Title

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Abstract

This work demonstrates the application of real-time adaptive management principles to the problem of controlling the salinity levels in, and/or protecting groundwater quality beneath, soils undergoing irrigation with relatively saline water (e.g., reclaimed wastewater) under arid/semi-arid conditions. Here, optimal feedback-control scheme known as Receding Horizon Control (RHC) previously applied offline to control soil moisture levels during irrigation (Park et al., 2009) is applied inline during a pilot-scale field test aimed at balancing reclaimed water reuse and soil/groundwater quality in real-time. RHC is supported by sensor measurements, physically-based state prediction models, and optimization algorithms to drive field conditions to a desired environmental state. A simulation model including a one-dimensional (vertical) form of the Richards equation coupled to energy and solute transport equations is employed as a state estimator to provide predicted soil moisture, temperature, and salinity data. Vertical multi-sensor arrays installed in the soil provide initial conditions and continuous feedback to the control scheme. An optimization algorithm determines the optimal irrigation rate and frequency based on the imposed salinity constraints while forced by the requirement to maximize water reuse. The small-scale field test demonstrated that the RHC scheme was capable of maintaining specified salt levels at a prescribed soil depth autonomously. This finding suggests that, given an adequately structured and trained simulation model, sensor networks, prediction models, and optimization algorithms can be incorporated in the context of RHC to achieve water reuse and agricultural objectives while minimizing negative impacts on environmental quality autonomously.

1. Introduction

Irrigation in arid or semi-arid climates tends to promote soil salinization, particularly when the applied water contains significant amounts of dissolved salts, as with reclaimed wastewater. Left unchecked, salinization will eventually render a soil non-arable (Schoups et al. 2005). At the same time increasing population pressure in regions with these climates, such parts of the western U.S., is creating greater demands for agricultural irrigation, and reclaiming water is an important potential alternative to inter-basin water transfers. Thus, it is critical to learn how to better manage against soil salinization in the context of crop irrigation with reclaimed water. This work focuses on the development of a real-time adaptive management strategy for managing irrigation from the perspective of avoiding excessive salt accumulation in soils.

Leaching salts from the soil root zone by applying relatively high quality water is the common procedure for controlling soil salinity. This practice is often quantified in terms of a leaching requirement (LR), which prescribes the fraction of irrigation water (beyond crop evapotranspiration requirements) needed to leach excessive soluble salts from the root zone. The traditional LR approach assumes steady state, uniform flow during the leaching process, and may lead to the over-application of high quality water. Recent simulations by Corwin et al. (2007) demonstrated that equivalent salinity objectives were achievable at significantly lower LR values using a transient management strategy. This finding suggests that adaptive management of soil salinity using transient models would be a more prudent approach.

While root zone leaching can minimize the impact of salinity on crops, drainage management remains an important issue. In cases where the leachate is not collected, there is the potential to negatively impact underlying groundwater. Schoups et al. (2005) reconstructed historical changes in salt storage by irrigated agriculture in the San Joaquin Valley of California over the prior 60 years and demonstrated that even deeper aquifers accumulate significant salt levels under salinity leaching conditions. Their finding supports the notion of including groundwater quality management as an aspect of soil salinity management in some cases. Musharrafieh et al. (1995) proposed two management approaches, one preventing salinity leaching to groundwater while maximizing crop yield and the other ensuring low salt concentration in the root zone (neglecting salt leaching to groundwater) while maximizing crop yield. While their investigation employed only a limited number of scenarios, their approach demonstrates the value of including groundwater protection in a salinity management paradigm.

This work examines the potential to adaptively manage soil salinity in real time by using *in situ* sensors and process simulation models to predict future states and define the current system state. The irrigated domain is described in terms of one-dimensional flow and solute transport models. A control algorithm known as Receding Horizon Control (RHC) is used to optimize current and future irrigation rates subject to salinity based constraints. The RHC scheme was adapted previously to the problem of irrigation management and demonstrated in an offline experiment (Park et al., 2009). In the present work, a small-scale pilot system equipped with vertical arrays of soil moisture, temperature, and salinity sensors, as well as a meteorological station, was used to test an RHC system as a potential means for autonomously controlling soil salinity.

2. Soil Salinity Control Scheme using Receding Horizon Control (RHC)

RHC is a control algorithm that utilizes process models to predict the future response and determine a sequence of control variable adjustments that optimize future system states (Clarke, 1994; Kouvaritakis and Cannon, 2001). The RHC scheme is executed to estimate a vector of control actions over multiple management time steps spanning the optimization horizon. After the first optimal control is applied for the current management time step, the optimization process is repeated with the same optimization horizon advancing one management period forward (Kwon and Han, 2005). RHC is a feedback-control algorithm because it cycles through the optimization step after each new control vector is applied, using system feedback to re-initialize state simulations prior to each optimization (Figure 1). As its name implies, RHC optimizes several control vector changes into the future in real-time, making it well-suited for adaptive management problems in open environmental systems (e.g. irrigation), where changes in key drivers (e.g., evapotranspiration) can occur. The RHC methodology was adapted to address irrigation management problems by Park et al. (2009).

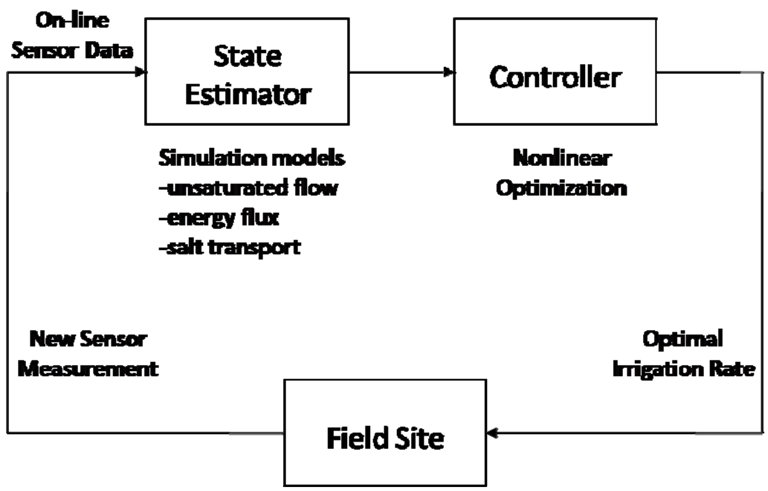


Figure 1. A diagram of the receding horizon control (RHC) feedback loop as applied to salinity management during irrigation

RHC is capable of addressing multiple objectives and constraints, including: (a) maximizing the amount of water being recycled by the farmer (e.g., wastewater disposal through reuse), (b) maintaining application rates below the maximum infiltration rate (e.g., supply conservation or avoiding health risks associated surface runoff of reclaimed water), and (c) maintaining salt concentrations near a threshold value at a given depth (or salt concentration and threshold values can be replaced by flux terms to protect groundwater quality). Several of these objectives can be achieved using the following objective function:

$$\min_{q_1,\ldots,q_N} \int_0^{T_f} \left| C(t) - C_{threshold} \right|^2 dt \qquad (1)$$
$$s.t. \quad q < K_s$$

where K_s is the saturated hydraulic conductivity, q_1, …, q_N are the application rates at each management time step in one optimization horizon, T_f is the prediction (optimization) horizon, $C(t)$ is time-varying salt concentration and $C_{threshold}$ is the desired threshold for salt concentration at a particular depth. This formulation permits salt concentrations up to the threshold value while allowing the applied water input to be maximized. Such a strategy might be desirable, for example, when irrigation is mainly a side-benefit associated with reclaimed water disposal and artificial recharge of an underlying aquifer. The need to avoid surface runoff is addressed as a constraint by bounding allowable irrigation rates from zero to the maximum soil infiltration rate.

When groundwater quality protection is relevant, a solute flux at a particular depth in the soil column may be used instead of salt concentration at a specified depth in equation (1). Or, if both soil salinity and groundwater quality need to be considered, the objective function for groundwater quality control can be added to the equation (1) so that a multi-objective function can be implemented (Park et al., 2009).

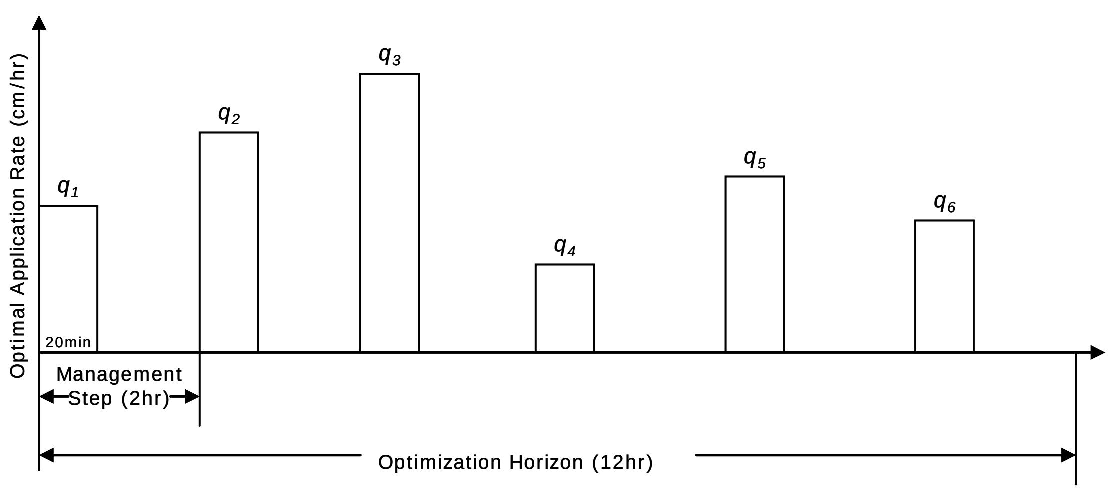
There are several possible approaches to incorporating the control vectors into the problem outlined above, and two are examined in this study (Figure 2). One approach is to consider irrigation rate as the control vector while irrigation frequency and duration are fixed. In this case, the application rate, *q,* is included in the boundary condition at the ground surface as follows:

$$-K(\theta)\left[\frac{\partial h(\theta)}{\partial z}-1\right]=q-E \quad 0 \leq t < 20\ min \qquad (2)$$

$$\frac{\partial \theta(0,\ t)}{\partial z}=-E \qquad 20\ min \leq t < 2\ hr \qquad (3)$$

where E is evaporation rate [cm/hr] which is calculated by Penman evaporation equation (Penman, 1948; Monteith, 1981; Allen *et al*., 1998) and meteorological data (the experiment here was performed in a bare soil), q is the reclaimed water application rate [cm/hr] in one management time step, and 2 h is the length of one management time step.

A second approach employs the irrigation frequency and duration as control vectors while the irrigation rate is fixed. When the irrigation frequency and duration are used for control vectors, each optimization horizon includes both the irrigation durations and the update time (i.e., the time, t_{mg}, between duration changes in Figure 2).



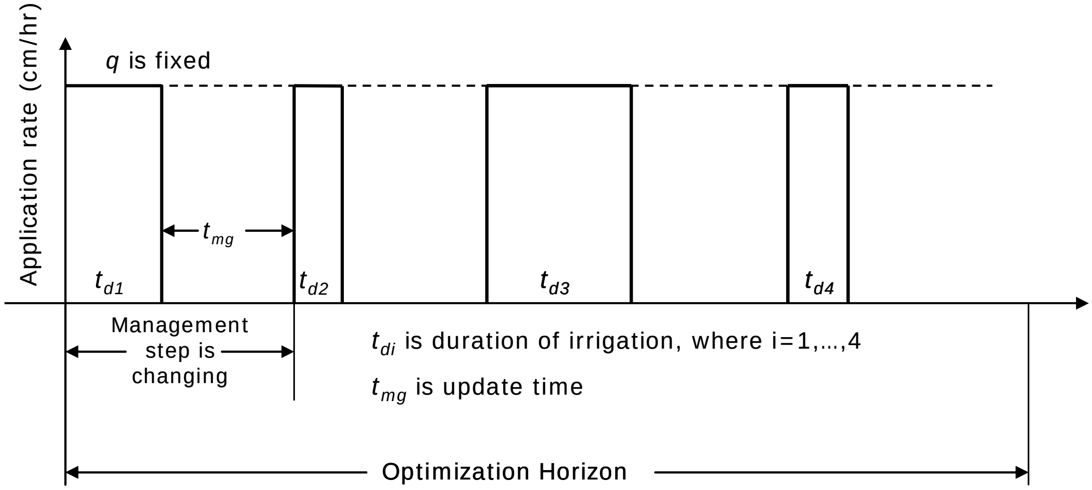


Figure 2. Control vector for the RHC applied to irrigation defined as (top) magnitude of the application rate changing at a prescribed time interval (shown arbitrarily for a optimization horizon with 6 application events), and (bottom) frequency and duration of a prescribed application rate (shown for 4 application events in one optimization horizon).

Process simulation models are used to predict the future state of the system, enabling the RHC to optimize the control vector. The state vectors for the problem at hand are moisture content, θ, temperature, T, and salt concentration, C. A conventional soil simulation model is employed here in which a one-dimensional form of the Richards equation is coupled to energy and solute transport equations (for details see Park 2008). The process simulation models are numerically solved in the MATLAB^{TM} software environment using finite difference method with Crank-Nicholson scheme (Gerald and Wheatley, 1970).

3. Experimental Materials and Methods

A closed-loop feedback-control system was constructed to test the autonomous RHC algorithm for two cases: (1) variable irrigation rate with fixed irrigation frequency and duration, and (2) variable irrigation frequency and duration with fixed irrigation rate. In each case, RHC was launched under an arbitrary initial application rate, while meteorological and soil sensor data acquisition commenced. The optimization algorithms employed predetermined parameter estimates and real-time sensor data to calculate the optimal control vector for the next management time step. At the time of the next management action, the RHC-prescribed optimal irrigation rate or irrigation frequency/duration is applied, closing the loop. This loop was then repeated until the total control horizon was completed.

The key components of the system were (see Figure 3): an irrigation apparatus, fabricated to provide uniform application over a 1 m^2 area; an array of sensors for soil moisture, temperature, and bulk electrical conductivity (EC) (ECH_2O-TE, Decagon Devices, Pullman WA), and for meteorological parameters, including solar radiation, air temperature, relative humidity, and wind speed (Vantage Pro2, Davis Instruments, Hayward, CA); and a flow controller (Alicat Scientific, Tucson, AZ) capable of automatic flow rate adjustments based on signals from the field laptop PC which received the sensor data, executed the simulation and optimization computations, and autonomously applied the resultingoptimal flow rates using a PCMCIA card (NI DAQcard-6024E, National Instruments, Austin, TX). The irrigation apparatus applied water from a reservoir containing water at a constant bulk EC ($EC_b \approx 8$ dS/m = 5g/L as NaCl). The soil sensors were installed at five depths: just below the ground surface, 10, 20, 40, and 60 cm. The uppermost sensor was used to provide surface information to the models.

Prior to the experiments, we calibrated the soil sensors (ECH_2O-TE) for salinity measurement with soil from the site and standard salinity (as *NaCl*) solutions. In the context of the simulation model, the aqueous calibration was used to convert measured EC_b values of the applied water to corresponding *NaCl* concentrations and the soil calibration curve is used to convert measured EC_b in soils to *NaCl* concentration. Soil samples were collected from the test site, where sandy loam was the predominant texture. Samples were homogenized and rinsed with deionized water to remove residual salts. These residual salt concentrations were found to be negligible compared to the salt loading in the irrigation water, and therefore soil sensor salinity readings could be attributed to aqueous salinity levels. Soil salinity standard mixtures were prepared using soil-water slurries spanning from the sensor detection limit to roughly 3 times the applied aqueous salt concentration in anticipation of concentration effects due to evaporation during the pilot test. Both the aqueous and the soil salinity standards resulted in strongly linear calibration models, in accord with the EC sensor specifications.

The control scheme with a variable application rate employed a two-hour management time step with a 12-hour optimization (prediction) horizon (6 management time steps) over the course of a 48-hour pilot test, for a total of 24 management steps. A threshold concentration in the soil water was fixed at 1.5 g/L at a depth of 20 cm. Allowable application rates were constrained between 0 and 3 cm/h due to the capacity of the flow controller. The parameterization process employed sensor observations at the 20 cm depth. The second test, for variable irrigation frequency and duration, was constrained by bounding these by 2 and 4 h and 0 and 36 min, respectively. In this case a control vector of four application durations and one update time was employed in each management step. The *NaCl* threshold was raised to 2.5 g/L because of the residual salinity in the soil profile from the preceding experiment. In order to see more sensitive response in salinity profile with respect to time, the threshold for the second test was applied at a 5 cm depth, and the 5 cm sensor observations were employed for simulation model parameter estimation.

For both pilot tests, inverse modeling for identifying simulation model parameters was performed offline prior to the RHC test using a least squares optimization scheme, specifically a trust region-based interior-reflective Newton gradient method (Coleman and Li, 1994; 1996) available in the MATLAB™ tool box. Then, in real-time, a MATLAB™ genetic algorithm (Joines *et al*., 1995) was used to identify optimal control vectors. In order to insure sufficiently rapid convergence of the RHC optimization algorithm within one management time step, the genetic algorithm was limited to a low population number (40). The MATLAB™ data acquisition tool box was used to interface with the system hardware in real-time (automatically collecting the sensor data and transmitting signal to flow controller for control action).

Figure 3. The pilot-scale closed-loop irrigation observation and management system constructed for testing the RHC algorithm (see text for component details).

4. Results and Discussion

Parameter estimation is a key component in the RHC scheme since the prediction and optimization of a dynamic system is accomplished using simulation models. Rapidly estimating parameters for transient water flow, heat and solute transport is not an easy task because models are highly nonlinear and obtaining either non-unique or unstable results is possible. Thus, parameters were estimated in advance of the RHC test using a 3 h observation period including a

20-min irrigation event. This is a reasonable approach given that the hydraulic properties of a given irrigation site will be stationary while the meteorological and crop conditions will vary over time. Both soil core samples and preliminary simulations assuming a homogeneous soil profile suggested that at least two dominant layers of contrasting hydraulic properties (0-30 cm and 30-60 cm) were necessary for capturing the vertical flow and transport adequately in the test zone. We focused the parameter estimation on observations at depths of 5cm and 20cm, respectively, in support of the two RHC formulations described above. The fitted flow and transport model parameters were limited to the key flow and mass transport parameters, including: the saturated hydraulic conductivity, saturated water content, residual water content, an empirical moisture retention constant (, *the* molecular diffusion coefficient), and *the* hydrodynamic dispersivity. Two additional parameters, a retardation factor and decay rate, were included despite the conservative characteristics of *NaCl* in an effort to capture the dynamics of chemical processes not accounted for in the model, such as salt precipitation and re-leaching. All other model parameters were estimated based on test site observations or from the literature for fine sand to sandy loam soil textures (Leij et al., 1996; Perfect et al., 2002)

The parameter estimates obtained in the offline simulations were generally reasonable and reproduced moisture and salinity profiles observed for the two depths, as shown in Figure 4. However, there were a few exceptions where the estimated value fell outside of the expected range for the soil textures present. For example, the model retardation factors for *NaCl* were approximately 1.0, as would be expected for this solute, but decay rate parameters were identified which varied from 0.001 h^{-1} at the shallow depth to about 1.4 h^{-1} for the deeper observation point. These results are indicative of an inadequacy in the model with respect to capturing the salt flux dynamics in the lower soil profile, and suggest the need for a more explicit precipitation-dissolution sub-model in the simulation model. Thus, while model used here appeared to capture the key dynamics of the test bed system, alternative models and exhaustive parameter identification measures are recommended prior to full-scale deployment of these techniques.

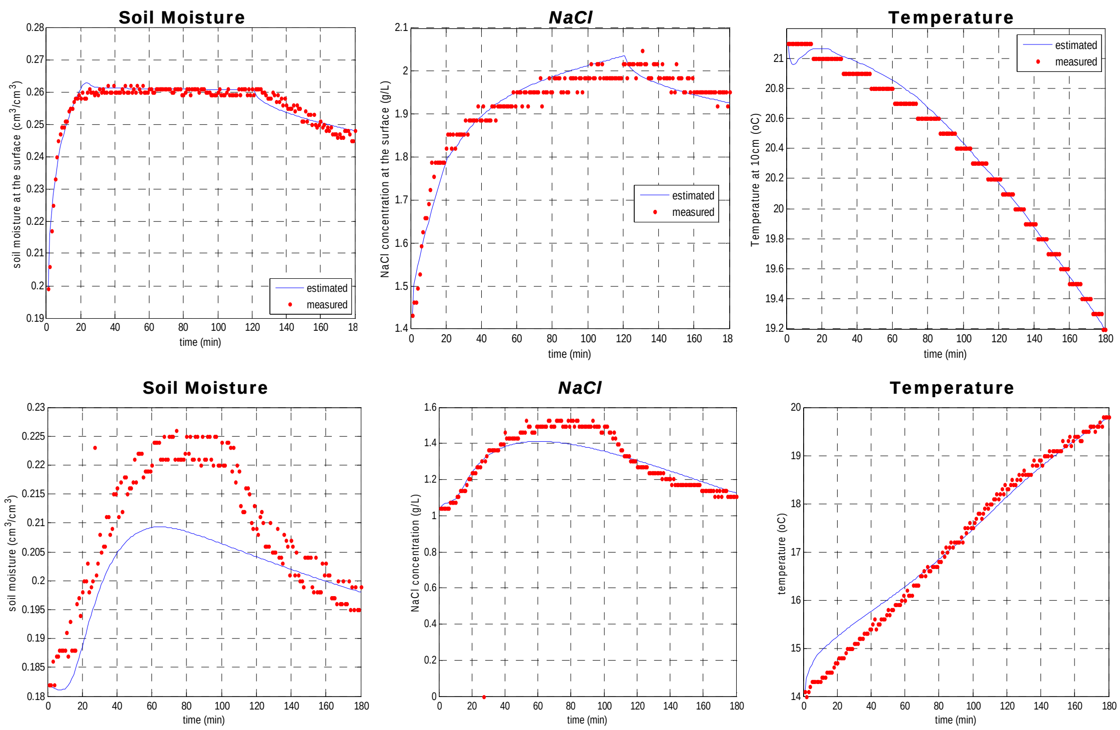


Figure 4. Best-fitting model simulation (line) and sensor data (symbols) for moisture content, salt concentration (as NaCl) and temperature for 5 cm (top) 20 cm (bottom) depths for the model calibration procedures prior to the RHC tests.

The plots in Figure 5 summarize the history of the first real-time RHC test, demonstrating the adjustment of the applied irrigation rate and accompanying change in the objective function with sequential management time steps. In this test, the algorithm autonomously updated the application rate vector 24 times, and successfully maintained the salinity level near the prescribed threshold. The application rates near the upper bound were prescribed until the *NaCl* concentration approaches the threshold value. When the *NaCl* concentration approached the threshold value, the optimal rates were reduced. The accompanying histories for soil moisture and salt concentration indicated a relatively large difference between the *NaCl* concentration at the end of each management step and the threshold value. The constraint placed on the upper bound application rate (3 cm/hr) under-utilized the amount of reclaimed water and resulted in overly conservative salt levels for this problem. The reason for the variable optimal application rate (Figure 5a) is that more than one local minima exist in the objective space. One of the possible reasons for the oscillating behavior in Figure 5 is that the salt response to the application rate change is slow; i.e., there is a lag-time between application rate change and *NaCl* concentration response. This effect can be reduced by using penalty or multi-objective functions (Park et al., 2009).

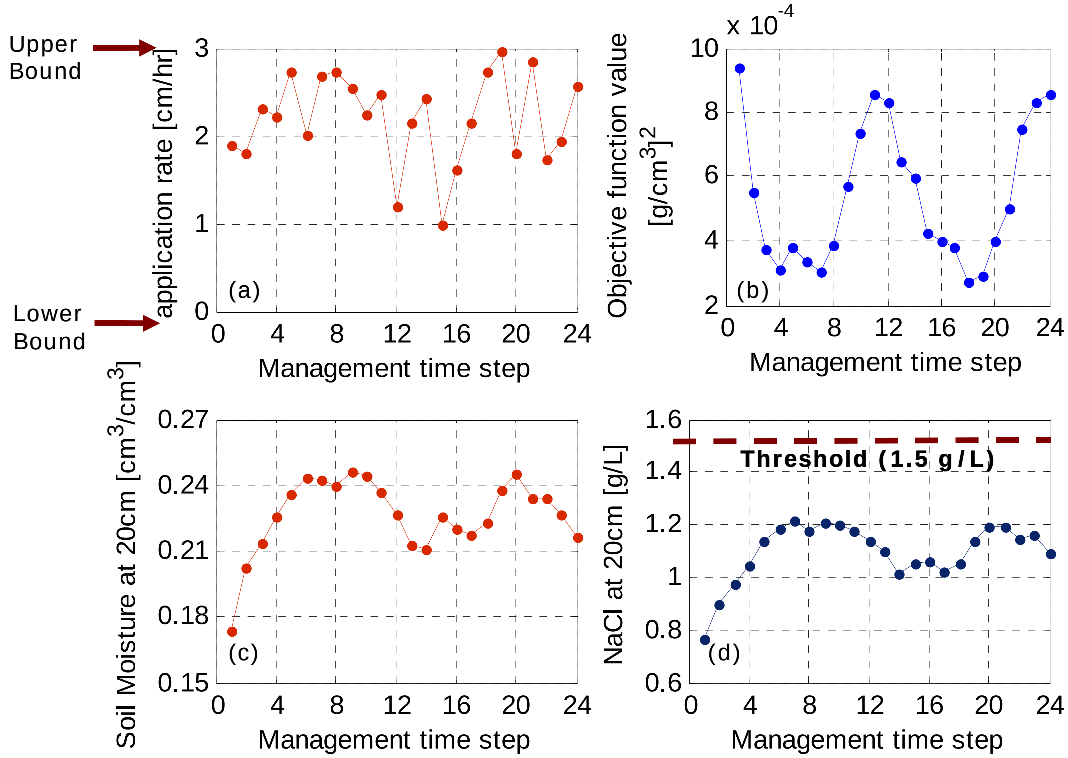


Figure 5. Results of salinity control: (a) saline water application rate at each management time step, (b) objective function value when the optimal application rate is applied at each management time step, (c) (d) soil moisture content and *NaCl* concentration at 20cm at the end of each management time step

In the second test case, a fixed application rate of 3 cm/h was applied, varying the frequency and duration of irrigation events. In this case, the RHC scheme employed 29 management time steps of variable length. Results plotted in Figure 6 demonstrate that initially the salt concentration increases due to the relatively long initial irrigation event of 20 min (Figure 6a) and the minimum irrigation interval of 2 h (Figure 6b). Subsequent irrigation events are changed to shorter durations and longer intervals, successfully avoiding an *NaCl* threshold violation. At the tenth management time step, however, a violation occurs. The RHC scheme attempts to avoid the threshold by reducing the irrigation duration and by increasing the time to the next event after the tenth management time step. However, the scheme subsequently falls into a cyclical pattern of recovery and violation, which erroneously satisfies our objective of maintaining the local salt concentration. The fact that the RHC could not then recover from the violation, and fall into the cyclical pattern is simply due to the fact that the objective function for the optimization algorithm equally penalizes *NaCl* concentration less than and greater than the threshold. Penalty or multi-objective functions can be used to prevent such violations (Park et al., 2009).

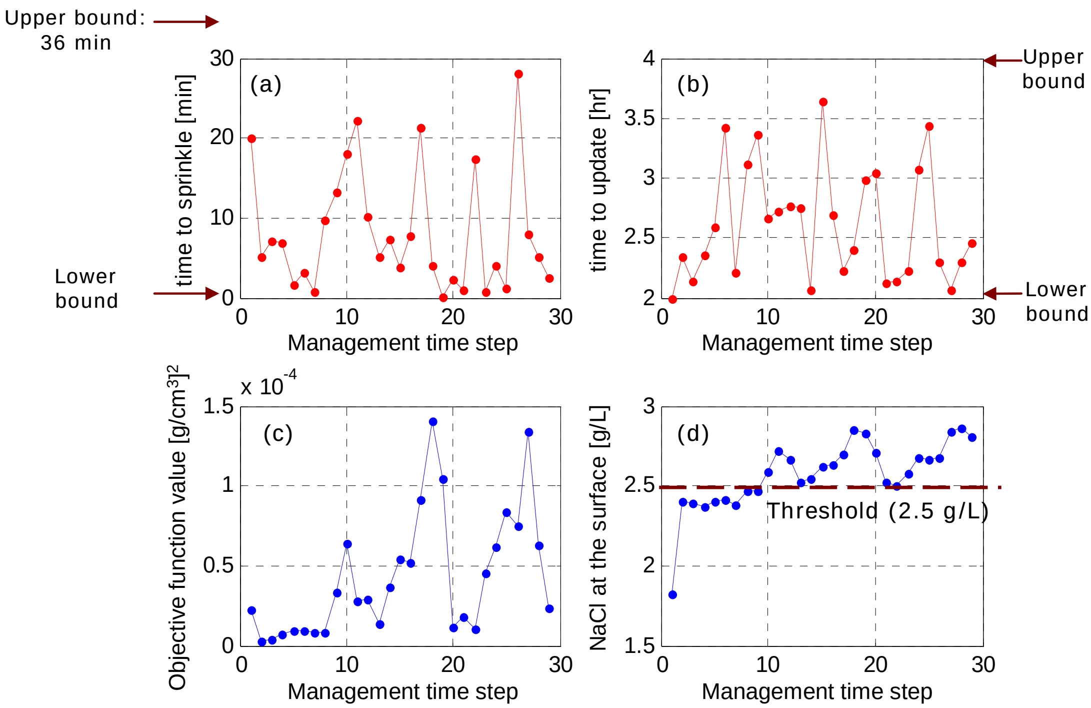


Figure 6. Results of soil salinity control when the control vectors are irrigation frequency and duration. (a) optimal duration of irrigation at each management time step, (b) Optimal management time step (irrigation frequency) when duration and frequency of irrigation are optimized, (c) objective function value when the optimal application rate is applied at each management time step, (d) *NaCl* concentration at the surface at the end of each management time step

5. Summary and Conclusions

Irrigation scheduling has evolved toward automated systems that integrate meteorological and soil sensor measurements with simulation models. This technology development is capable of more precise management of soil and plant status in time and space, thereby enabling agriculturalists to minimize negative impacts on the environment. Irrigation management strategies that incorporate currently available technologies for contaminant control are highly desirable in the context of making agriculture more sustainable. In this study, a receding horizon control (RHC) theory was tested in real time for autonomous soil salinity control with the dual objectives of maximizing reclaimed water reuse while preventing from soil salinization. The test bed field experiment demonstrated the potential for autonomous contaminant control with the RHC scheme in soil systems for reclaimed water disposal and/or salinity control. This work can be further developed by integrating salt concentration inside the root zone over the field area, or by controlling salt leaching flux below the root zone over the research area to prevent groundwater degradation by salts.

The RHC scheme can provide a strategy for minimizing negative impacts such as soil salinization and salt leaching into groundwater given support in the form of state observations and meteorological data, and a well-trained soil flow and transport model. Since the solute control response to irrigation rate and irrigation frequency/duration is a multi-objective management problem addressing water reuse, agronomic needs, environmental quality, and possibly other factors, it will typically be necessary to tailor the RHC scheme to site-specific objectives and constraints. Hence, site-specific management and optimization parameters will be required to realize successful control. Further, many groundwater degradation and agricultural sustainability problems occur slowly over long periods of time, thus the RHC schemes developed here should be investigated over longer term operational horizons (months, years, decades) in a large field application.

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