Characterizing root distribution with adaptive neuro-fuzzy analysis

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Abstract. 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. 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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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):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (Z_k - Z_o)^2},$$

where: $Z_k$ 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 in root mass modelling.](image-url)
TABLE 2. Main characteristics of the testing process

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Number of test data pairs</th>
<th>Average testing error</th>
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<tbody>
<tr>
<td>Root length density (km m⁻³)</td>
<td>12</td>
<td>7.7513</td>
</tr>
<tr>
<td>Root mass density (kg m⁻³)</td>
<td>12</td>
<td>0.0273</td>
</tr>
</tbody>
</table>

Using the ANFIS approach, little effect of CO₂ 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 CO₂ with a concomitant reduction in allocation to aboveground biomass; this resulted in a large increase in root:shoot ratio (R:S) under elevated CO₂. 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 CO₂ occurred in tuber crops. Idso et al. (1988) found R:S increased ~36% in tuber crops exposed to elevated CO₂, while R:S of non-tuber crops showed no response. In addition to these allocation shifts, the low growing season...
temperature in the subarctic study may have contributed to
the limited potato response to CO₂ enrichment; it is likely
that the combination of these factors also limited fine root
response to elevated CO₂.

Despite the lack of a CO₂ 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 envi-
ronment (Prior et al., 2005). Again, this pattern was re-
flected 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 rela-
tionships 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 CO₂ had little effect on potato rooting patterns in subarctic Alaska.
2. Simulation shows that the ANFIS technique gives com-
parable results, indicating that the fuzzy method offers a via-
bable alternative to more traditional statistical techniques.
3. A reasonable relative error warrants further use of
ANFIS with more extensive datasets to improve characteri-
zation of complex rooting patterns in heterogeneous soil
environments.

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