Optimal use and economic value of weather forecasts for lettuce irrigation in a humid climate

D.S. Wilks a,*, D.W. Wolfe b

a Dept. of Soil, Crop and Atmospheric Sciences, Cornell University, Ithaca, NY, USA
b Dept. of Fruit and Vegetable Science, Cornell University, Ithaca, NY, USA

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Abstract

The problem of analyzing a sequence of daily irrigation decisions utilizing weather forecast information is formulated for the case of lettuce grown in central New York state, and solved using a stochastic dynamic programming algorithm. The crop response is represented using a simple but physiologically-based model of lettuce growth [van Henten, E.J., 1994. Validation of a dynamic lettuce growth model for greenhouse climate control, Agric. Sys. 45, pp. 55–72], modified to allow the stomatal conductance for CO₂ to depend on a simple soil moisture budget. A negative crop response to prolonged wet soil conditions combined with warm temperatures is also included in the crop model. Operationally available precipitation and temperature forecasts are incorporated in a way that preserves the effect of time correlation in the weather. The results suggest that irrigation is quite viable even in the relatively humid climate of New York, with the economic value of irrigation (scheduled according to a conventional, non-optimal rule) vs. no irrigation estimated at approximately US$4000–US$5000 per hectare per year for lettuce. Optimal use of weather forecasts to schedule irrigations is estimated to provide additional value of approximately US$1000 per hectare per year, much of which is derived from avoiding crop damage due to excessive soil moisture. © 1998 Elsevier Science B.V.

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1. Introduction

1.1. Background

Management of weather-sensitive systems frequently requires that decisions be made in the face of uncertainty regarding future weather events. For many such problems the decision making process is dynamic in nature, which is to say that the opportunities for, constraints on, and outcomes of future decisions depend on previous decisions and events. A further complication is that series of uncertain weather events are typically serially correlated. In this kind of situation, it is natural to attempt to improve decision making through the use of forecasts, although progress on these kinds of problems has been impeded by their complexity.

This paper will present a dynamic decision-analytic model of irrigation scheduling for lettuce in...
New York state, in the northeastern US. Lettuce has been chosen here because it is a high-value crop, it is relatively susceptible to drought damage (Peirce, 1987), and the fact that only a single phenological stage (vegetative) is relevant greatly simplifies the plant modelling aspects of the problem. Even though New York state is located in a relatively humid region, the precipitation climate is sufficiently variable that periods of sub-optimal soil moisture can occur during ‘normal’ or even ‘wet’ years, which can have significant economic effects on high-value, intensively managed crops such as vegetables. The problem is interesting because the climate in New York is moist enough that lettuce can be grown successfully in many years without irrigation, so that calendar scheduling of irrigation sometimes will be uneconomical. Furthermore, poorly timed irrigation may be harmful to the extent that excessive soil moisture may cause crop damage or excessive leaching of fertilizers and pesticides if the irrigation is followed closely by significant rainfall events. An optimal solution of this decision problem will balance the costs of potentially unneeded or damaging irrigations, versus the cost of crop damage due to possible excessive dryness if needed irrigation is not performed, in the light of available probability information for rainfall in the upcoming days.

There is a fairly large literature on optimizing irrigation decisions using the dynamic decision-making approach to be adopted here (e.g., Kennedy, 1986; McGuckin et al., 1987; Rhenals and Bras, 1981). However, this literature does not include the use of weather forecasts in optimizing the irrigation problem. The reluctance of farmers in humid regions to utilize available irrigation scheduling technology and software is often associated with the fact that these approaches do not incorporate rainfall forecasts (Wolfe, 1990). A small number of studies (Allen and Lambert, 1971a,b; Rogers and Elliott, 1988; Swaney et al., 1983) have attempted to incorporate weather forecasts into analysis of irrigation scheduling, but all of these have ignored the dynamic nature of the problem by treating irrigation on a given day as separate and independent of the other days in the decision sequence. Wilks (1997) contains a fuller discussion of these papers.

The present analysis incorporates weather forecasts into a fully time-dependent analysis of sequences of irrigation decisions to be taken over an entire cropping period. The approach is analogous to that taken in a previous study on timing the harvest of alfalfa for hay or silage, to avoid rain damage during drying (Wilks et al., 1993), but extends the structure of the analysis to include rainfall forecasts two days into the future.

1.2. Decision analysis

An attractive mathematical structure within which to model and prescribe optimal decision making in the face of uncertain future events is that of Decision Analysis (e.g., Clemen, 1996; Keeney, 1982). In this approach, actions are prescribed as optimal which maximize expected (in the statistical sense of probability-weighted average) economic returns in the face of uncertainty with respect to the relevant unknown future events. In the present context, the unknown events will relate to weather in the upcoming two days. When incorporating forecast information into the decision problem, the expectations are taken with respect to probabilities for the future events that are derived from the forecasts (see, e.g., Katz and Murphy, 1997).

As mentioned above, analysis of optimal irrigation scheduling is complicated by the fact that it is a time-dependent problem. That is, the irrigation decision on a given day cannot be considered in isolation, since both the biological and economic consequences of a particular decision will depend on the sequence of decisions and weather events that have occurred to date. Within the literature on decision analysis, problems of this kind are called ‘dynamic’, in order to recognize their time-dependent nature. For dynamic decision problems to be treated realistically, it is necessary to maximize expected economic return over the full sequence of related decisions rather than for individual decisions.

Large dynamic decision problems are most conveniently analyzed using a technique called stochastic dynamic programming (e.g., Kennedy, 1986). Essentially, this procedure solves a decision tree, in which there are for each time period (here, each day) a set of allowable actions (decisions) $a_i, i = 1, \ldots, I$; a set of unknown future (here, weather) events $x_j, j = 1, \ldots, J$; regarding which, probability forecasts
The decision sequence is solved in reverse time using the recursion

\[
ER_t(\lambda_t) = \max_i \left[ \sum_j \left( C_i + ER_{t-1} \right) \right]
\]

\[
\times \left[ O(\lambda_t, x_j, \lambda_t) \right] p(x_j|f_k) \].
\] (1)

Here \( ER_t \) is the expected (monetary) return on day \( t \), which is a function of the state of the decision problem on that day as indexed by the (generally vector-valued) state variable \( \lambda_t \). In essence, the state variable \( \lambda_t \) specifies the particular node on the decision tree in which the decision process presently resides. For a given value of \( \lambda_t \), each combination of the action taken and the event that subsequently occurs yields a particular known outcome \( O(\lambda_t, x_j, \lambda_t) \). Another way of looking at this outcome function is as a pointer to the state of the system on the next day (i.e., on day \( t-1 \)),

\[
O(\lambda_t, x_j, \lambda_t) = \lambda_{t-1}.
\] (2)

That is, given that the current state of the decision sequence is \( \lambda_t \), the action \( a_i \) is taken, and the event \( x_j \) occurs; the state of the decision sequence on the next day will be \( \lambda_{t-1} \).

In Eq. (1), the expected return for today, \( ER_t \), is computed as a function of weighted averages of expected returns for tomorrow, \( ER_{t-1} \) (which will have already been computed because the recursion proceeds in reverse time). The summation in Eq. (1) represents the computation the expected return given a particular action \( a_i \) is taken after having received the forecast \( f_k \), and so is a probability-weighted average with respect to the conditional probabilities of the possible weather events given that forecast, \( p(x_j|f_k) \). The optimal action in this circumstance at decision node \( \lambda_t \), is determined by computing this expectation for all \( I \) possible actions, including the known monetary cost \( C_i \) of each action, and choosing the action with the highest expected return. This maximum expected return pertains—because of the recursive nature of Eq. (1)—to the expected economic return for this and all subsequent time periods. The outer expectation in Eq. (1), denoted as \( ER[ \] ], is a probability-weighted average over the frequencies of use of the possible probability forecasts \( f_k \). At the end of the recursion (which corresponds to the beginning of the decision sequence), the variable \( ER \) contains the expected economic return deriving from optimal decisions being made at each juncture of the entire decision sequence. During the calculations it is also possible to save the values of the optimal actions at each stage for subsequent analysis, or for use in decision support.

The economic value of information is conventionally measured in a relative sense, as the difference in economic returns achieved when using the information optimally, and the expected returns achieved under some information baseline (e.g., Clemen, 1996; Wilks, 1997). This difference can be simply and generally expressed as

\[
V = ER - ER_{base},
\] (3)

where \( ER \) is the expected return derived from optimal use of the information in question as computed using Eq. (1), \( ER_{base} \) is the expected return achieved using the (typically lower-quality) baseline information, so that the difference \( V \) is the value of the information in question in relation to the baseline information. The quantity \( V \) will therefore be positive to the extent that, on average, irrigation according to the weather forecasts (\( ER \)) produces a greater economic return than does irrigation according to the baseline decision rule (\( ER_{base} \)). In the present context it is probably most appropriate to use as a baseline the conventional rule that specifies irrigation whenever the soil moisture falls below 50% of the available water capacity, which considers neither the weather forecasts nor the cost of irrigation.

Accounting for serial dependence in weather events (the tendency for 'runs' of several days of similar weather) is an important aspect of analyzing daily sequences of related weather-sensitive decisions (Wilks, 1991). This can be achieved by extending the dimensionality of the state vector \( \lambda \) to include elements representing yesterday's forecast. The probabilities in the expectation \( ER_{j[} \) in Eq. (1), representing frequencies of use of the possible forecast values, then depend on the state vector. In Wilks (1991) and Wilks et al. (1993) these probabilities were derived from time-series models for one-day-ahead temperature and precipitation probability fore-
casts. The present analysis will include consideration of precipitation forecasts for both one and two days ahead, for which purpose the time-series model for precipitation probability forecasts is extended to the bivariate (today, tomorrow) sequence of forecasts available each day. This extension is described in Section 2.

The details of the crop responses are contained in the outcome function Eq. (2), which despite its notational simplicity contains a large amount of structure. In order to represent the responses of lettuce, values of the outcome function have been derived using an existing simple but physiologically realistic model of lettuce growth (van Henten, 1994). This model has been modified for outdoor growing conditions in New York, and simplified somewhat to improve the computational economy of Eq. (1). Details of this portion of the work are given in Section 3. Finally, Section 4 presents results for economic returns, economic value of the forecast information, and the prescribed optimal actions; and Section 5 concludes with a brief discussion.

2. Forecasts

2.1. Precipitation

The forecasts of primary interest here are precipitation probabilities for the upcoming two days. These are assumed to be taken from 0000 UTC cycle of the NGM–MOS (Dallavalle et al., 1992) guidance forecasts, which would become available during the night before an irrigation would be performed. These forecasts include probabilities for measurable precipitation (> 0.01) in each of four consecutive 12 h periods beginning the following morning at 1200 UTC (8 A.M. Eastern Daylight Time). Historical NGM–MOS forecasts for Buffalo and Syracuse, New York, for the period July 1989 through June 1994, were used in the following. Only forecasts during the ‘warm season’ (April–September) were considered. The four 12 h precipitation probabilities were transformed into probabilities pertaining to the two 24 h periods 12–36 h (‘today’) and 36–60 h (‘tomorrow’) from the 0000 UTC initial time using the algorithm in Wilks (1990a). Forecast probability distributions for the corresponding 24 h rainfall amounts were then constructed from these 24 h occurrence probabilities using the procedure of Wilks (1990b).

In earlier work (Wilks, 1991; Wilks et al., 1993), only forecasts for the first day (12–36 h following initial time) were considered. The day-to-day persistence of precipitation occurrence was represented through a first-order autoregressive (AR(1)) model for the scalar series of daily forecast probabilities, after mapping these probabilities to the standard Gaussian distribution through a fitted beta distribution for the frequency of use of the various possible probabilities. That is, the marginal (frequency-of-use) distribution of a series of probability forecasts was modeled as following a fitted beta distribution with cumulative distribution function \( \beta(f) \),

\[
\beta(f) = \frac{\Gamma(p + q)}{\Gamma(p)\Gamma(q)} \int_0^f (1 - f)^{q-1} f^{p-1} df, \tag{4}
\]

where \( p \) and \( q \) are the distribution parameters, and \( \Gamma(\cdot) \) is the gamma function. The time series of the standard Gaussian variable \( z_t = \Phi^{-1}[\beta(f)] \) was then modeled as following a first-order autoregression. Here \( \Phi(z) = P[Z \leq z] \) is the cumulative distribution function of the standard Gaussian.

In the present analysis, daily series of 1 and 2 days ahead precipitation probabilities are modeled as following a bivariate AR(1) process after transformations to standard Gaussian variables. Naturally, the frequencies of use of the possible probabilities are different for the two projections, with more frequent and more extreme deviations from the climatological probability occurring for the shorter lead time. Pooling the forecast data for Buffalo and Syracuse, the fitted beta distribution \( \beta_i(f_i) \) for the 12–36 h forecasts is characterized by the parameters \( p = 0.43 \) and \( q = 0.69 \). The second day (36–60 h) forecasts are less variable, with parameters for the distribution \( \beta_2(f_2) \) being \( p = 0.72 \) and \( q = 1.16 \). The two-element vector \( z = [z_1, z_2]^T \) is then modeled as following the bivariate autoregression

\[
z_t = [\Theta] z_{t-1} + [\Psi] e_t, \tag{5}
\]

where now time \( t \) is enumerated in the forward direction, the \( e_t \) are bivariate vectors of independent standard Gaussian variates, and the parameter matri-
ces \([\Theta]\) and \([\Psi]\) estimated from the Buffalo and Syracuse data are
\[
[\Theta] = \begin{bmatrix} 0.058 & 0.743 \\ -0.118 & 0.266 \end{bmatrix},
\]
and \([\Psi] = \begin{bmatrix} 0.647 & 0.000 \\ 0.168 & 0.951 \end{bmatrix}. \tag{6}

Two diagnostic checks on the adequacy of the model (Eq. (5)) were performed. First, the residuals \(e_t\) were obtained by substituting into Eq. (5) the time series of transformed forecast vectors \(z_t\) and \(z_{t-1}\) from the historical warm-season forecasts at eighteen US cities, located north of 33° latitude, and between 70° and 83° longitude. These residuals were found to behave as independent standard Gaussian variates to very good approximation.

Second, assuming that the precipitation probability forecasts are well calibrated, Eq. (5) implies a particular daily precipitation occurrence climate. Note here that probability forecasts for daily precipitation occurrence are typically very well-calibrated, in the sense that \(\Pr(X = 1 | f) \approx f\) (e.g., Murphy and Brown, 1984), where \(X = 1\) if precipitation occurs and \(X = 0\) otherwise. Fig. 1 illustrates the efficacy of Eq. (5) in representing aspects of the implied climate, in relation to those implied by the real time series of historical precipitation forecasts for the warm season at the same set of eighteen locations. The four panels

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**Fig. 1.** Comparison of the dependence structure of time series of daily precipitation occurrence, simulated using real historical precipitation probability forecasts (vertical axes) and generated according to Eq. (5) (horizontal axes), for the warm half of the year at eighteen locations in the eastern United States. Top panels, day 1 (12–36 h projection) series; bottom panels, day 2 (36–60 h projection) series. Left panels, conditional probabilities of wet days following dry days \((p_{01})\); right panels, conditional probabilities of wet days following wet days \((p_{11})\). The symbols 'B' and 'S' locate points for Buffalo and Syracuse, New York, respectively.
in Fig. 1 shows conditional probabilities of wet days, given that the previous day was dry (left panels) and given that the previous day was wet (right panels) as estimated from Monte-Carlo simulations using time series of daily precipitation probability forecasts. These two parameters are commonly used to characterize the frequency of precipitation and the degree of autocorrelation in daily precipitation occurrence series (e.g., Katz, 1977). In the simulations on which this figure is based, a day is declared to be wet if a uniform [0,1] random number is less than the forecast probability for that day. The vertical axes represent results of the simulations using the empirical forecast series, and the horizontal axes shows the corresponding results for forecast series generated from Eq. (5). Overall, there is quite good agreement, although simulations for the 12–36 h period (upper two panels) indicate that Eq. (5) produces a slight dry bias (of approximately 0.01 to 0.02 probability units) for most of these stations. Fig. 1 also indicates that Buffalo (symbol ‘B’) and Syracuse (symbol ‘S’) are among the wettest (in terms of rainfall occurrence) of these locations.

2.2. Temperature and evaporation

Following Wilks et al. (1993), corresponding temperature forecasts for the 12–36 h projection are considered in the present decision problem as well, both to allow representation of the growth of the crop, and specification of conditional probability distributions for pan evaporation from which the potential evapotranspiration is derived. A scalar AR(1) model is fit to time series of standardized anomalies (forecast minus mean, divided by standard deviation; with mean and standard deviation varying smoothly through the season) of daily average temperature forecasts. A bivariate normal distribution is assumed for the forecasts and observations, with (again, time-dependent) variance for the implied conditional distribution of observed temperature given the forecast determined by the mean-squared error for temperature forecast verifications at Syracuse. Daily pan evaporation values are represented as following Weibull distributions with parameters varying smoothly through the growing season, which were fitted separately for days with average temperature less than 10°C, between 10°C and 20°C, and above 20°C, and separately for days with and without precipitation. Further details on the temperature and evaporation components are available in Wilks et al. (1993).

3. Lettuce model

3.1. Plant and soil models

The responses of the lettuce crop to irrigation management and the environment are contained in the outcome function \(O[a, x, \lambda] \) in Eq. (1). These have been derived from a modified version of the mechanistic lettuce growth model of van Henten (1994), which has been coupled to a simple soil water balance model. The van Henten model carries two prognostic variables: the plant non-structural dry matter \(X_N\), which represents free photosynthate; and the structural dry matter \(X_S\), which represents dry matter that has been committed to particular plant organs. Both variables are expressed in g/m² land area.

The basic dynamics of the van Henten model are contained in the coupled equations

\[
\frac{dX_N}{dt} = 0.68 P - R_M - 1.45 G_S X_S \quad (7a)
\]

and

\[
\frac{dX_S}{dt} = G_S X_S. \quad (7b)
\]

Here \(P\) is the gross canopy photosynthesis which is assumed here to depend on the leaf-area index (LAI) and the maximum CO₂ assimilation rate \(P_{\text{max}}\) according to

\[
P \propto P_{\text{max}} \left[ 1 - \exp\left( -\text{LAI}/2 \right) \right], \quad (8)
\]

where \(P_{\text{max}}\) itself varies as a function of light, temperature and stomatal conductance as described in van Henten (1994), and the temperature dependence of the maximum stomatal conductance given there has been assumed as well in the following. The factor 0.68 in Eq. (7a) relates the molecular weights of CO₂ and carbohydrate. The term \(R_M\) in Eq. (7a) is the maintenance respiration, which depends on the product of the structural dry matter and an exponential temperature function; and \(G_S\) is the specific growth rate, which is given by the product of a maximum growth rate and the ratio of the nonstructural dry matter to the total dry matter, multiplied by another exponential temperature function. The factor
1.45 in Eq. (7a) represents the efficiency of conversion of non-structural to structural dry matter, and was taken from Both (1995). The LAI in Eq. (8) is assumed here to increase with structural dry matter according to

\[ \text{LAI} = \frac{0.625 X_s}{5 + 0.125 X_s}, \tag{9} \]

in which a maximum LAI of 5 has been assumed. This relationship is indicated by the heavy solid line in Fig. 2. Specific numerical constants and more detailed interpretation of this model are available in van Henten (1994).

A simple single-layer soil moisture balance model is used, in which the soil is assumed to provide 0.1667 cm/cm of available water. The depth of the usable soil is defined by the rooting depth (m) of the crop, which in turn depends on the structural dry matter according to

\[ D_r = 0.01 + 0.29 \left( 1 - \exp\left[ - X_s^{1/3} \right] \right). \tag{10} \]

Here it has been assumed that the initial seeding depth is approximately 1 cm and the average maximum rooting depth is 30 cm (Peirce, 1987). The soil profile is assumed to begin at 100% of available water capacity throughout the full 30 cm depth. Evapotranspiration in the absence of water supply limitations is specified by the product of the daily pan evaporation and the pan factor \( F_{\text{pan}} \), which depends on the structural dry matter through its relationship (Eq. (9)) with LAI according to

\[ F_{\text{pan}} = 0.2 + \frac{0.7}{1 + \exp[4 - 2.2 \text{LAI}]}, \tag{11} \]

and so varies from 0.2 for bare ground to 0.9 for a full canopy. These two relationship are shown as the lighter solid lines in Fig. 2.

Effects of water stress on evapotranspiration are introduced through multiplication of \( F_{\text{pan}} \) by the idealized stress function

\[ F_{\text{stress}} = \min\left[ \frac{\% \text{ available soil water}}{70\%},1 \right]. \tag{12} \]

which specifies no reduction in evapotranspiration if the available soil water is at least 70% of maximum, and a linear decrease to zero evapotranspiration at zero available soil water. This same stress function is also used to produce reduced photosynthesis and growth, through multiplication of the unstressed stomatal conductance for \( CO_2 \) that affects \( P_{\text{max}} \) in Eq. (8).

An important practical problem involving Eq. (1) is that the computing time required for solution increases exponentially with the number of state variables, i.e. with the dimensionality of \( \lambda \) (e.g., Kennedy, 1986). In order to make analysis of this problem more tractable, we have reparameterized the lettuce model above in terms of a single variable for the total dry matter, \( X \), which is the sum of the structural and non-structural dry matter. The ratio of structural to total dry matter increases from relatively low levels in seedlings to much larger values at plant maturity. Analysis of daily results for \( X_s \) and \( X_N \) produced by integration of Eqs. (7a) and (7b) using observed historical weather data for Ithaca, New York, leads to the following regression equation summarizing the resulting structural dry matter ratio as a function of the total dry matter:

\[ \frac{X_s}{X} = \left[ 1 + \exp(2.0 - 0.029 X + 0.000048 X^2) \right]^{-1/2}, \tag{13} \]

This function is indicated by the dashed curve in Fig. 2. For the results reported in Section 4, Eq. (13) has
been used to reduce the two equations in Eqs. (7a) and (7b) to a single differential equation for the rate of change of the total dry matter. The coefficient of determination for Eq. (13) is approximately 94%, and simulations using this reduced form of the lettuce model exhibit responses to observed weather sequences that are very similar to Eqs. (7a) and (7b). Employing Eq. (13), the state vector $\lambda$ in Eq. (1) has six dimensions. Three of these pertain to the crop: total structural dry matter, percent of total available soil moisture, and a drought- and excess-moisture stress index (to be explained in Section 3.2). The remaining three state variables are yesterday's temperature forecast, yesterday's day 1 precipitation forecast, and yesterday's day 2 precipitation forecast, which are included to allow Eq. (1) to represent realistic time dependence for the weather variables (Wilks, 1991).

The lettuce model outlined above is clearly idealized, but produces reasonable responses for non-irrigated lettuce when forced by observed weather data for central New York state in terms of typical yields, qualitatively correct responses to atypical weather variations, and overall frequencies of crop losses due to inadequate or excessive soil moisture. It has been 'tuned' to outdoor conditions in this area only by varying on an exploratory basis the maximum growth rate which is a factor of $G_5$ in Eqs. (7a) and (7b), the constant (= 0.125) controlling the rate at which the LAI approaches its maximum value of 5 in Eq. (9), and the functional form of the rooting depth Eq. (10).

3.2. Irrigation costs and gross economic returns

In the following, it will be assumed that the model irrigator has three choices (actions $a_i$ in Eq. (1)) each day: $a_1 =$ do not irrigate, $a_2 =$ irrigate 12.7 mm, or $a_3 =$ irrigate 25.4 mm. Using a representative price for energy in New York state, the pumping cost for the two irrigation amounts are approximately US$6.25 and US$12.50 per hectare irrigated, respectively (L. Geohring, personal communication). In addition, it is estimated that approximately 2.5 h of labor (expended primarily in moving pipelines) are required to irrigate 1 ha (L. Geohring, personal communication), regardless of how much water is applied. Results for two assumptions about labor costs will be presented in the following. In the first, a typical farm-labor cost of US$8/h (T. Maloney, personal communication) will be assumed, so that the total cost of applying the two irrigation amounts is US$26.25 and US$32.50 per hectare, respectively. While these figures are reasonable for a large operation which can maintain a permanent workforce, they are probably underestimates for a small enterprise (perhaps a family operation supplying a roadside stand) which must balance competing demands on the primary operator's time. This latter situation is modeled here by assuming (somewhat arbitrarily) that the labor cost is effectively US$100/h, so that the total costs for the two irrigation amounts are US$256.25 and US$262.50 per hectare, respectively.

The gross (i.e., costs of planting, harvesting, irrigation, etc., not deducted) economic value of the crop is assumed to follow the dash-dot curve in Fig. 2, which is a representation of the interplay between average head size and marketable yield per hectare for New York conditions. Assuming that the lettuce is planted at a density of 8 plants/m$^2$ and that 85% of the dry matter is above ground, it is estimated that yields smaller than 220 g dry matter/m$^2$ will typically not produce an economic yield (L. Ellerbrock, personal communication). The assumed gross value of the crop increases sharply from this point, to a maximum of approximately US$12,500/ha at a dry matter yield of 320 g/m$^2$. It is assumed here that the maximum length of the growing period is 62 days from seeding. Although lettuce planting occurs in New York from late April through mid-August, results will presented below only for planting on 1 May and 15 July.

Sublethal water stress affects the crop by slowing growth through decreases in stomatal conductance in proportion to Eq. (12), which reduces the size of the harvested lettuces, and thereby, reduces the value of the crop. In addition to failure to reach marketable size, two other causes of crop failure are included in the model. First, the plants are assumed not to survive if the rooting zone dries to zero available water, or if soil water is at or below 20% of maximum for five consecutive days. The assumption here is that under such severe drought stress, accelerated leaf senescence (Wolfe et al., 1988), xylem cavitation (Oertli, 1987), or other irreversible and ultimately fatal damage occurs.

Second, crop failure is assumed to occur when
soil moisture is 100% of the available water capacity for seven consecutive days. This process is accelerated at warmer temperatures, and it is assumed here that average daily temperatures of 24°C and warmer are twice as damaging. Thus, three waterlogged warm days ('counting double') in a sequence with one waterlogged day cooler than 24°C would be sufficient to kill the model crop. This rule for specifying excess-moisture damage is an abstraction intended to represent simultaneously several negative effects of anaerobic and warm, wet conditions: plant mortality associated with impaired root function (Jackson and Drew, 1984; Lakitan et al., 1992); promotion of root or foliar disease (Horsfall and Cowley, 1977); and promotion of the physiological disorder, leaf tipburn. Lettuce tipburn is caused by localized calcium deficiency associated with a slowed influx of water and nutrients into expanding cells (Collier and Tibbitts, 1982), and is a common cause of marketable yield losses during wet, warm periods in New York (L. Ellerbrock, personal communication). The impaired root function under waterlogged conditions is also reflected in a diminishment of stomatal conductance, which is assumed to begin on the third day after the onset of waterlogged conditions. The 24°C threshold for accelerated damage has been chosen in order that the model replicates approximately the frequency of non-irrigated lettuce losses in New York due to excessive soil moisture, which (depending on planting date) is on the order of 10% (L. Ellerbrock, personal communication). This formulation would probably not be appropriate in other, particularly less humid, lettuce production areas.

4. Results

4.1. Optimal actions

A full solution of Eq. (1) produces a large volume of optimal actions, only a subset of which can be reproduced here because of space limitations. Fig. 3 shows representative optimal irrigation actions for the US$8/h labor cost as a function of date following 1 May planting (horizontal axes), and crop development in terms of dry matter per square meter (vertical axes, logarithmic scale). The optimal actions are indicated by the contour lines, which specify the available soil moisture percentage at or below which irrigation is called for. The nine panels show the variation of optimal actions as a function of probability-of-precipitation forecast for today (PoP$_i$) and tomorrow (PoP$_r$), given a moderate temperature forecast (17.5°C for the upcoming day. The dash-dot line shows the average date/yield trajectory of lettuce crops managed according to the prescribed optimal actions. The upper-left portions of these panels are blank because even ideal growing conditions cannot produce growth rates sufficient for growth trajectories to enter this region. The lower-right portions of the figures are blank because trajectories entering here have no chance to produce an economic yield even if growing conditions are ideal for the remaining time until harvest. The 50% contours are darkened to facilitate comparison with the conventional decision rule that specifies irrigation when soil moisture reaches this level. Shading indicates regions where the full (25.4 mm) irrigation amount may be called for.

As might have been expected, Fig. 3 shows that lower soil moisture values are tolerated when the rainfall probabilities are relatively high, and irrigation is triggered at higher soil moisture when rain is quite unlikely. It can also be seen that the model calls for irrigations under fairly moist conditions both very early in the season and very late in the season, particularly when the plants are relatively small (below the dash-dot line) for the date. In the middle portion of the (logarithmic) dry matter scale, the model is more parsimonious in its irrigation decisions. At this stage of growth the rooting depth is increasing rapidly (Fig. 2), which provides additional water because of the assumption that the newly exploitable soil depths are fully charged with water. The full 25.4 mm irrigation is only called for when the crop is larger than approximately 10 g/m$^2$, when the LAI (and thus, the potential evapotranspiration) is high and additional root growth is limited. The corresponding optimal actions for 15 July planting (not shown) are quite similar to those shown in Fig. 3. The patterns of optimal actions for the more expensive (US$100/h) labor cost are also similar, but generally allow the soil to dry somewhat further before calling for irrigation.

For the most part, the corresponding diagrams for other temperature forecasts are similar as well, but with drier conditions being tolerated for cooler con-
Fig. 3. Optimal irrigation actions, expressed as the available soil moisture percentage at or below which irrigation is called for; as a function of date following 1 May planting, and crop development in terms of dry matter per square meter (logarithmic scale). The nine panels show the variation of optimal actions as a function of probability-of-precipitation forecast for today (PoP₁) and tomorrow (PoP₂). The dash-dot line shows the average date/yield trajectory of lettuce crops managed according to the prescribed optimal actions. The 50% contours are darkened to facilitate comparison to the conventional decision rule that specifies irrigation when soil moisture reaches this level. Shading indicates regions where the full (25.4 mm) irrigation amount may be called for.

An important exception to this general pattern is that the model can be quite conservative in calling for irrigation when both the rainfall probabilities and the temperature forecast are high. A view of this phenomenon is provided in Fig. 4, which shows optimal actions as a function of the date on the horizontal vs. the available soil moisture percentage on the vertical, for crops which have achieved the average dry matter for the date. That is, Fig. 4 shows a kind of cross-section along the dash-dot trajectory in Fig. 3. In Fig. 4, the panel columns show results for three temperature forecasts (‘cool’ = 10°C; ‘moderate’ = 17.5°C, as in Fig. 3; and ‘warm’ = 25°C), and the rows shows three rainfall probabilities for tomorrow (PoP₂). The contours shows rainfall probabilities for today (PoP₁) below which an irrigation is called for. Thus, irrigation is never optimal for soil moisture levels above the 0.0 contour for a given date, and irrigation is called for regardless of today’s rainfall forecast at soil moisture drier than those indicated by...
the 1.0 contours. As before, the shading indicates regions in which the full 25.4 mm irrigation may be called for. Fig. 4 shows very prominently that the irrigation decision is strongly suppressed when the temperature forecast is high, unless the rainfall probability for tomorrow is zero. This reluctance is most marked for the smaller plants earlier in the season (primarily in May, corresponding to dry matter less than 10 g/m²), for which the maximum evaporation rate per unit ground area is relatively small even when the pan evaporation is large (Eq. (11)).

The numbers of irrigations applied during a given growing period depends both on the amount and distribution of rainfall, and on the decision rules used to schedule the irrigations. Fig. 5 compares the frequency distributions of numbers of irrigations per growing period, according to optimal actions derived from Eq. (1) on the basis of both the standard (US$8/h) and US$100/h labor costs, and according to the conventional rule of thumb that irrigation is applied when the soil dries to 50% of maximum available water capacity. These curves have been
Fig. 5. Frequency distributions, derived from 10,000 forward-time simulations with synthetic weather, of numbers of irrigations per growing period for the standard (US$8/h) labor cost (heavy lines), the US$100/h labor cost (medium lines), and the non-forecast-based decision rule of irrigation at 50% of maximum available soil moisture (light lines). Solid and dashed lines show results for 1 May and 15 July planting, respectively. Arrows indicate average numbers of irrigations for each case.

derived from forward-time simulations using 10,000 yr of synthetic weather, and using the optimal actions saved from solution of Eq. (1) for the two cost-based irrigation policies. The distributions for 1 May (solid lines) and 15 July (dashed lines) planting dates are quite similar for a given irrigation criterion, but the three irrigation scheduling criteria yield quite different distributions. For optimal scheduling under the standard irrigation cost (heaviest lines) 3.2 to 3.5 irrigations on average (indicated by the arrows) are called for. However, the decision model specifies that irrigation is unnecessary in approximately 1 out of 20 yr, while in some years as many as seven or more irrigations may be called for. When irrigation is expensive (medium lines) the proportion of years in which irrigations are not scheduled increases to approximately 15%, the average number of irrigations per season is reduced to approximately 1.5, and only very rarely are more than four irrigations per season called for. The results for the 50% available-water criterion (light lines) are intermediate, and do not depend on the cost of the irrigations. For this case, no irrigations are scheduled in approximately 5% of years, the average number of irrigations per season is approximately 2.2, and more than five irrigations per season are rare.

4.2. Economic value

Section 4.1 sketched aspects of optimal use of weather forecasts for irrigation scheduling, but did not specifically address the economic benefits that might result. In the following, the economic value as computed using Eq. (3) will be computed for three cases. First, \( V_F \) will denote the difference between expected (effectively, averaged over many years) returns for irrigated lettuce using both the day 1 and day 2 precipitation forecasts (representing \( ER \) in Eq. (3)), and expected returns using the 50% available-water criterion (as \( ER_{50\%} \)). These returns consider only gross crop value at harvest minus costs of any irrigations performed, although other costs (e.g., planting, fertilization, pest control, harvest) would be comparable for the two cases and thus, cancel in the difference (Eq. (3)). Also computed in the following will be the value of the day 2 forecasts \( V_2 \), computed as the difference in expected returns between optimal use of both the 1- and 2-day ahead forecasts vs. optimal use of only the 1-day ahead forecasts (i.e., ignoring tomorrow’s rainfall forecast); and the value of irrigation \( V_I \), computed as the difference in expected economic returns between irrigation using the 50% available-water criterion, and the expected (again, averaged over many years) gross value of the crop without irrigation.

Fig. 6 shows, as bar charts, expected returns in dollars per hectare for optimal irrigation using both the day-1 and day-2 precipitation forecasts (‘2 Day’), optimal irrigation using only the day-1 forecasts (‘1 Day’), irrigation at 50% of maximum available soil water regardless of the forecast (‘50% AWC’); and for no irrigation (‘No Irr’). The upper two panels show results for 1 May planting, the lower two panels show results for 15 July planting, the left-hand panels shows results for the standard irrigation costs, and the right-hand panels show results for the US$100/h irrigation costs. The economic values \( V_F \), \( V_2 \) and \( V_I \) described in the previous paragraph are shown as the vertical differences between the appropriate bar heights.

The most prominent feature of Fig. 6 is the very large increase in expected economic return for irrigation using only the 50% available-water criterion, in relation to unirrigated lettuce, which is measured by \( V_I \). These values are larger for the 1 May planting,
mainly because of the greater risk of excess-moisture damage in the later cropping period; and of course are larger for the less expensive irrigation costs since the 50% available-water criterion does not consider the cost of irrigation. Summing over both cropping periods, the estimated expected annual value of irrigation vs. no irrigation is approximately US$5500/ha for the standard irrigation cost, and approximately US$4000/ha for the US$100/h labor cost.

Less prominent in Fig. 6, but still quite appreciable, are the economic values associated with optimal use of forecast information, in relation to the base-line 50% available-water irrigation criterion. Here the value of forecast information is greater for the more expensive irrigation cost, because the optimal actions reflect a balance between the cost of an irrigation and its potential benefits, so that the expensive irrigations are used much less frequently (Fig. 5). Totalling over both planting dates, the expected annual value of the forecasts, $V_F$, is nearly US$900/ha for the standard irrigation cost, and more than US$1000/ha for the higher irrigation costs. Fig. 6 also indicates that consideration of the day 2 forecasts contributes substantially to the overall forecast value (i.e., $V_2$ is an appreciable fraction of $V_F$). Results of calculations not including excess-moisture damage yield $V_2$ values that are quite small (on the order of a few dollars per hectare), indicating that the primary value of looking further into the future for this decision problem derives from avoiding extended periods of very high soil moisture.

5. Discussion and conclusions

The results presented here suggest that irrigation decisions in the relatively humid climate of New York can be improved through optimal use of weather forecasts, which provide substantial economic value relative to a conventional irrigation decision rule based only on soil water content. The economic value of the forecasts is achieved through the explicit balancing in Eq. (1) of the costs of irrigation vs. the probable enhanced crop growth resulting from the irrigation vs. possible growth diminishment or crop loss if an extended period of wet weather follows the irrigation. The corresponding economic value for the forecasts would be expected to be much less for lettuce grown in arid regions, where the uncertainty about rainfall occurrence is much less, and therefore there is little scope for improving management through use of rainfall forecasts.

The modified van Henten (1994) lettuce model used here is based on sound physiological concepts, but it is essentially a generic model of plant growth. The numerical constants used for quantification of crop response to soil moisture and temperature are estimates. Complete reliance on this model for irrigation management would require field experiments for
site-specific fine-tuning of model parameters. Additionally, several practically important considerations have been omitted entirely from the analysis. For example, potential for leaching and other water-related losses of fertilizers and pesticides have not been included, although optimal use of weather forecasts would tend to minimize these relative to irrigation decisions made without regard to the forecasts. The opportunity to replant after a crop failure relatively early in the cropping period has not been included here, so that expected returns for less-well managed irrigation scheduling are probably underestimated, which would lead to overestimates for the value of the weather forecasts. On the other hand, experience with the automatic statistical weather forecasts employed here in the setting of a university forecast contest (Hamill and Wilks, 1995) indicates that consistent improvements to these forecasts can be made by competent human forecasters, particularly with respect to the probabilities for precipitation amounts. That the forecasts used here are less accurate than those which might be provided in practice is a conservative influence on the dollar values computed.

These results points to several areas in which irrigation management in this region might be improved. The most prominent among these is the decision of whether or not to invest in irrigation equipment, regardless of whether weather forecast information will be used to schedule its use. The capital cost of this equipment for a modestly sized enterprise in New York is on the order of US$1000/ha (L. Geohring, personal communication), which the results in Fig. 6 suggests would be repaid quite rapidly, even if only the 50% available-water criterion were used for the tactical irrigation decisions. Vegetable growers in New York may be hesitant to irrigate because of the potential to exacerbate crop damage during wet periods, although the present results suggest that this damage can be greatly limited through optimal use of the weather forecasts.

In addition, the model suggests that the most critical times for irrigation of lettuce are very early and very late in the season, when irrigation of soil holding more than 50% of the available water capacity may be optimal even if the weather forecast indicates an appreciable chance of rain. Of course, the specific decision rules such as those shown in Fig. 3 should not be regarded as a substitute for the judgement of the grower, but rather might be used most effectively in practice as guidance to help sharpen that judgement in the context of other management considerations specific to a particular enterprise. However, this study demonstrates the feasibility and utility of including forecast information in formal decision-making models of practical decision problems involving weather uncertainty.

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References


