $g(x)$.

Finally, the spatial mean value of each output flux is the integral over the derived distribution, or

$$\bar{y} = \int_{-\infty}^{\infty} f_Y(y)dy \tag{3}$$

where again, y represents either recharge, N leaching, or surface runoff integrated over the full time period of simulation. In this application the lower limit of integration is 0, because fluxes are always non-negative. In general, the lower limit could be negative.

Downscaled ensemble of projected climate change

The projected climate scenarios used for this study were taken from Islam et al. (2012b), who used the Hybrid Delta Method (Hamlet, Salathé, & Carrasco, 2010) with bias corrected and spatially disaggregated (BCSD) climate projections from the World Climate Research Program's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) dataset (IPCC, 2007). Details of the climate downscaling can be found in Islam et al. (2012b). The CMIP3 projections used 16 general circulation

Table 1. Derived average fluxes under historical climate (1950–1999) for different ranges of irrigation amounts, and corresponding ratios of these averages divided by fluxes for uniform irrigation at 140% of full ET demand.

Irrigation Fraction of Full ET Demand			Derived Average Flux			Ratio vs 140%		
Range	Minimum	Maximum	Recharge (mm/y)	N leached (kg/ha/y)	Runoff (mm/y)	Recharge	N Leached	Runoff
0.4	1.2	1.6	115	4.23	8.78	1.02	1.03	0.999
0.8	1.0	1.8	120	4.30	8.78	1.07	1.05	0.998
1.0	0.9	1.9	124	4.36	8.78	1.10	1.07	0.998
1.4	0.7	2.1	134	4.52	8.78	1.19	1.11	0.998
1.8	0.5	2.3	153	4.93	8.77	1.36	1.21	0.997
2.2	0.3	2.5	160	5.12	8.77	1.42	1.25	0.997

models (GCMs) with three greenhouse gas emission scenarios representing low (B1), medium (A1B) and high (A2) emissions paths. The simulated ensemble average atmospheric CO_2 concentrations were 330 ppm for the historical period, and 460, 623, and 790 ppm for projections centered on the years 2020, 2050, and 2080, respectively.

CMIP3 climate projections are used for consistency with previous simulations, noting that the current emphasis is on the framework for simulating effects of irrigation efficiency. One may question the use of CMIP3 versus more recent CMIP5 climate simulations (IPCC, 2013), because more climate models were used for CMIP5, and some of the newer GCMs are considered more advanced. CMIP5 used Representative Concentration Pathways (RCPs), which differ from the emissions scenarios used in CMIP3, making direct comparisons difficult. However, projections from CMIP3 and CMIP5 are generally consistent.[1] For North America, Sheffield et al. (2014) concluded, 'Overall, the multi-model ensemble (MME) mean performance has not improved substantially in CMIP5 relative to CMIP3 for climatological variables … Projected increases in moderate to extreme precipitation events are similar to CMIP3.' Sun et al. (2015) provided additional details on the similarities and differences between CMIP3 and CMIP5 climate projections for the United States. Soon CMIP5 will be superseded by CMIP6 (Eyring et al., 2016) and so on, which is why we focus here on the methods for simulating responses to irrigation variability more than on the specific climate change results.

Results

Example results are presented for the 50-year historical climate and for one climate projection period (50 years of simulation centered on the year 2050). We also ran equivalent simulations for near-term (2020) and longer-term (2080) climate scenarios, yielding more subdued and amplified results, respectively, but the illustrations would be similar to the examples shown below. As noted in the methods above, each period was simulated four times, wherein the final simulation state of each run was saved and used to reinitialize the next run, thereby reducing artificial effects of the initial conditions (particularly soil moisture and nutrient pools) on the final results.

Simulated fluxes

Historical climate data (1950–1999) include inter-annual and intra-annual variability. In particular, precipitation amounts within the growing season and extreme events vary from year to year. Daily historical precipitation amounts are shown together with simulated evapotranspiration (ET) in Figure 3(a). Despite variability in precipitation, ET is relatively consistent from year to year under full irrigation (100% of ET demand). On the other hand, recharge of water beneath the root zone ('deep percolation' at 3 m) varies dramatically among the 50 years simulated, and Figure 3(b) shows four large recharge events with peak fluxes exceeding 2 mm/d (indicated with green circles). Likewise, nitrate leaching follows the temporal pattern of recharge. Daily surface runoff is also simulated with several peaks within a range of 2–6 mm/d. However, these events

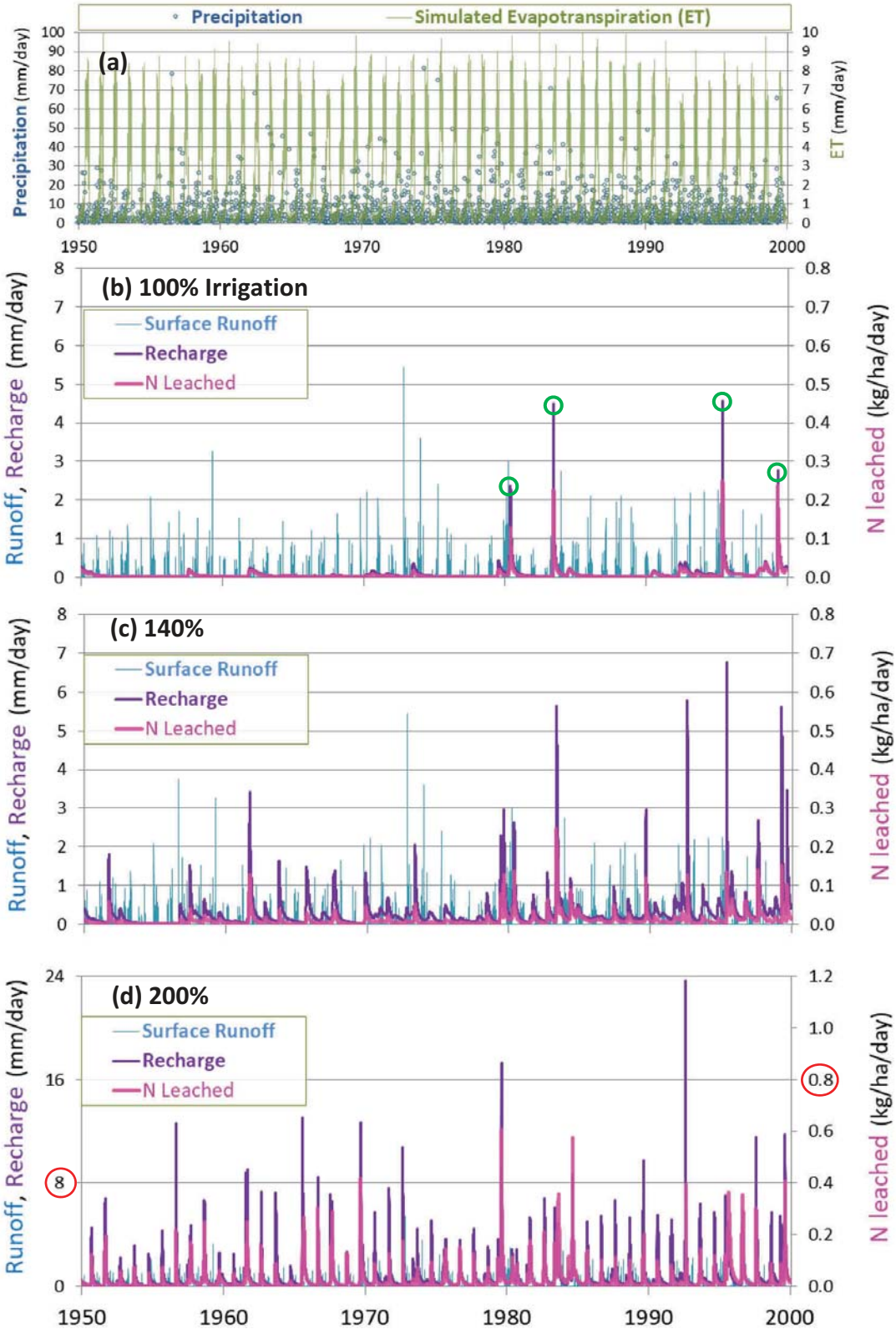

Figure 3. Daily simulation results for historical climate (1950–1999): (a) Precipitation data and simulated evapotranspiration (actual ET); and simulated runoff, recharge and N leached under irrigation meeting: (b) full (100%), (c) 140% and (d) double (200%) of the full ET demand. Green circles highlight four main recharge events with peaks >2 mm/d in (b). In (d), the red circles highlight the maximum scales used in (b) and (c).

are infrequent, such that annual runoff volumes are very small (<8.7 mm y^{-1}) compared with precipitation (average annual equals 341 mm y^{-1}).

The base scenario used here for uniform irrigation is 140% of full ET demand (Figure 3(c)). Although simulated ET increased slightly compared with the scenario of irrigation at 100% of ET demand (Figure 3(b)), ET under full irrigation is driven primarily by the energy budget, so in both cases, ET approximately met the potential ET demand. Thus excess irrigation water is available to increase soil-water storage and eventually flow below the root zone. Consequently higher irrigation produced more frequent recharge events (Figure 3(c), with peaks approaching or exceeding 1 mm/d in many years, and significantly higher recharge in the four years with high peaks under irrigation at 100% ET demand (see green circles in Figure 3(b)). Again N leaching follows the temporal pattern of recharge, so much more nitrate is leached through the profile to the 3-m depth.

Finally, Figure 3(d) shows even greater output fluxes when irrigation is applied to meet 200% of ET demand for the historical climate. In this case, significant water recharge and N leaching events occur every year, and there are 8 recharge peaks exceeding 10 mm/d (note the greater maximum value of the vertical axis compared with Figure 3(b,c)). However, simulated ET continues to meet the potential ET (energetic demand), and surface runoff does not increase with increased irrigation.

Figure 4 is a one-year window (1980) showing a zoomed in view of Figure 3 that includes the lowest of the top four recharge events (first green circle in Figure 3(b)) over the 50-year historical period. This illustrates dynamics within the growing seasons and effects of Spring precipitation. Thus, the previously calibrated RZWQM2 model captures the agricultural system and vadose zone processes needed to develop transfer functions from irrigation inputs under different periods to output fluxes, including water recharge and nitrate leaching at 3 m and surface runoff.

Results for the ensemble climate change scenario are not illustrated here, but the temporal behaviours are similar to the historical simulations. An important difference in the simulated transpiration process is the plant response to increased atmospheric CO_2. In the plant model (DSSAT 4.6), the radiation use efficiency increases with CO_2 to produce higher average leaf areas, and stomatal conductance decreases to conserve water. In combination, the average ET is reduced, which causes the average recharge under climate change (2050 scenario) to be greater than historical recharge.

Transfer functions: irrigation inputs to model output fluxes

As described in the methods, average annual input (irrigation) and output (recharge, N leaching, and runoff) are computed for each irrigation scenario (spatial representation). These simulated data are then fit using polynomial regression to compute a relationship of the form:

$$y = g(x) = ax^3 + bx^2 + cx + d \tag{4}$$

where the symbols a through d are fitting parameters, and selection of a 3rd order polynomial is based upon achieving nearly perfect fits ($R^2 > 0.99$) for the recharge and

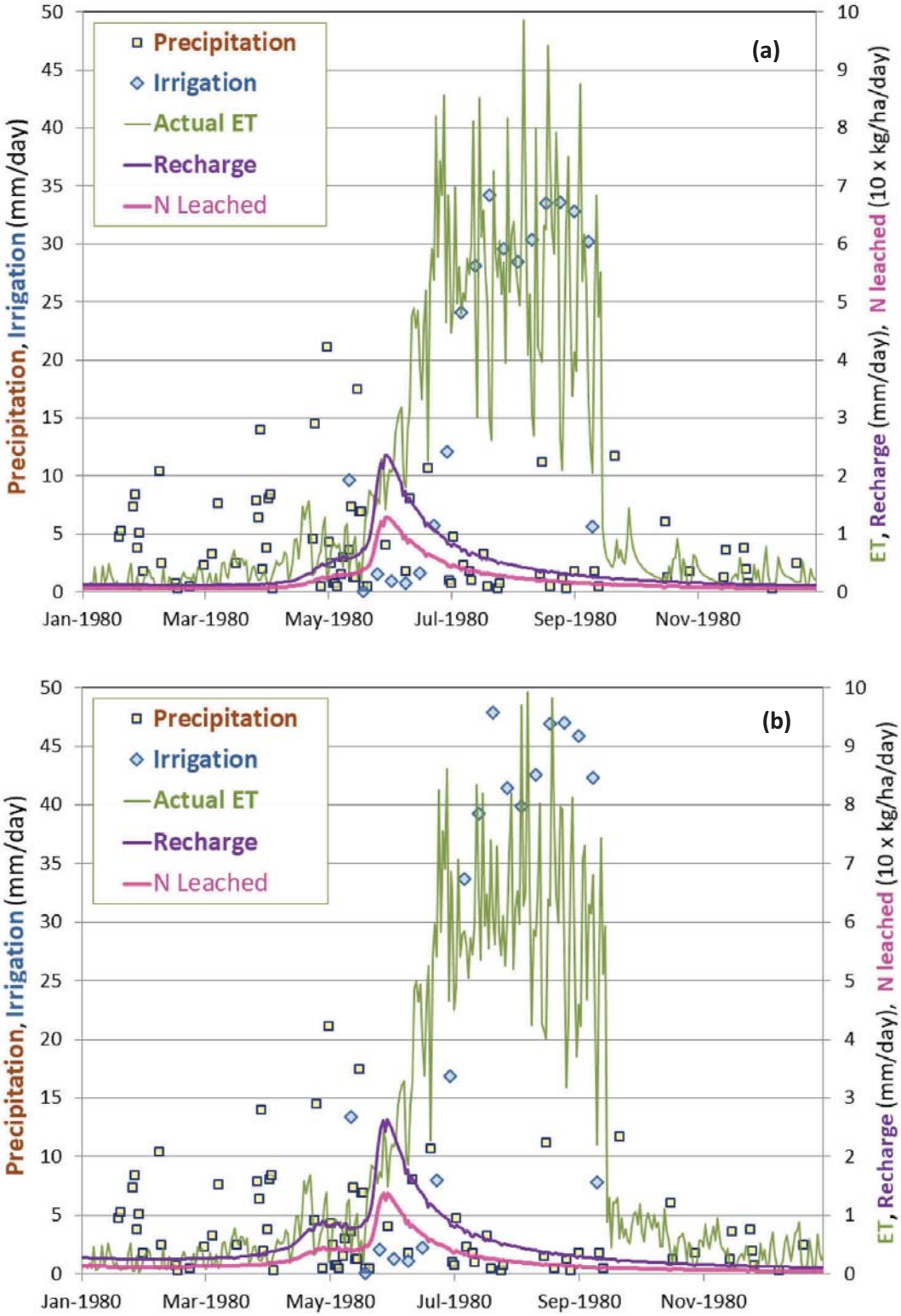

Figure 4. Daily simulation results illustrating one year (1980) under historical climate using irrigation schedules of (a) 100% and (b) 140% of the full ET demand (zoom-in view of Figure 3).

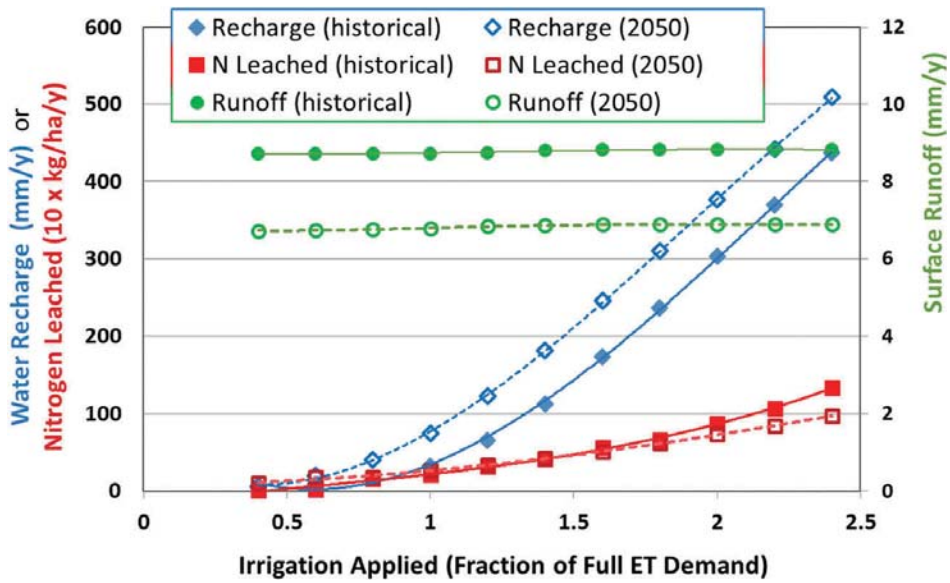

Figure 5. Average values of simulated deep percolation and nitrogen (NO_3-N) leached to 3-m depth as functions of the fraction of full ET demand for historical climate and projected climate (2050). Symbols are computed from RZWQM2 simulations for surface water runoff (green), deep percolation of water (blue) and nitrogen (NO_3-N) leached (red); lines are polynomial regressions through these points used as transfer functions ($g(x)$ in Figure 2).

N leaching transfer functions. Figure 5 shows the resulting transfer functions for historical and 2050 projected climate scenarios.

Recharge transfer functions behave as expected with nonlinear responses to irrigation between 0.4 and 1.5 times full ET demand, followed by nearly linear increases at higher irrigation rates. The nonlinear feature requires a system model like RZWQM2 to capture complex biophysical interactions over time. Interestingly, the nonlinear portion goes beyond irrigation amounts designed to meet 100% of full ET, so the inflection point of linear extension is also identified by these simulations. Simulated nitrate leaching at 3 m is also nonlinear, but the monotonic curve never becomes completely linear even at irrigation rates exceeding 2 times full ET.

Comparing the 2050 projected climate with historical climate results, recharge increased consistently for all irrigation rates. On the other hand, simulated surface runoff decreased, but absolute changes were very small (~ 2 mm y^{-1}). Responses of N leaching to climate change varied with the irrigation scheme, showing increased N leaching under deficit irrigation (<100% of full ET demand), but decreased at levels above approximately 1.5 times full ET demand for irrigation. The projected change in N leaching is thus very small for uniform irrigation at the base rate of 1.4 times full ET demand.

Derived distributions and average fluxes

For simplicity, the input distribution for irrigation variability was assumed to be a uniform distribution for the present results. The derived distributions were computed using the polynomial transfer functions (Equation 4) in Figure 5, which were averaged by discrete integration of Equation (3). The derived average fluxes are tabulated in

Table 2. Differences (2050 Projection – Historical) for deep percolation (recharge at 3-m depth), N leached, and surface runoff. Mean irrigation applied is 1.4 times the full evapotranspiration (ET) demand for all cases with uniform distributions for the given ranges from minimum (Min.) to maximum (Max.) levels. Average flux differences and percentage changes between projected and historical climates are computed from derived distributions using simulated transfer functions (Figure 5).

Irrigation Fraction of Full ET Demand			Derived Average Flux Difference			Percentage change (%)		
Range	Min.	Max.	Recharge (mm/y)	N leached (kg/ha/y)	Runoff (mm/y)	Recharge	N Leached	Runoff
0.4	1.2	1.6	66.7	−0.046	−1.93	57.9	−1.1	−21.9
0.8	1.0	1.8	64.4	−0.061	−1.93	53.4	−1.4	−22.0
1.0	0.9	1.9	62.8	−0.076	−1.93	50.5	−1.7	−22.0
1.4	0.7	2.1	59.0	−0.132	−1.94	43.9	−2.9	−22.1
1.8	0.5	2.3	55.1	−0.242	−1.94	37.6	−5.1	−22.1
2.2	0.3	2.5	51.8	−0.435	−1.94	32.4	−8.5	−22.2

Table 1 for the historical climate with different levels of spatial variability in irrigation quantified by the range of irrigation amounts quantified by the fraction of full ET demand. Water recharge increased from 115 to 160 mm y^{-1} as the spatial variability (range) increased from 0.4 to 2.2. The average flux of N leached to a 3-m depth also increased with spatial variability of irrigation, but only from 4.23 to 5.12 kg-N ha^{-1} y^{-1}. The derived average surface water runoff changed very little, decreasing from 8.78 to 8.77 mm y^{-1} (note that runoff is less than 8% of recharge, and the change in runoff is insignificant).

The derived average fluxes with spatially variable irrigation are compared with uniform irrigation at the same mean value (140% of full ET demand) on the right side of Table 1. As expected, the lowest variance (small range) produced average values very similar to the uniform irrigation case (ratio = 1). In the most extreme spatial variability explored, the average recharge increased by 42% (ratio = 1.42), and N leached increased by 25%. Runoff did not increase with greater irrigation variability, indicating that irrigation events did not produce runoff in these simulations.

Similar tables could be given for the climate change scenario projected into the short and long term (2020 to 2080). Table 2 reports the differences between derived average fluxes using projected climate for 2050 versus the historical simulations (Table 1). Differences in recharge are positive (i.e., simulated recharge in 2050 is greater than historical values), but the differences decrease as the range of spatial irrigation values increase. The corresponding percentage change went from 58% down to 32%. By contrast, changes in N leached and runoff were all negative but small in absolute terms. The absolute change in N leached was less than 0.44 kg-N ha^{-1} y^{-1}, and runoff decreased by less than 2 mm y^{-1}.

Discussion of results

The present study is primarily an illustration of the framework presented for derived flux distributions and the associated ensemble average effects of irrigation efficiency under historical and projected climate change effects on deep water percolation (pre-groundwater recharge) and N leaching. Surface runoff was also simulated, but found to be minimal even

under excessive (>200% of ET demand) irrigation. A caveat of the latter result is that RZWQM2 was not calibrated to match observed runoff from the field plots, because runoff was not measured and assumed to be minimal in field research. Surface detention storage is not simulated in RZWQM2, which would further reduce simulated runoff and even eliminate many of the small events (e.g., <2 mm d^{-1}). It is possible that careful study of runoff could yield different model results, but that is beyond the current scope. Thus surface runoff results are reported for the calibrated model, but not emphasized here.

The vertical fluxes of water and N below the root zone at 3-m deep showed dramatic temporal variability. As illustrated in Figure 3, simulation over a long time period (50 years in this study) is essential for capturing episodal recharge and leaching events under full (100% of ET demand) irrigation. Even at 140% of full ET, interannual variability was pronounced.

The resulting transfer functions were nonlinear and could not be estimated without an agricultural systems and vadose zone process model, which simulated interactions of highly nonlinear processes. Because the runoff component was not calibrated against measurements, we hesitate to draw any firm conclusions from those results, and more work is needed to investigate the transfer functions for runoff. Transfer functions for water recharge and N leaching were similar for both historical and projected climates. The simulated effects of climate change caused recharge under high irrigation to be greater in the projected climate, but the amount of N leached decreased. For now, we hypothesize that the nitrogen cycling processes in the model caused greater denitrification in the root/vadose zone due to higher profile soil-water contents and higher surface temperatures. Further study is needed to explore this in more detail.

Conclusions

The present study led to the following conclusions:

(1) A systems model such as RZWQM2 is needed to simulate deep percolation of water and N leaching under historical and projected climates.
(2) Temporal averaging of fluxes over a sufficient time period can provide well-defined transfer functions, as illustrated here, to convert variable inputs (irrigation) to the output fluxes of interest.
(3) Irrigation 'return flows' to groundwater (renewable 'blue' water) respond nonlinearly to irrigation (in)efficiency.
(4) The derived distribution approach allows distributional uncertainty of irrigation efficiency (spatial variability) to be translated to output distributions and mean fluxes over space and time.
(5) The current simulations of climate change showed potential for large increases (32 to 58%) in recharge (2050 versus historical climate).
(6) Smaller negative changes in nitrate leaching indicated complex N cycling processes may have a compensating effect on increased recharge fluxes under climate change, despite monotonic increases in nitrate leaching with increased irrigation under both historical and projected climates.
(7) The water footprint of cropping systems, including blue and green water, can be estimated along with the combined return flow to groundwater available for

future pumping (more blue water). Such analyses may require complex systems models and should not be oversimplified.

Note

1. http://climatechange.environment.nsw.gov.au/Climate-projections-for-NSW/About-NARCliM/CMIP3-vs-CMIP5.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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