Agricultural Water Management 143 (2014) 48–58

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Exploring irrigation behavior at Delta, Utah using hidden Markov models

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ARTICLE INFO

Article history:
Received 25 September 2013
Accepted 21 June 2014
Available online 16 July 2014

Keywords:
Decision
Markov
Viterbi
States
Probability

ABSTRACT

In on-demand irrigation systems, canal operators divert water from rivers to be delivered to the fields after receiving a water order from a farmer. These water orders are the result of a farmer's decision to irrigate. If farmers' irrigation decisions could be better anticipated, it might be possible to improve canal operations using improved future short-term water demand estimates. The importance of how farmers make these irrigation decisions, however, is often overlooked because of their high variability and unpredictable nature. A hidden Markov model (HMM) was built to analyze irrigation decision behavior of farmers and make forecasts of their future decisions. The model inputs were relatively easily measured, or estimated, biophysical data, including such factors (i.e., those variables which are believed to affect irrigation decision-making) as cumulative evapotranspiration, depletion, soil stress coefficient, and canal flows. Irrigation decision series were the hidden states for the model. The paper evaluates data from the Canal B region of the Lower Sevier River Basin, near Delta, Utah. The main crops of the region are alfalfa, barley, and corn. A portion of the data was used to build and test the model capability to explore that factor and the level at which the farmer takes the decision to irrigate for future irrigation events. It was found that the farmers cannot be classified into certain classes based on their irrigation decisions, but varies in their behavior from irrigation-to-irrigation across all years and crops. The factors and the level selected can be adequately used to explore the future irrigation decisions in the short term. HMMs can be used as a tool to analyze what factor and, subsequently, what level of that factor the farmer most likely based the irrigation decision on. This was possible only when the maximum likelihood (ML) estimates of model parameters were known based on the historical evidence. The study shows that the HMM is a capable tool to study irrigation behavior which is not a memory-less process.

1. Introduction

Operators of on-demand irrigation canal systems can benefit from better methods to predict short-term irrigation demands. Such predictions could be used to improve the efficiency of system operation and could become vital information for the canal operators. Given that farmer irrigation decisions initiate the diversions in the first place, accurate forecasts of farmer irrigation decisions might provide the key to forecast these short-term demands.

Practically, we do not know much about the thought processes involved in farmers' irrigation decisions. Farmers' decisions are varied from farmer to farmer, from crop to crop, and from year to year, and presumably depend on a wide array of factors such as weather, market prices, water remaining in their share for the season, the crop stress indicators, etc. These factors cannot all be directly measured and there is minimal understanding of how farmers take them into consideration in making their irrigation decisions.

On-demand surface irrigation is practiced in the study site selected for this work. Real-time monitoring of reservoir releases and canal diversions, and reliable forecasts of evapotranspiration (ET) are other data readily available to both system operators and farmers, alike. Agricultural water use in the area can be studied by using real-time soil moisture measurements for which soil moisture probes are installed on some fields. However, day-to-day irrigation demands of the area are still difficult to forecast. A reliable method to predict farmer irrigation decisions might provide a means to improve forecasts of short-term irrigation demand.

Irrigation decision behavior is complicated because every farmer is different in his approach toward crops. Some farmers aim for good crop quality, while others use water sparingly by using information about soil moisture, yet others may irrigate as soon as

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http://dx.doi.org/10.1016/j.agwat.2014.06.010
0378-3774/

they see some stress in the plants. As a result, there can be several farmer paradigms, making the forecasting problem even more complex.

Since farmer decision behavior is unlikely to depend on one factor, we can roughly define it as a multivariate process. There are some factors in the system which are likely to influence a farmer's decisions and which are indirectly affected by his behavior. For example, the soil moisture content generally decreases through time because of evapotranspiration (ET), but it is the farmer who chooses to replenish the soil reservoir through irrigation. Interaction between factors can decrease the significance of important/main factors in such a dynamic system. This makes a case for studying the factors in isolation to discover that important variable which can best represent behavior. This problem can be thought of as randomly observed data whose values are dependent on some unobserved or hidden random states.

A Markov model is a tool to estimate the unseen states which the system passed through to produce the observations that have been made available through some measurement mechanism. Even simpler are the HMMs which have been used to study speech recognition (Rabiner, 1989), and weather states (Hughes and Guttorp, 1994; Hughes et al., 1999; Zucchini & Guttorp, 1991). HMMs are first order Markov models. The literature documenting the application of HMMs to human subjects is limited. Jeong et al. (2008) in their psychological study found patterns in students' learning activities while interacting with a computer, which can be a characteristic of their behavior.

Farmer behavior has been simulated in some studies. Becu et al. (2006) built a multi-agent system to study water sharing between two villages located at the extreme ends of a watershed. The basis on which the farmers make irrigation decisions was studied. This included cropping practices and irrigation strategies. Farmers groups were identified by studying their cropping patterns. Once the crop grown by the farmer was decided, irrigation decisions were simulated accordingly. This study provided solutions to the villages to avoid water scarcity. Le Bars et al. (2005) also modeled a multi-agent system to simulate agent-farmers who made irrigation decisions under conditions of limited water supply. Farmers had water quotas, against which they placed water orders in the beginning of the irrigation season. The quotas depend on the crop and farm size. A water manager agent managed the water using allocation rules. Random climate variables were assumed. Bontemps and Couture (2002) created a sequential decision model to simulate farmer decision making when they paid a minimal amount for ordering water. The water itself was supplied for free. These few studies do not analyze existing farmer decision behavior but, instead, try to recreate farmer actions that have been observed under different scenarios.

Modeling farmer irrigation decision behavior and forecasting future decisions can help improve canal operations. This type of modeling can be useful in estimating short-term irrigation demands and prepare the canal operators for anticipated water demands as the season goes along. This work is a first attempt of studying farmer decision behavior using HMMs. We have tried to use measurable biophysical variables that reflect the results of irrigation decision behavior to deduce information about variables that are important from the decision-making perspective. A hidden Markov modeling framework has been used for the problem, and information about biophysical data and related decisions have been used from Canal B command area in Sevier River Basin, Utah.

2. Hidden Markov models

The very well-known first-order hidden Markov model (HMM) is specifically a simple probability model and can be represented graphically as shown in Fig. 1. If a simple system that is evolving over discrete time steps is described by observed variables X_t, which are related to an unobserved hidden state, S_t, then such a system follows a hidden Markov process (Rabiner, 1989). The parameters defining such a process are called a hidden Markov model (HMM). Our problem is a "decoding" type problem wherein HMMs are used to find the most probable sequence of hidden states. This is done here with the Viterbi Algorithm. This and other HMM algorithms are discussed in Rabiner (1989).

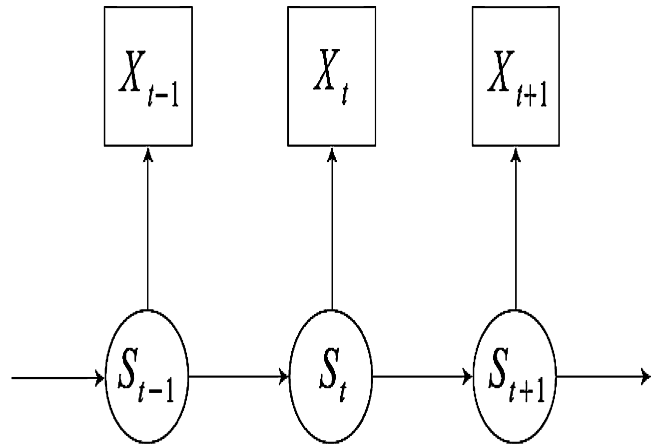

Fig. 1. Graphical representation of a hidden Markov process where X is the observed variable and S is the unobserved hidden state.

2.1. The Viterbi algorithm

The Viterbi algorithm, initially given by Forney (1973), assumes an initial HMM for an observation sequence, and determines one single "most likely sequence" of underlying hidden states that might have generated the sequence.

A HMM, represented as $M = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$, is specified by the following probabilities (Rabiner, 1989):

1. A vector of initial state probabilities, $\boldsymbol{\pi} = \pi_i$.
2. A matrix of transition probabilities, $\mathbf{A} = a_{ij}$, where, $a_{ij} = P(s_i|s_j)$ and $P(s_i|s_j)$ is the conditional distribution of the present state, s_i, given the previous state, s_j.
3. A matrix of emission/observation probabilities, $\mathbf{B} = b_i(v_m)$, where, $b_i(v_m) = P(v_m|s_i)$ and $P(v_m|s_i)$ is the conditional distribution of v_m given the hidden state, s_i.

The observation sequence, $O = o_1\ o_2\ \cdots\ o_k$ is given. We have to find the state sequence, $Q = q_1\ \cdots\ q_k$, which maximizes $P(Q \mid o_1 o_2 \cdots o_k)$. To find the most probable sequence of hidden states, we list all possible sequences of hidden states and find the probability of the observed sequence for each of the combinations. Out of all the combinations, the most probable sequence of hidden states is one that maximizes P (observed sequence|hidden state combination).

The maximum probability is:

$$\delta_k(i) = \max(P(q_1 \cdots q_{k-1}, q_k = s_i, o_1 o_2 \cdots o_k))$$

and produces observation sequence $o_1 o_2 o_3 \cdots o_k$ while walking through any hidden state sequence $q_1 \cdots q_{k-1}$ and getting to $q_k = s_i$. In other words, if the best path ending in the present state, $q_k = s_i$, passes through the previous state, $q_{k-1} = s_j$, then it should coincide with best path ending in the previous state, $q_{k-1} = s_j$. The procedure for finding the best state sequence is as follows (Rabiner, 1989):