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Note

Characterizing root distribution with adaptive neuro-fuzzy analysis

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A b s t r a c t. Root-soil relationships are pivotal to understanding crop growth and function in a changing environment. Plant root systems are difficult to measure and remain understudied relative to above ground responses. High variation among field samples often leads to non-significance when standard statistics are employed. The adaptive neuro-fuzzy inference system (ANFIS) has been applied in many agricultural and environmental fields and may represent a viable means for dealing with complexities of root distribution in soil. We applied this method to vertical and horizontal root distribution data collected from a potato (*Solanum tuberosum* L.) cropping system grown under ambient and elevated levels of atmospheric CO_2. The lack of a CO_2 effect on root length or dry mass densities was most likely due to the low growing season temperature limiting root growth in this subarctic system. At all CO_2 levels, potato roots were concentrated near row centre, particularly in the upper soil profile. Simulations indicated that ANFIS gave plausible results, indicating it offers a viable alternative to more traditional statistical techniques for evaluation of complex root distribution patterns.

K e y w o r d s: fuzzy logic, roots, potato

INTRODUCTION

Root-soil relationships are pivotal in understanding crop growth and function, especially given the predicted impacts of global change (Rogers *et al.*, 1994). The well-documented rise in atmospheric CO_2 concentration (Keeling and Whorf, 2001) increases aboveground plant growth (Kimball, 1983). Although less studied, plants often show increased rooting under elevated CO_2 (Rogers *et al.*, 1994, 1996) which is important for acquisition of soil resources.

Plant root systems are understudied relative to aboveground responses because they are notoriously difficult to measure, especially in the field. Removing roots from soil and debris is tedious and time consuming, which limits sample numbers. High variation among field samples often leads to non-significance when standard statistics are employed. Accurate descriptions of complex root distribution patterns require simulation of a non-linear system with poorly quantified uncertainties and the adaptive neuro-fuzzy system may offer a viable alternative. A fuzzy inference system (FIS) and its adaptive version (adaptive neuro-fuzzy inference system or ANFIS) employ fuzzy if-then rules to model the qualitative aspects of knowledge and reasoning processes without precise quantitative analyses (Jang, 1993). Compared to traditional regression approaches, ANFIS does not require *a priori* regression models which can be difficult to justify (Schaap *et al.*, 1998). Recent examples of ANFIS applications in agricultural research include soil erosion (Akbarzadeh *et al.*, 2009) and yield modelling (Arkhipov *et al.*, 2008).

This study aims to evaluate ANFIS application for exploring complex root distribution patterns under field conditions.

MATERIALS AND METHODS

The foundation of ANFIS is the data driven fuzzy modelling approach. This allows model extraction from input-output data represented as FIS (Zadeh, 1973). This is a rule based system with three components: membership functions of input-output variables, fuzzy rules, and output characteristics, membership functions, and system results.

Fuzzy inference systems are one of the most famous applications of fuzzy logic and fuzzy sets theory (Zadeh, 1973). The strength of FIS is the ability to handle linguistic concepts and perform non-linear mappings between inputs and outputs (Serge, 2001). ANFIS is a combination of a Sugeno-type FIS (Sugeno, 1985) and artificial neural

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T a b l e 1. Main characteristics of the designed fuzzy inference system

Parameter	Number							Training error
	Input data	Input variables	Output variables	Membership functions			Epochs	
Root length density (km m^{-3})	36	3	1	32	32	32	100	0.3 10^{-4}
Root mass density (kg m^{-3})	36	3	1	28	28	28	100	0.115 10^{-6}

networks (ANN) (Jang, 1993) which are universal estimators of multivariate non-linear mappings capable of learning and generalising from training data. To determine membership function of input-output variables, two methods (backward propagation and hybrid-learning algorithms) are used for ANFIS learning and rule construction. Model performance is examined using the root mean square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(Z_S - Z_o\right)^2},$$

where: Z_s is the measured value, Z_o is the predicted value, and n is the sample number. The RMSE evaluates the agreement between measured and predicted values.

To generate FIS using ANFIS, we applied MATLAB's Fuzzy Logic Toolbox (Mathworks, 2004) which enables creation and editing of FIS, manually or automatically driven by the data. The test data utilized was from a potato study conducted in Fairbanks, AK, USA on a Tanana silt loam using open top field chambers at three atmospheric CO_2 levels (369, 543, and 707 µmol mol^{-1} CO_2) as described in detail by Conn and Cochran (2006). Soil cores (60 cm length; 38 mm diameter) were taken (0, 19, and 38 cm from row centre), processed into 15 cm increments, and root length and dry mass (55°C) were determined (Prior *et al.*, 2005).

RESULTS AND DISCUSSION

Using ANFIS, two three-input FISs were built to define the contiguous relations between root characteristics and atmospheric CO_2 levels (Table 1). The training process and the step-size variation for the input model at each iteration are shown in Fig. 1. Usually the error curve goes downhill until the end of training. After training completion, the evaluation phase occurs. Performance of the ANFIS model is compared in two data sets: training and testing.

Figure 2 shows the correlation between observed and forecast values. Main characteristics of the testing process are shown in Table 2. As seen in the figures, the ANFIS successfully learned the relationship between the input and output data. The results indicate the generalization properties of the ANFIS model during training, verification, and testing are comparable (Fig. 2). Graphical results of computations are presented in Figs 3 and 4 where treatments 1-3 (CO_2 concentration) are defined as 369, 543, and 707 µmol mol^{-1} CO_2, respectively. The absence of sharp ascent or descent indicates that the training data were distributed across the input space of the model in a somewhat uniform manner and that the model captured the underlying process dynamics which were in general agreement with data collected using traditional approaches (Prior *et al.*, 2005).

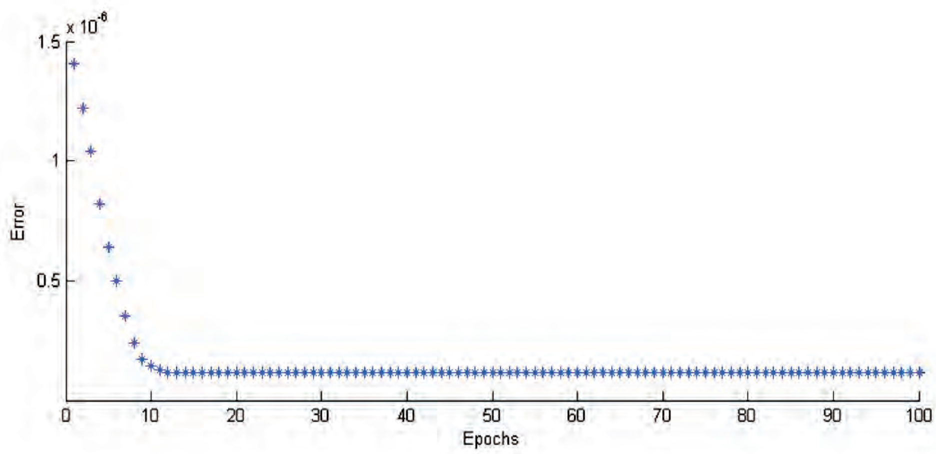

Fig. 1. Error curve during the learning process *ie* root mass modelling.

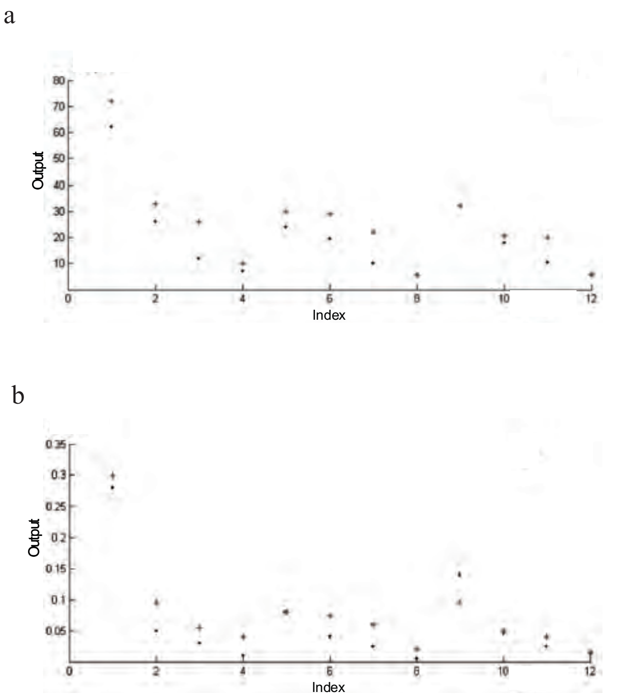

Fig. 2. Correlation between observed values (dots) and forecast values (stars) during testing of the: a – root length density, and b – root mass density models.

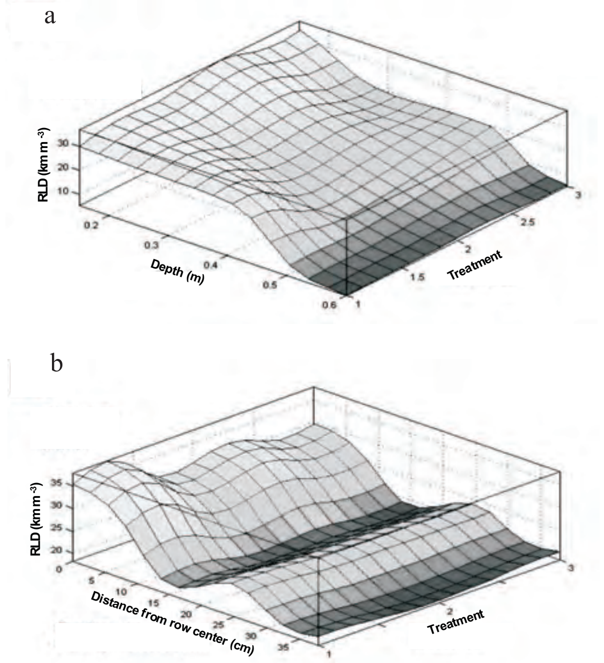

Fig. 3. Adaptive neuro-fuzzy inference system surface after training describing the relation between: a – root length density (RLD), depth, and CO_2 treatments, b – RLD, distance from crop row centre, and CO_2 treatments; treatment 1 = 369 μmol mol^{-1} CO_2; treatment 2 = 543 μmol mol^{-1} CO_2; treatment 3 = 707 μmol mol^{-1} CO_2.

T a b l e 2. Main characteristics of the testing process

Parameter	Number of test data pairs	Average testing error
Root length density (km m^{-3})	12	7.7513
Root mass density (kg m^{-3})	12	0.0273

Using the ANFIS approach, little effect of CO_2 concentration was found for either root length or root mass density regardless of position or depth increment (Figs 3 and 4). This is in agreement with data collected using root cores (Prior *et al.*, 2005). In this same Alaska potato study, Conn and Cochran (2006) found an increase in allocation to tubers under elevated CO_2 with a concomitant reduction in allocation to aboveground biomass; this resulted in a large increase in root:shoot ratio (R:S) under elevated CO_2. They suggested that, since tubers represent a stronger sink for carbon, this reduced carbon allocation to aboveground plant organs. A review of 264 crop species by Rogers *et al.* (1996) found that the highest and most consistent R:S response to elevated CO_2 occurred in tuber crops. Idso *et al.* (1988) found R:S increased ~36% in tuber crops exposed to elevated CO_2, while R:S of non-tuber crops showed no response. In addition to these allocation shifts, the low growing season

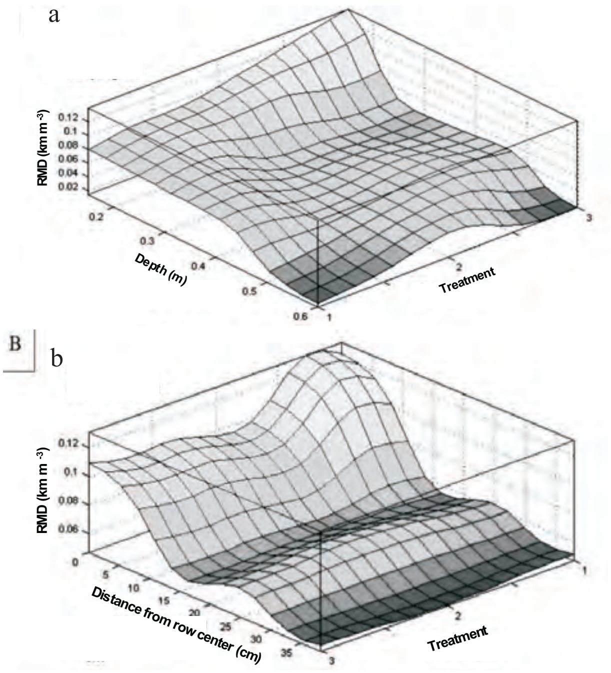

Fig. 4. Adaptive neuro-fuzzy inference system surface after training describing the relation between: a – root mass density (RMD), depth, and treatments, b – RMD, distance from crop row centre and CO_2 treatments. Explanations as in Fig. 3.

temperature in the subarctic study may have contributed to the limited potato response to CO_2 enrichment; it is likely that the combination of these factors also limited fine root response to elevated CO_2.

Despite the lack of a CO_2 response, more of the potato root system grew closer to the row centre (Prior *et al.*, 2005). This response pattern was also observed in the ANFIS analysis (Figs 3b and 4b). In addition, while it is common for more roots to occur in the upper soil profile (Rogers *et al.*, 1994), the low soil temperature at the lowest depth increments may have limited root growth in this subarctic environment (Prior *et al.*, 2005). Again, this pattern was reflected using the ANFIS approach (Figs 3a and 4a).

Characterizing root distribution in complex plant/soil systems is important for developing decision support tools to solve farm problems in a changing environment. In this work, the unique potential of ANFIS to identify these relationships was in agreement with traditional methods of analysing root data. Adaptive neuro-fuzzy inference systems also easily provide excellent visual representations of the rooting patterns in a complex soil environment.

CONCLUSIONS

1. Elevated CO_2 had little effect on potato rooting patterns in subarctic Alaska.

2. Simulation shows that the ANFIS technique gives comparable results, indicating that the fuzzy method offers a viable alternative to more traditional statistical techniques.

3. A reasonable relative error warrants further use of ANFIS with more extensive datasets to improve characterization of complex rooting patterns in heterogeneous soil environments.

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