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Artificial neural network and time series models for predicting soil salt and water content

Ping Zou[a,b], Jingsong Yang[a,*], Jianrong Fu[b], Guangming Liu[a], Dongshun Li[a]

[a] Institute of Soil Science, Chinese Academy of Sciences, 210008 Nanjing, China
[b] Institute of Environment, Resource, Soil and Fertilizer, Zhejiang Academy of Agricultural Sciences, 310021 Hangzhou, China

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ABSTRACT

Volumetric water content of a silt loam soil (fluvo-aquic soil) in North China Plain was measured in situ by L-520 neutron probe (made in China) at three depths in the crop rootzone during a lysimeter experiment from 2001 to 2006. The electrical conductivity of the soil water (EC_{sw}) was measured by salinity sensors buried in the soil during the same period at 10, 20, 45 and 70 cm depth below soil surface. These data were used to test two mathematical procedures to predict water content and soil water salinity at depths of interest: all the available data were divided into training and testing datasets, then back propagation neural networks (BPNNs) were optimized by sensitivity analysis to minimizing the performance error, and then were finally used to predict soil water and EC_{sw}. In order to meet with the prerequisite of autoregressive integrated moving average (ARIMA) model, firstly, original soil water content and EC_{sw} time series were likewise transformed to obtain stationary series. Subsequently, the transformed time series were used to conduct analysis in frequency domain to obtain the parameters of the ARIMA models for the purposes of using the ARIMA model to predict soil water content and EC_{sw}. Based on the statistical parameters used to assess model performance, the BPNN model performed better in predicting the average water content than the ARIMA model: coefficient of determination (R^2) = 0.8987, sum of squares error (SSE) = 0.000009, and mean absolute error (MAE) = 0.000967 for BPNN as compared to R^2 = 0.8867, SSE = 0.000043, MAE = 0.002211 for ARIMA. The BPNN model also performed better than the ARIMA model in predicting average EC_{sw} of soil profile. However, the ARIMA model performed better than the BPNN models in predicting soil water content at the depth of 20 cm and EC_{sw} at the depth of 10 cm below soil surface. Overall, the model developed by BPNN network showed its advantage of less parameter input, nonlinearity, simple model structure and good prediction of soil EC_{sw} and water content, and it gave an alternative method in forecasting soil water and salt dynamics to those based on deterministic models based on Richards' equation and Darcy's law provided climatic, cropping patterns, salinity of the irrigation water and irrigation management are very similar from one year to the next.

1. Introduction

Soil salinity, defined as the concentration of soluble mineral salt that exists in the soil, is one of the most severe environmental factors limiting the productivity of agricultural crops (Pitman and Läuchli, 2002). It is also a type of soil degradation, which is one of the great problems in sustainable agriculture. It may bring about severe consequences, such as loss of productivity in soils with shallow saline water tables, reduced plant growth, contamination of surface flows of water and loss of stream and wetlands habitat (Qadir et al., 2000). Continuous attention has been paid to soil salinization and secondary salinization for many years by farmers, government officers and scientists around the world.

In saline soil, the salt moves with water in soil profile. The mechanism of soil water and salt dynamics is essential for controlling soil salinization and secondary salinization in salt-affected agricultural fields. Dynamics of soil water and salt is very complex and depends considerably on local environmental conditions, the dominant one of which is the meteorological factor. Soil salt content and volumetric water content are key factors in agricultural management and soil salinity control especially in salt-affected soil. Great attention has been paid on the research of soil water and salt dynamics. The central problem is to predict soil water and salt in the profile. Models used to describe soil water and salt dynamics are either deterministic or stochastic. Deterministic models for soil water and salt movement are commonly based on Richards' equation and convection–dispersion equation (Chen

* Corresponding author at: Institute of Soil Science. Tel.: +86 25 86881222; fax: +86 25 86881000.
E-mail address: jsyang@issas.ac.cn (J. Yang).

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et al., this issue; Khan et al., 2003; Pang and Letey, 1998; Ragab et al., 2005; Shani et al., 2007; Simunek et al., 1996). Stochastic models used in description of soil water and salt dynamics generally belong to the black box models, in which only the input and output of the models can be obtained while the intermedial processing is ignored. Much work has been done in deterministic models for simulating soil water and salt dynamics. Recently stochastic models such as artificial neural networks (ANNs) have attracted great interest due to their simple, fast and comparable performance in most cases compared with deterministic models (Sarangi et al., 2006).

ANNs are mathematical models, the architecture of which has been inspired by biological neural networks (Erzin et al., 2007). ANNs are very appropriate for the modeling of nonlinear processes, such as the case of soil water and salt dynamics (Jahangir and Jagath, 1998). During the last decades, there has been a significant increase in their application in different scientific areas due to the development of computer technologies. ANNs have been employed for modeling processes, pattern recognition and time series analysis in different scientific fields such as financial and economic research, industrial engineering research, hydrology, meteorology, and agroecological research studies (Baker and Ellison, 2008; Co and Boosarawongse, 2007; Erzin et al., 2007; Koekkoek and Booltink, 1999; Liu et al., 2008; Patil et al., 2008; Xu et al., 2008). There are also many publications focused on application of ANN models in agricultural water management. Sharma et al. (2003) developed two ANN models, a trainable fast back propagation (FBP) network and a self-organizing radial basis function (RBF) network, to simulate subsurface drain outflow and nitrate–nitrogen concentration in tile effluent. The results show that the performance of the RBF neural network was superior to the FBP model in predicting the concentration of nitrate–nitrogen in drain outflow due to the application of manure and/or fertilizer. Sarangi and Bhattacharya (2005) developed two ANN models, one geomorphology-based (GANN) and another non-geomorphology-based (NGANN) to predict sediment loss. The feed-forward ANN models with back propagation algorithm performed well for both the GANN and the NGANN models. The study also revealed that inclusion of morphological parameters in ANN models improved the prediction of sediment loss. Sarangi et al. (2006) studied the relative performance of ANN and SALTMOD models in simulating subsurface drainage effluent salinity. Kim et al. (2007) used a Generalized Regression Neural Network (GRNN) model and evaluated its capability to predict the nutrient loading into the neighboring water. Morimoto et al. (2007) investigated an optimal watering scheduling that improves the quality of Satsuma mandarins grown in the field using neural networks combined with genetic algorithms. Landeras et al. (2008) compared artificial neural network models with empirical and semi-empirical equations in estimating daily reference evapotranspiration in the Basque Country (Northern Spain). Chinh et al. (2009) used a feed-forward artificial neural network (FFANN) to model and estimate the water levels in the main drainage canal. The study indicated that the artificial neural network could successfully model the complex relationship between rainfall and water levels in a flat and low-lying agricultural area.

The general objective of this study was to simulate soil water and salt content using classical time series analysis and artificial neural network. The specific objectives were: (i) to examine autocorrelation and partial autocorrelation function of soil water and salt time series, and then create classical time series models; (ii) to train and optimize back propagation network using soil water and salt time series data combined with correspondent ARIMA models; and (iii) to evaluate the performance of the two black box models for predicting soil water content and the electrical conductivity of the soil water (EC_{sw}).

2. Materials and methods

2.1. Experiment outline

North China Plain is a warm temperate semi-humid and semi-arid monsoon climate zone, one of major agricultural area in China. It has an annual average rainfall of 500–800 mm, the annual evaporation of 1500–2000 mm, while the ratio of evaporation to precipitation around 2.5–3.0. The rainfall in one year is mostly concentrated in late summer and early autumn, and the rainfall in this period accounts for 24–30% of average annual precipitation. This area is also suffered from soil salinization and secondary salinization.

In 1989, for the purpose of investigating soil water and salt regime in North China Plain, 30 soil columns of three different soil texture profiles with five representative groundwater depths were installed in the Soil Salt-Water Dynamics Simulation Laboratory, at the Fengqiu Agroecological Experimental Station (35°5′30.22″N, 114°18′37.75″E) located near Kaifeng City. All the columns made of steel sheet had a diameter of 61.8 cm and five different lengths (100, 150, 200, 250 and 300 cm). Three types of soil texture profiles with relative representativeness were designed according to the features of the texture profiles in the North China Plain. The first was a single layer of silt loam soil throughout the profile, the second was silt loam soil with a clay interlayer 30 cm thick, and the third was a 100-cm thick clay layer overlying a silt loam soil. Each type of soil texture profile had five different groundwater treatments, i.e., 1.0, 1.5, 2.0, 2.5 and 3.0 m in depth. A Marriott bottle was connected to an inlet near the bottom of each column to supply water and control the groundwater level. All the details about soil columns installation and experiment arrangement were described in the series of publications: You et al. (1992), You and Meng (1992, 1993, 1995), Meng and You (1994), Zhang (2001), and Xu et al. (2005, 2008).

Fifteen of the soil columns were cropped, the other 15 were not. Typical local crop rotation which is maize–wheat in one year was chosen for the soil column experiment. In 2001, soil water content (θ) was measured by neutron probe (Type L520, Institute of Atomic Energy, Jiangsu Academy of Agricultural Science), and EC_{sw} was measured by traditional soil salinity sensors (Corwin and Lesch, 2005). A hollow aluminum tube was inserted into soil columns near the centre of the cylinders. This was the access tube for the neutron probe; θ was measured at intervals of 20 cm starting a depth of 20 cm below soil surface. Salinity sensors were installed in each soil column 7 cm from the edge of the column, through observation holes on one side of the column. The installation depths measured from the top of the column were 10, 20, 45, 70 and 100 cm, at intervals of 30 cm below 100 cm depth. The columns were irrigated according to the local farmers' practice with local groundwater with a salt content of about 1 g L^{-1}. The depth of water applied was about equal to the depth that farmers used in the field. Irrigation frequency, time and method were kept similar to those used in local agricultural irrigation operation. For this study, we used data obtained from 2001 to 2006. Each measurement was usually performed every five days, but additional observations were conducted when necessary (Zhang and Yang, 2001).

2.2. Data collection and preliminary treatment

Silt loam soil is the major type in North China Plain. The data used for this study was obtained from a cropped column where the soil texture was silt loam in the whole profile. Salinity and soil water content data from this column was chosen to build time series and artificial neutral network models. Soil water content was measured at the depths of 20, 40, 60 cm below soil surface, and soil salinity sensors were buried at the depths of 10, 20, 45, 70 cm below the soil surface. Soil water content measured by neutron probe needed