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Artificial neural networks for rice yield prediction in mountainous regions

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SUMMARY

Decision-making processes in agriculture often require reliable crop response models. The Fujian province of China is a mountainous region where weather aberrations such as typhoons, floods and droughts threaten rice production. Agricultural management specialists need simple and accurate estimation techniques to predict rice yields in the planning process. The objectives of the present study were to: (1) investigate whether artificial neural network (ANN) models could effectively predict Fujian rice yield for typical climatic conditions of the mountainous region, (2) evaluate ANN model performance relative to variations of developmental parameters and (3) compare the effectiveness of multiple linear regression models with ANN models. Models were developed using historical yield data at multiple locations throughout Fujian. Field-specific rainfall data and the weather variables (daily sunshine hours, daily solar radiation, daily temperature sum and daily wind speed) were used for each location. Adjusting ANN parameters such as learning rate and number of hidden nodes affected the accuracy of rice yield predictions. Optimal learning rates were between 0·71 and 0·90. Smaller data sets required fewer hidden nodes and lower learning rates in model optimization. ANN models consistently produced more accurate yield predictions than regression models. ANN rice grain yield models for Fujian resulted in R^2 and RMSE of 0·67 and 891 *vs* 0·52 and 1977 for linear regression, respectively. Although more time consuming to develop than multiple linear regression models, ANN models proved to be superior for accurately predicting rice yields under typical Fujian climatic conditions.

INTRODUCTION

Rice is vital to more than half of the worlds population. It is the most important food grain in the diets of hundreds of millions of Asians, Africans and Latin Americans living in the tropics and subtropics (Yoshida 1981). China represents more than 0·20 of the worlds population, while its arable land is only some 0·07 of the global total. There is no doubt that increased yields must be achieved by improved grain yield per unit area rather than an increase in total area.

The Fujian province of China is a mountainous region where *c.* 0·5 of the land is hilly; 0·7 of the rice in the present study was planted on mountain farms. Fujian has a subtropical climate, warm and humid. There are distinct differences in the climate between north and south, coastal and inland regions, and valleys and mountains. It has an annual temperature of 17–21 °C and an annual precipitation of 1100–2000 mm, both increasing from northwest to southeast. Typhoons occur frequently from July to September. Since 1993, the government has been carrying out province-wide surveys for crop monitoring and for yield forecasting. Yield components data collected from 48 to 160 random plots across the province are used to calculate the final yield. Plot yields are aggregated to project the crop production of 16 counties making up the coterminous Fujian province.

Rice production is affected by sets of varietals and environmental parameters, including genetic characteristics, soil, weather and cultivation management.

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Rice grain yield for a given cultivar is mainly dependent upon local weather conditions such as sunshine hours, solar radiation and temperature, when plants are grown with ample nutrients and water. In other words, the variation in rice production along spatial and temporal gradients would be attributable to different climates when other conditions are suitable for plant growth and development. In addition, the different climatic conditions are mostly associated with either cropping season or crop yield in the same year for a particular area. For those regions such as the Yangtze River Valley and its adjacent area, where there is a single rice cropping system, its rice production is different from the Fujian province with its mountainous terrain and double-cropping system.

Weather and climate affect plant growth and development and the fluctuations and occurrences of climatic extremes, particularly at critical crop growth stages, may reduce yield significantly (Satake & Yoshida 1978; Peng *et al*. 1996). Concern about past, present and future weather aberrations, climate trends and their effects on agriculture has continued to stimulate research as well as public and policy-level interest in the analysis of climate variability and agricultural productivity (Matthews *et al*. 1996; Houghton *et al*. 1996). The occurrence of abnormal weather episodes during the growing season or during critical development stages may hamper growth processes, resulting in yield reduction. This makes climate variability a threat to food production, with serious social and economic implications (Geng & Cady 1991; Hossain 1997). However, a clear understanding of the vulnerability of food crops as well as the agronomic impacts of climate variability in mountainous areas enables implementation of adaptive strategies to mitigate the negative effects and make better yield predictions.

In recent years, crop growth models have become increasingly important as major components of agriculture-related decision-support systems (Jones 1993; Jame & Cutforth 1996; Stephens & Middleton 2002). Crop growth and yield models are based on a combination of soil, crop and climatic variables. Sadras & Calviño (2001) determined that 0·90 of soybean and 0·76 of maize yield variation were linked to water deficits. Rainfall was deemed to be primarily responsible for yield variability within a region. Crasta & Cox (1996) determined that temperature did not influence yields in the northeastern US during years with adequate rainfall as compared with years with moderate to severe water stress. According to Bandel & Heger (1994), differences of growing season length within Maryland had little influence on yield, but soil water holding capacity and land capability class were important factors in the Maryland Agronomic Soil Capability Assessment Program (MASCAP) yield predictions. Environmental factors, such as climatic information, in addition to multiple soil properties related to crop rooting depth and water availability, are significant factors for crop yield models (Huddleston 1984; Gbadegesin 1987; Liang *et al*. 1986; Whisler *et al*. 1986).

Agronomic models are based on mechanistic or empirical approaches (Poluektov & Topaj 2001). Mechanistic models use mathematical functions to represent physical, biological and chemical processes (Whisler *et al*. 1986). Although these models are suitable for areas outside the data range used for development, they tend to be complex and require many input parameters (Basso *et al*. 2001; Wang *et al*. 2002). Empirical models attempt to determine functional relationships between crop yield and other factors using either an existing or a specially designed agronomic experiment. Regression or correlation analyses are generally used to characterize the statistical relationship between controlled variables and crop yield. Technologically, empirical crop growth models are relatively simple to build or develop, but these models cannot take account of temporal changes in crop yields without long-term field experiments (Jame & Cutforth 1996). Furthermore, the derived functional equation is locally specific, and it is thus difficult to extrapolate to other areas unless environmental conditions are similar.

In view of the fact that even the most deterministic models still rely heavily on empirical functional relationships to varying degrees (Jame & Cutforth 1996), empirical crop growth models may play an important role as explanatory tools for identifying the hidden structure of crop growth processes. They may even offer a more reliable method of investigating crop response than poorly calibrated process models when the necessary data are available. The main limitation of traditional regression-based empirical models is the lack of non-linear modelling ability, which is apparent in crop responses to agro-ecological conditions. This may be the case particularly when various land management practices are applied under different scenarios.

Some adaptive and non-parametric models have been recently introduced in environmental science for predictive purposes. Artificial neural network (ANN) models are a powerful empirical modelling approach and yet relatively simple compared with mechanistic models. It is felt that ANN models offer a more versatile empirical modelling approach in comparison to the linear regression methods used in rice yield since the rice yield is non-linear and autoregressive in nature. Because ANN models allow an illustration of complex and non-linear relationships without rigorous assumptions regarding the distribution of samples (Bishop 1995; Breiman *et al*. 1984), the method is gaining popularity for research areas where there is little or incomplete understanding of the problem to be solved, but where training data are available.

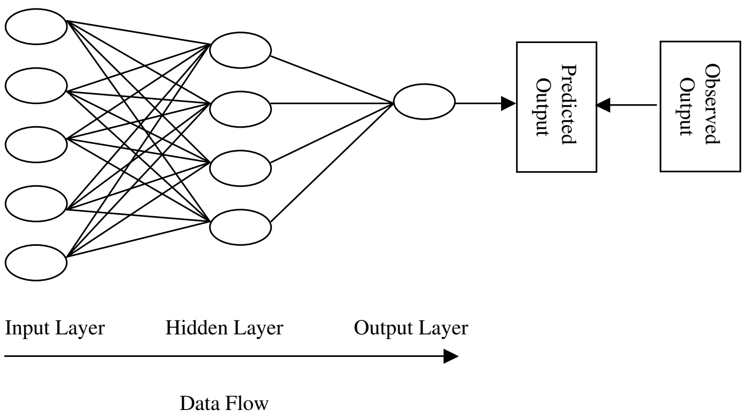

Fig. 1. Layers and connections of a feed-forward back-propagating artificial neural network.

Artificial neural networks can be used to develop empirically based agronomic models. The ANN structure is based on the human brain's biological neural processes. Interrelationships of correlated variables that symbolically represent the interconnected processing neurons or nodes of the human brain are used to develop models. ANN models find relationships by observing a large number of input and output examples to develop a formula that can be used for predictions (Pachepsky *et al.* 1996). Non-linear relationships overlooked by other methods can be determined with little a priori knowledge of the functional relationship (Elizondo *et al.* 1994). A minimum of three layers is required in an ANN model: the input, hidden and output layers (Fig. 1).

The input and output layers contain nodes that correspond to input and output variables, respectively. Data move between layers across weighted connections. A node accepts data from the previous layer and calculates a weighted sum of all its inputs, t:

$$t_i = \sum_{j=1}^{n} w_{ij} x_j \tag{1}$$

where n is the number of inputs, w is the weight of the connection between node i and j, and x is the input from node j. A transfer function is then applied to the weighted value, t, to calculate the node output, o_i.

$$o_i = f(t_i) \tag{2}$$

The most commonly used transfer function is a sigmoidal function for the hidden and output layers and a linear transfer function is commonly used for the input layer.

The number of hidden nodes determines the number of connections between inputs and outputs and may vary depending on the specific problem under study. If too many nodes are used then the ANN may become over-trained, causing it to memorize the training data and resulting in poor predictions (Lawrence 1994). The learning rate determines the amount the weights change during a series of iterations to bring the predicted value within an acceptable range of the observed value. The training tolerance refers to the maximum error rate at which the network must converge during training. Once the network converges, an approximate function is developed and utilized for future predictions (Schmueli 1998). The trained network is then tested with a separate data set with its output information omitted.

Agronomic ANN applications include crop development modelling (Elizondo *et al.* 1994), pesticide and nutrient loss assessments (Yang *et al.* 1997), soil-water retention estimations (Schaap & Bouten 1996), and disease prediction (Batchelor *et al.* 1997). Pachepsky *et al.* (1996) reported an ANN model's estimated soil-water content based on soil physical properties better than regression techniques. Starrett *et al.* (1997) reported that an ANN model performed better ($R^2 = 0{\cdot}984$) than a regression model ($R^2 = 0{\cdot}780$) when predicting applied-nitrogen leaking below the root zone of turf grass. According to Batchelor *et al.* (1997), ANN models produced better results than traditional statistical methods when predicting soybean rust.

The objective of the present study was to develop simple rice yield prediction models with readily available data that could be easily applied by an end user. The specific objectives were to: (1) investigate if artificial neural network (ANN) models could effectively predict Fujian rice yield for typical mountainous climatic conditions; using field-specific rainfall, field-specific weather variables (daily sunshine hours, daily solar radiation, daily temperature sum and daily wind speed) values, and historic yield data; (2) note changes of model performance with variations of

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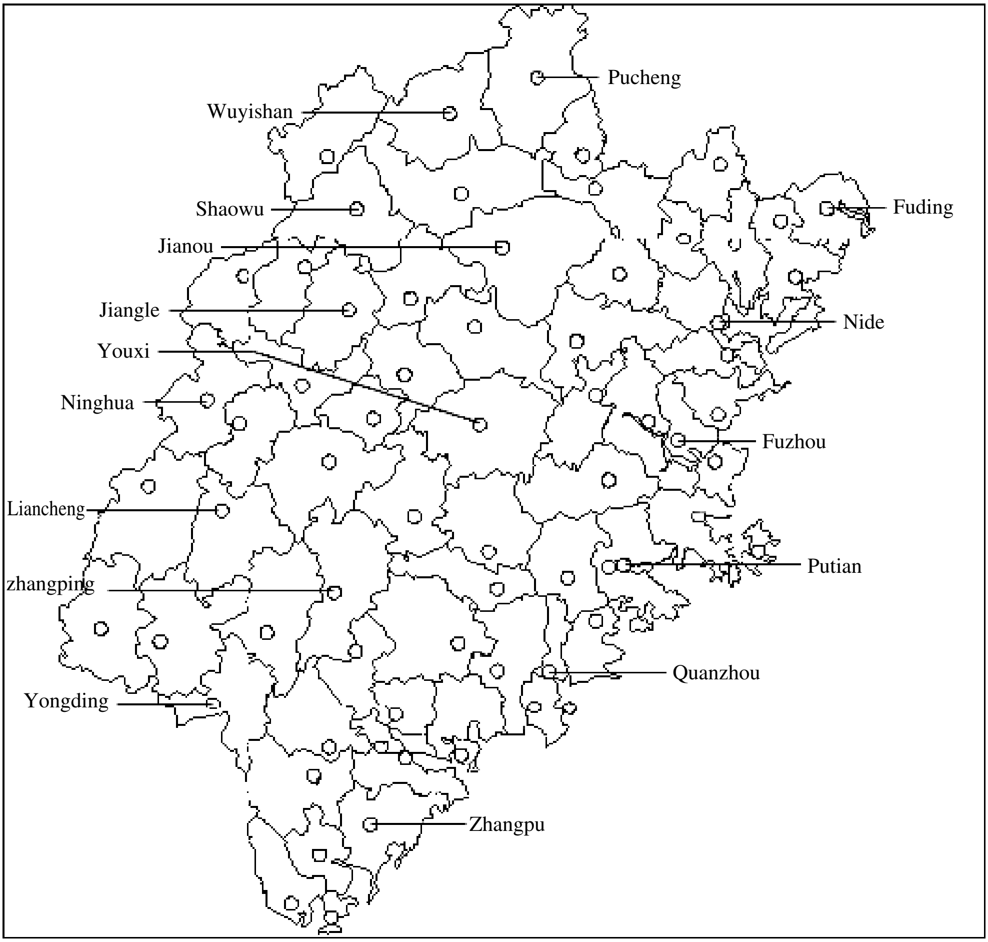

Fig. 2. Locations within Fujian province where rice yields, soil fertility level means, precipitation, sunshine hours, solar radiation, temperature sum, wind speed information were obtained and used for the development of yield prediction models.

ANN model parameters; and (3) compare the effectiveness of multiple linear regression models with ANN models for predicting Fujian rice yields.

MATERIALS AND METHODS

Data

Historical (1993–2003) Fujian rice yield data from the Hybrid Variety Performance trials Fujian Agricultural Administration were accessed. The rice data included 16 locations and seven different soil types (Fig. 2; Table 1). The location-specific rainfall data and the weather variables (daily sunshine hours, daily solar radiation and daily temperature sum) were obtained from weather stations in each location.

The mean yield of all hybrids at a test location was used to reduce the inherent variability associated with individual hybrids when approximating expected yields for Fujian. Hybrid variety data included early, mid and late season maturing rice. Varieties are grouped based on the number of days needed from planting to maturity. These rice maturity groups represent the most commonly used groupings planted on Fujian and the majority of China agricultural land. The t test for early-mid, mid-late and early-late rice maturity group comparisons of mean yield resulted in P values of 0·54, 0·66 and 0·86, respectively. Thus, maturity group data sets could be combined for developing yield prediction models.

Precipitation data were obtained from weather station records from each location. Monthly rainfall

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Table 1. *Different soil types* (*United States Soil Types, USST*) *of the test sites in Fijian province*

Soil types	Test sites
Typic Haplohumults	Fuding, Nide
Typic Palehumults	Fuzhou, Putian
Humic Dystrudepts	Quanzhou, Zhangpu
Typic Hapludults	Pucheng, Wuyishan, Shaowu
Histic Humuaquepts	Jianou, Jiangle, Youxi
Typic Humuaquepts	Liancheng, Ninghua
Typic Dystrudepts	Youding, Zhangping

means from February to November were used. Locations with mean seasonal rainfall outside of one standard deviation of the 20-year mean rainfall during February–November were used to ensure that models would be developed for typical weather conditions representing Fujian rice-growing seasons.

Solar radiation and temperature vary significantly in mountainous areas because they are controlled by various factors and the spatial variation is expected to vary substantially even within a location. Thus, daily sunshine hours, daily solar radiation, daily temperature sum and daily wind speed were recorded at an agricultural experiment station situated at the study area.

Additional data included were the field conditions. Soil was collected from the cropped and adjacent areas to evaluate the amount of organic N as a result of soil fertility level. The data included 5 years of soil fertility level means in each location, obtained from the Fujian soil survey database. The fields consisted of seven soil types (Table 1).

Artificial neural network model development

The ANN method was first used in artificial intelligence research that attempted to mimic the capacity to learn through biological neural systems. Many different types of neural nets are available and their structure is described in Bishop (1995), Ripley (1996) and Principe *et al*. (2000). The ANN structure used in the present paper is a feed-forward back-propagating ANN model, the structure of which is illustrated in Fig. 1. The feed-forward network is a common ANN architecture that requires relatively little memory and is generally fast (Lawrence 1994). Data move through the layers in one direction, from the input through the hidden to the output layers without loops, in contrast to feedback networks.

Feed-forward networks may be based on linear or non-linear transfer functions that affect the output from the input and hidden layers. Non-linear networks may be trained using supervised learning, learning by example with outputs, or unsupervised learning, self-organizing without outputs. Supervised learning uses known outputs to train the ANN and is more commonly used than unsupervised learning. Back-propagation is a form of supervised learning where the error rate is sent back through the network to alter the weights to improve prediction and decrease error.

The general process to build a neural network model including the creation of data sets for training and testing, training multiple networks with varied parameters, analysing network results, and testing the models (Broner & Comstock 1997). Training sets used to develop models included field-specific rainfall, solar radiation, temperature and wind speed as inputs with associated yields as outputs. The monthly means of the sunshine hours, solar radiation, temperature sum and wind speed from February through to November and 10-day sunshine hours means for June, July and August were used (Table 2).

Because the assignment of connection weights in an ANN model is sensitive to differences in the magnitude of input variables, yield values were scaled to range from 0 to 1 so that the values were within a similar numerical range as other input values. Multiple combinations of monthly mean rainfall, sunshine hours, solar radiation, temperature and wind speed inputs were used during training to determine critical periods for model development. It was necessary to include soil fertility level as an input for all models containing multiple soils types to obtain convergence. Both training and testing data sets contained data from all locations and were randomized before model development. Training data consisted of 290 rice observations of a total of 399 rice observations. The remaining data were used to test the models.

Yield prediction models were developed at the province, regional and local levels. Province level models included all locations, and regional models were based on the coastal plain (Fuding, Nide, Fuzhou, Putian, Quanzhou and Zhangpu) and Wuyi mountain regions (other locations in Fig. 2) within the Fujian province. Local level models were developed for each location.

Adjustment of ANN parameters included the number of hidden nodes, learning rate and training tolerance. The number of hidden nodes selected per model was equal to one-half the total number of inputs plus outputs. The number of nodes were then increased and decreased by one to improve model performance. The learning rate was adjusted between 0·71 and 0·90. Preliminary trials indicated that lower learning rates produced poorly developed models. During early trials, the training tolerance was set at 0·1. Better results were found when the training tolerance was initially set higher and decreased linearly as the network trained. Thus, the training tolerance was generally set at 0·4 and decreased to 0·1 as the network's performance improved.

Table 2. *Inputs used for development of rice yield prediction models*

Input number	Description
1	February mean rainfall
2	March mean rainfall
3	April mean rainfall
4	May mean rainfall
5	June mean rainfall
6	July mean rainfall
7	August mean rainfall
8	September mean rainfall
9	October mean rainfall
10	November mean rainfall
11	February mean sunshine hours
12	March mean sunshine hours
13	April mean sunshine hours
14	May mean sunshine hours
15	June mean sunshine hours
16	July mean sunshine hours
17	August mean sunshine hours
18	September mean sunshine hours
19	October mean sunshine hours
20	November mean sunshine hours
21	February mean solar radiation
22	March mean solar radiation
23	April mean solar radiation
24	May mean solar radiation
25	June mean solar radiation
26	July mean solar radiation
27	August mean solar radiation
28	September mean solar radiation
29	October mean solar radiation
30	November mean solar radiation
31	February mean temperature sum
32	March mean temperature sum
33	April mean temperature sum
34	May mean temperature sum
35	June mean temperature sum
36	July mean temperature sum
37	August mean temperature sum
38	September mean temperature sum
39	October mean temperature sum
40	November mean temperature sum
41	February mean wind speed
42	March mean wind speed
43	April mean wind speed
44	May mean wind speed
45	June mean wind speed
46	July mean wind speed
47	August mean wind speed
48	September mean wind speed
49	October mean wind speed
50	November mean wind speed
51	1–10 June mean sunshine hours
52	11–20 June mean sunshine hours
53	21–30 June mean sunshine hours
54	1–10 July mean sunshine hours
55	11–20 July mean sunshine hours
56	21–31 July mean sunshine hours
57	1–10 August mean sunshine hours
58	11–20 August mean sunshine hours
59	21–31 August mean sunshine hours
60	Soil fertility level means

Regression model development

Multiple linear regression models were developed and tested with the same data sets used for ANN development. This regression method was selected, since it served as a direct technique in Hybrid Variety Performance trials Fujian Agricultural Administration. Field-specific rainfalls, sunshine hours, solar radiation, temperature sum, wind speed and soil fertility level were independent variables and yield was the dependent variable (Table 2). Thus, independent and dependent variables correspond to ANN input and output variables, respectively.

Raw rice yield was scaled to range from 0 to 1 so that values were within a similar numerical range as the other input variables. The regression equations that were developed are referred to as trained models. These models were then validated with the same data sets used to test the ANN models, thus making the results comparable, and are referred to as validated models. The validated models are indicative of the models' capabilities to predict yield, since the testing data are independent of the data used for model development. Specific comparisons were based on RMSE and R^2 of the validated regression model results and the ANN model results.

RESULTS

Over 270 ANN yield prediction models were developed and tested for at the province, regional and local spatial levels. Discussion of ANN model results refer to the tested models. At all spatial levels, models that used monthly means of rainfall and wind speed for February–November in addition to the soil fertility level means failed to converge during training, indicating that the ANN was unable to develop a yield prediction function (Table 3). The lack of convergence also indicated that use of monthly rainfall and wind speed means for February–November did not adequately account for rice yield variability.

Rice prediction at the province level

At the province level, models that used monthly means of sunshine hours ($R^2=0{\cdot}73$), solar radiation ($R^2=0{\cdot}70$), and temperature sum ($R^2=0{\cdot}68$) from February–November for inputs did not predict yield as well as models using 10-day sunshine hours means for June, July and August ($R^2=0{\cdot}76$) in addition to soil fertility level means (Table 3). The model that combined 10-day sunshine hours means for June, July and August and soil fertility level means with monthly means of rainfall for May–September predicted yield more accurately ($R^2=0{\cdot}79$) than models that combined them with monthly means of solar radiation ($R^2=0{\cdot}77$), ($R^2=0{\cdot}76$) and wind speed ($R^2=0{\cdot}78$) for May–September.

Table 3. *Results of tested artificial neural network (ANN) rice yield prediction models with varying model inputs and ANN parameters*

Inputs *	Optimum No. of hidden nodes	Optimum Learning rate	RMSE (kg/ha)	R^2
Province-level				
1–10, 60		Did not converge		
11–20, 60	5	0·83	1213	0·73
21–30, 60	5	0·85	1245	0·70
31–40, 60	5	0·81	1350	0·68
41–50, 60		Did not converge		
51–60	5	0·86	1243	0·76
4–8, 51–60	8	0·84	1212	0·79
24–28, 51–60	8	0·80	1289	0·77
34–38, 51–60	8	0·81	1256	0·76
44–48, 51–60	8	0·82	1225	0·78
4–8, 24–28, 51–60	9	0·85	967	0·81
4–8, 34–38, 51–60	9	0·87	1123	0·80
4–8, 44–48, 51–60	9	0·86	954	0·82
4–8, 24–28, 34–48, 51–60	9	0·84	998	0·84
4–8, 24–28, 44–48, 51–50	9	0·85	989	0·85
4–8, 34–38, 44–48, 51–60	9	0·88	891	0·87
24–28, 34–38, 44–48, 51–60	9	0·83	950	0·85
4–8, 24–28, 34–38, 44–48, 51–60	10	0·82	1251	0·79
Region level				
Coastal plain				
51–60	5	0·81	1345	0·61
4–8, 51–60	7	0·83	1322	0·62
4–8, 44–48, 51–60	7	0·85	1314	0·65
4–8, 34–38, 44–48, 51–60	9	0·86	1221	0·70
Wuyi mountain				
51–60	5	0·85	1243	0·76
4–8, 51–60	7	0·86	1212	0·79
4–8, 44–48, 51–60	7	0·87	954	0·87
4–8, 34–38, 44–48, 51–60	9	0·89	871	0·90
Local level				
Fuding				
51–60	5	0·81	1375	0·62
4–8, 51–60	6	0·84	1342	0·64
4–8, 44–48, 51–60	6	0·87	1304	0·67
4–8, 34–38, 44–48, 51–60	7	0·88	1213	0·70
Nide				
51–60	5	0·81	1385	0·63
4–8, 51–60	6	0·82	1362	0·65
4–8, 44–48, 51–60	6	0·85	1334	0·68
4–8, 34–38, 44–48, 51–60	7	0·87	1201	0·70
Fuzhou				
51–60	5	0·71	1355	0·63
4–8, 51–60	6	0·77	1342	0·65
4–8, 44–48, 51–60	6	0·74	1414	0·62
4–8, 34–38, 44–48, 51–60	7	0·76	1421	0·60
Putian				
51–60	5	0·72	1335	0·61
4–8, 51–60	6	0·78	1312	0·68
4–8, 44–48, 51–60	6	0·75	1444	0·62
4–8, 34–38, 44–48, 51–60	7	0·75	1431	0·61

Table 3 (*cont.*)

Inputs *	Optimum: No. of hidden nodes	Optimum: Learning rate	RMSE (kg/ha)	R^2
Quanzhou				
51–60	5	0·71	1345	0·60
4–8, 51–60	6	0·73	1322	0·62
4–8, 44–48, 51–60	6	0·75	1614	0·55
4–8, 34–38, 44–48, 51–60	7	0·76	2221	0·40
Zhangpu				
51–60	5	0·74	1315	0·61
4–8, 51–60	6	0·76	1202	0·69
4–8, 44–48, 51–60	6	0·75	1514	0·59
4–8, 34–38, 44–48, 51–60	7	0·76	2321	0·41
Pucheng				
51–60	5	0·81	1223	0·74
4–8, 51–60	6	0·82	1202	0·79
4–8, 44–48, 51–60	6	0·85	1094	0·84
4–8, 34–38, 44–48, 51–60	7	0·87	831	0·86
Wuyishan				
51–60	5	0·81	1234	0·77
4–8, 51–60	6	0·82	1162	0·80
4–8, 44–48, 51–60	6	0·85	934	0·86
4–8, 34–38, 44–48, 51–60	7	0·90	721	0·90
Shaowu				
51–60	5	0·82	1233	0·76
4–8, 51–60	6	0·84	1205	0·79
4–8, 44–48, 51–60	6	0·86	956	0·87
4–8, 34–38, 44–48, 51–60	7	0·89	706	0·90
Jianou				
51–60	5	0·80	1221	0·74
4–8, 51–60	6	0·82	1200	0·76
4–8, 44–48, 51–60	6	0·85	1154	0·80
4–8, 34–38, 44–48, 51–60	7	0·86	810	0·86
Jiangle				
51–60	5	0·81	1237	0·76
4–8, 51–60	6	0·82	1214	0·77
4–8, 44–48, 51–60	6	0·85	967	0·81
4–8, 34–38, 44–48, 51–60	7	0·89	829	0·87
Youxi				
51–60	5	0·80	1238	0·75
4–8, 51–60	6	0·83	1219	0·78
4–8, 44–48, 51–60	6	0·84	923	0·82
4–8, 34–38, 44–48, 51–60	7	0·89	817	0·87
Ninghua				
51–60	5	0·80	1235	0·74
4–8, 51–60	6	0·83	1201	0·78
4–8, 44–48, 51–60	6	0·84	1156	0·79
4–8, 34–38, 44–48, 51–60	7	0·86	817	0·86
Liancheng				
51–60	5	0·80	1233	0·74
4–8, 51–60	6	0·81	1202	0·77
4–8, 44–48, 51–60	6	0·85	944	0·86
4–8, 34–38, 44–48, 51–60	7	0·88	710	0·90

Table 3 (*cont.*)

	Optimum			
Inputs *	No. of hidden nodes	Learning rate	RMSE (kg/ha)	R^2
Zhangping				
51–60	5	0·81	1233	0·74
4–8, 51–60	6	0·84	1202	0·77
4–8, 44–48, 51–60	6	0·87	1174	0·80
4–8, 34–38, 44–48, 51–60	7	0·88	800	0·87
Yongding				
51–60	5	0·82	1237	0·74
4–8, 51–60	6	0·83	1233	0·76
4–8, 44–48, 51–60	6	0·85	931	0·80
4–8, 34–38, 44–48, 51–60	7	0·89	803	0·87

* Inputs are defined in Table 1.

The model that combined monthly means of rainfall, 10-day sunshine hours means for June, July and August and soil fertility level means with monthly means of wind speed for May–September predicted yield more accurately ($R^2 = 0{\cdot}82$) than models that combined them with monthly means of solar radiation ($R^2 = 0{\cdot}81$), temperature sum ($R^2 = 0{\cdot}80$) for May–September. The model that included monthly means of rainfall, wind speed, and temperature sum for May–September, 10-day sunshine hours means for June, July and August and soil fertility level means resulted in the best fit of predicted to measured yield for the state ($R^2 = 0{\cdot}67$, RMSE = 891; Fig. 3).

Rice prediction at the region level

The coastal plain region and Wuyi mountain region rice yield prediction models with the highest R^2 (0·70 and 0·90, respectively) and lowest RMSE (1221 and 871, respectively) included soil fertility level means, monthly means of rainfall, wind speed and temperature sum for May–September, and 10-day sunshine hours means for June, July and August (Table 3). The coastal plain models did not predict yield as well as the Wuyi mountain models. The disparity in the accuracy of yield prediction between regions may have been the result of different soil fertility level means, rainfall, wind speed, sunshine hours and temperature in each region. The coastal plain region included six locations, while the Wuyi mountain region included 10 locations. The coastal plain region had highly productive soils. The standard deviation for soil fertility level means values in this region was 0·09 and the mean was 0·87. The Wuyi mountain region had more variable cropping conditions than the coastal plain region with a fertility level means standard deviation of 0·23 and a mean of 0·56.

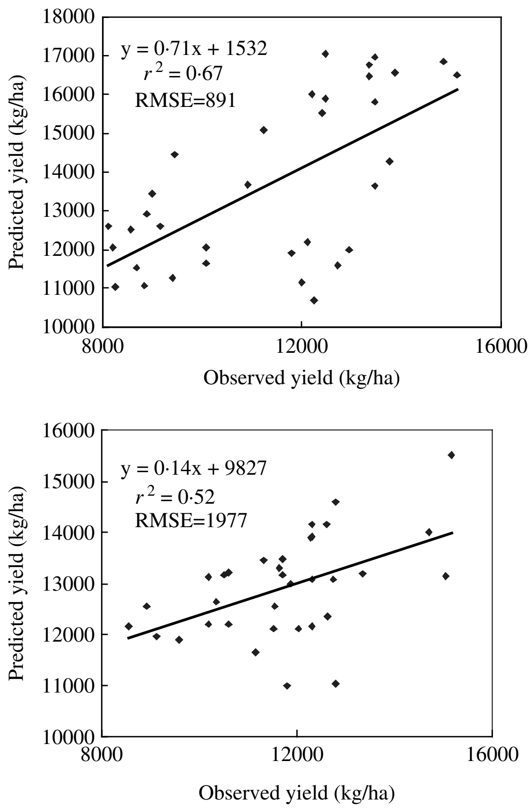

Fig. 3. Scatter plots displaying results of artificial neural network (*a*) and multiple regression (*b*) predicted versus observed rice yields for Fujian from the validation data set. The line represents a least-squares linear regression of predicted versus observed rice yields.

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In the coastal plain region, tropical cyclones, usually characterized by strong high winds, little sunshine, reduced temperature and heavy rainfall are destructive to annual rice. Damage to rice may range from negligible to total destruction depending on the intensity and duration of the storm event, as well as the prevailing rice growth stage during the occurrence of the cyclone. However, the damage to rice may be decreased by hillsides in mountainous regions, thus, the models in mountainous regions predicted yield more accurately than models in the coastal plain.

The Quanzhou location model, located in the coastal plain, had the poorest yield predictions as measured by R^2 (0·40–0·60) and RMSE (2221–1322), indicating a level of variability that was not adequately explained by the chosen input variables. Including this location in the coastal plain model probably increased the amount of variability and may have resulted in decreased performance of the coastal plain regional model.

Rice prediction at the local level

With the exception of the locations in coastal plain, local level models predicted yield more accurately ($R^2 \geqslant 0{\cdot}86$ and RMSE $\leqslant 831$) than region and state models. The inputs used to develop the most accurate local-level rice yield prediction model for each location are similar. The best predictive models were obtained for all locations that utilized monthly means of rainfall, wind speed and temperature sum for May–September, 10-day sunshine hours means for June, July and August and soil fertility level means.

The range of soil fertility level means values decreased as the size of the spatial area being modelled decreased. This result was expected since soil fertility level means values indicate soil and land characteristics and the range of characteristic values decreased with smaller spatial areas.

The timing of sunshine hours inputs for all models is consistent with rice growing season. Peak rice growth occurs during May–September, while plants are in the productive stages of development. Since monthly sunshine hours means for May–September provided insufficient information to predict rice yield, and 10-day sunshine hours means during the same months did provide useful information, it is evident that the models are sensitive to the timing of precipitation as an important factor for rice development.

Comparison of ANN and regression models

ANN parameters were optimized for each combination of sunshine hours, rainfall, temperature sum, wind speed and soil fertility level means inputs. These parameters included training tolerance, number of hidden nodes, learning rate and presentation of data. Adjusting these parameters facilitated the ability of the network to develop an optimal function to predict crop yield. The learning rate and number of hidden nodes had a large effect on model behaviour. Generally, fewer hidden nodes were required as the quantity of data decreased (Table 3). The best models had fewer hidden nodes than the starting number of nodes. ANN models with more nodes may have memorized the input and output connections instead of learning their relationships (Batchelor *et al*. 1997).

The regression models resulted in lower R^2 and higher RMSE than ANN models (Table 4). Although the non-validated regression results were generally better than the validated results, the validated models are indicative of the capability of the models to predict yield with new data. Discussion of regression models will refer to the validated models unless otherwise indicated.

At the state level, the same input groupings were used to develop ANN and regression models that resulted in the most accurate yield predictions. As seen in Fig. 3, yield predictions from regression models ($R^2 = 0{\cdot}52$, RMSE = 1977) were not a good fit to observed yields when compared with ANN yield prediction ($R^2 = 0{\cdot}67$, RMSE = 891). Comparisons of observed versus predicted yields for multiple regression models resulted in a least squares linear regression line with a slope of 0·14 and y-intercept of 9827, while the ANN model comparisons resulted in a line with a slope of 0·71 and y-intercept 1532. The Wuyi mountain region regression model gave the best predictions ($R^2 = 0{\cdot}84$, RMSE = 893) of all rice regression models and performed similarly to maize ANN yield models developed for the Wuyi mountains.

DISCUSSION

The government of the Fujian province has been carrying out a province-wide survey for crop monitoring and for yield forecasting. It has led to a need for simple and accurate techniques to estimate crop yields. Previous efforts resulted in the development of a multiple regression product based solely on soil properties, which did not adequately account for the variability associated with observed yields. The present paper describes the development of artificial neural network models as an alternate and more accurate technique for yield prediction in Fujian province.

As an empirical crop prediction model ANN produced consistently higher R^2 and lower RMSE values than multiple linear regression-based yield models. The R^2 values for validated regressions were lower than those of the non-validated regressions, indicating that testing regression equations with independent data is critical for the evaluation of regression-based rice yield prediction models.

Table 4. *Results of multiple regression rice yield prediction models with varying model inputs*

Input *	Training RMSE (kg/ha)	Training R^2	Validation RMSE (kg/ha)	Validation R^2
Province-level				
11–20, 60	2120	0·44	1213	0·33
21–30, 60	2131	0·42	1245	0·40
31–40, 60	2132	0·42	1350	0·38
51–60	2100	0·49	1143	0·43
4–8, 51–60	2102	0·48	1112	0·44
24–28, 51–60	2198	0·44	1289	0·37
34–38, 51–60	2124	0·43	1256	0·36
44–48, 51–60	2137	0·42	1225	0·38
4–8, 24–28, 51–60	2127	0·45	1267	0·41
4–8, 34–38, 51–60	2109	0·47	1123	0·40
4–8, 44–48, 51–60	2112	0·46	1154	0·44
4–8, 24–28, 34–48, 51–60	2129	0·44	1198	0·41
4–8, 24–28, 44–48, 51–50	2127	0·45	1134	0·42
4–8, 34–38, 44–48, 51–60	1977	0·52	1149	0·45
24–28, 34–38, 44–48, 51–60	2122	0·43	1250	0·35
4–8, 24–28, 34–38, 44–48, 51–60	2147	0·42	1251	0·39
Region level				
Coastal plain				
51–60	2425	0·41	1345	0·41
4–8, 51–60	2312	0·43	1322	0·42
4–8, 44–48, 51–60	2244	0·45	1314	0·45
4–8, 34–38, 44–48, 51–60	2121	0·46	1221	0·50
Wuyi mountain				
51–60	1155	0·75	1043	0·76
4–8, 51–60	1027	0·76	1032	0·79
4–8, 44–48, 51–60	1014	0·77	954	0·87
4–8, 34–38, 44–48, 51–60	1021	0·79	893	0·84

The validated results are indicative of the model's capability to predict yield, since the validation data are independent of the training data used for model development.
* Inputs are defined in Table 1.

The complex initial parameterization procedures of ANN networks need further attention. Furthermore, it is necessary to reserve certain portions of the data for procedures to avoid over fitting, which is not a desirable characteristic for an empirical model-building tool. However, the sensitivity procedure for identifying causal relationships for crop yield offers the most robust interpretability regarding important input factors for crop response.

Park & Vlek (2002) found the topography to be a predominant predictor for spatial distribution with marginal contributions from vegetation patterns. The distribution of soil properties shows a clear linear response to the water-energy-mass flow processes governed by surface topography, even though this generalization strongly depends on measured soil attributes (Odeh *et al.* 1994; Park & Vlek 2002). Many previous regression models have already shown that the response of crops to a single given soil nutrient is already complex enough, and should be modelled as cubic or quadratic functions (e.g. Tejeda *et al.* 1980; Campbell *et al.* 1988). In contrast, crop yield shows more complex, non-linear dynamics among yield responses and soil-management inputs. The combination of these soil nutrient factors in addition to climatic conditions, water variability and land management practices results in complex causal responses (Bouman *et al.* 1996).

Rainfall inputs required for the ANN model correspond to crop developmental phases. Although rainfall during May–September tends to be the most critical for rice growth and development, monthly rainfall means during these months were inadequate for effective crop yield prediction. Weekly rainfall during June–August was necessary to account for the variability associated with rice yield.

The soil fertility values provided a concise and effective method for including many soil and land characteristics related to crop yield. The soil fertility value was a critical input variable for ANN model convergence. Models developed for areas with multiple soil types were especially reliant on soil fertility level means to improve yield prediction accuracy.

Yield predictions using both ANN and regression models improved as the geographic area being modelled decreased. Larger spatial levels included more locations and, therefore, more variability of cropping conditions. With one exception, for rice, local level models predicted yield more accurately than region and province models. ANN models, like regression models, are applicable only to the conditions for which they were developed. The models reported here are appropriate for predicting rice yields in Fujian province in China for average climatic conditions and for the specific soil types used to develop the models.

Since there is no set methodology for ANN development, the approach differs for specific problems and thus requires more time for development than regression models. The learning rate, number of hidden nodes, and the training tolerance had an effect on model development and the accuracy of ANN crop yield predictions. As the quantity of data being modelled decreased due to smaller spatial levels, fewer hidden nodes were required. As the number of hidden nodes decreased, the optimum learning rate decreased, with optimum learning rates falling between 0·71 and 0·90. As the number of nodes decreased, ANN training tended to be slower and required smaller increments of change in the assignments of weights which is reflected by the assigned learning rate. Improved ANN models were produced with training tolerances set high and gradually lowered as the networks trained.

These ANN models show promise as a more accurate technique and have the potential to be useful for the Fujian government's crop monitoring and yield forecasting. With additional information of the soil types, cropping system, crop management should broaden the usefulness, and possibly increase the predictive capabilities of ANN-based yield prediction in mountain areas.

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