Performance evaluation of a variable rate application (VRA) system by artificial neural network (ANN) models

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Abstract: To evaluate the performance of a variable rate boom sprayer, an artificial neural network (ANN) was employed. To model output flow of nozzles, 727 nets by four neural net models, namely, linear, MLP, RBF and GRNN were tested. For each nozzle, 45, 22 and 23 experimental data were used for train, verification and test, respectively. The results indicated that RBF model as the best by regression ratio at 0.2 and coefficient of determination (R2) at 0.98. Based on the results, average value of R2 and coefficient of variation (CV) for RBF model were 0.99 and 18.96%, respectively. From the results, it is concluded that ANN model could be a good predictor to evaluate the performance of a variable rate application system.

Keywords: ANN, control system, precision agriculture, sprayer, VRA.

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1 Introduction

With development of site-specific farm management, construction of variable rate application (VRA) systems is increased and different types of these systems are reported in literatures (Schrock et al., 2001; Carrara et al., 2004; Bora et al., 2005; Kim et al. 2008; Bennur and Taylor 2009). To evaluate the performance of VRA systems, experimental and statistical methods are used which are usually time consuming with and they have low accuracy. Whereas, ANN has become a very powerful and practical method to model systems specially complex and non-linear systems (Chen and Ramaswamy 2002) and it has a good approximation capabilities and offers additional advantages such as short development and fast processing times. In addition, for processes where no satisfactory analytical model exists or where a low-order empirical polynomial model is inappropriate, ANN is a good alternative approach (Miao, et al., 2009; Wang, et al., 2011). The results of studies indicated that the ANN performance for prediction of flow rate and evaluation of variable rate systems was satisfactory. Pokrajac and Obradivic (2001) recommended a neural network-based decision support system for site-specific fertilization in order to optimize financial gain in agricultural works. Both direct and inverse modeling were performed by using linear models and multi-layer neural networks, with use sigmoidal and radial-basis activation functions . The results showed that the proposed direct modeling technique has a high potential for significantly increased financial gain. Yang et al. (2003) used ANN and fuzzy logic for a precision herbicide-spraying system. In this system, ANN evaluated the accuracy of image processing data and a simulated fuzzy logic system controlled variation of application rate and the results were satisfactory. Moshou et al. (2004) presented a technique based on self-organizing neural networks for prediction of

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fertilizer distribution patterns as a function of spreader settings and fertilizer properties. RBF neural network model was used to treat data and carry out decision-making of variable-rate fertilization. Model inputs were soil nutrient (N, P and K) and application rate of fertilizer while the output was yield. The model reflected the nonlinear relationship among soil nutrient, application rate of fertilizer and yield. This model provided evidence for decision-making of variable-rate fertilization (**Juan et al. 2007).** Gao et al. (2012) used an intelligent decision-making method for variable spraying of mobile robot in greenhouse based on a fuzzy neural proposed. The simulation experiment results showed that the intelligent decision-making method could work on real-time and quick. It has the greater decision accuracy than the fuzzy decision system on the samples not appearing in training but has a good fit for the uncertain work environment.

According to the importance of performance evaluation of VRA systems and the ability of ANN in modeling and predicting, the main objective of this research is to evaluate the performance of a variable rate boom sprayer by ANN models.

2 Materials and methods

In this study, a map based variable rate boom sprayer was used. The hardware of this system was composed of different parts, namely, T–GK Solenoid valves (pressure 4Mpa, voltage12VDC, Power 14W and Frequency of 25Hz) which were controlled by changing pulse wide modulation (PWM) method through changing duty cycle (DC) of pulses, digital turbine flow sensors (Model: Vision 2000,REMAG, Mittelholzerstr, Switzerland) for measuring valves flow to reduce error in close-loop control system with accuracy of 3%, 4600 pulse/ liter and Pressure 25 Mpa, GPS module (NEO–DK) with 2.5 m accuracy to distinguish oline coordination of boom sprayer, control board, AVR microcontrollers, supply power and power circuit. Power circuit was used to amplify microcontroller's current (20mA) to the required current to excite solenoid valves (1.2 A).

2.1 Compute program

A computer program with graphical user interface (GUI) was designed by Visual Basic6 in order to connect system hardware with operator. This program was able to: receive online coordination from GPS, receive map data, compare online coordination of sprayer with map coordination, send application order to the solenoid valves, receive nozzle flow values and compare them with map data and finally, apply close-loop control system (Bagheri et al. 2013). The position of solenoid valves, flow sensors and nozzles on the boom sprayer is shown in Figure1. RBF network structure used for evaluation of the VRA system. So, the block diagram of proportional close loop control system is shown in Figure 2. Comparison of experimental and predicted values by ANN model. Proportional close-loop control system was used in order to reduce error and turbulence effect on system. In that system nozzles flow values were read by flow sensors and compared to map data and then a signal was sent to the control system input for reducing error.

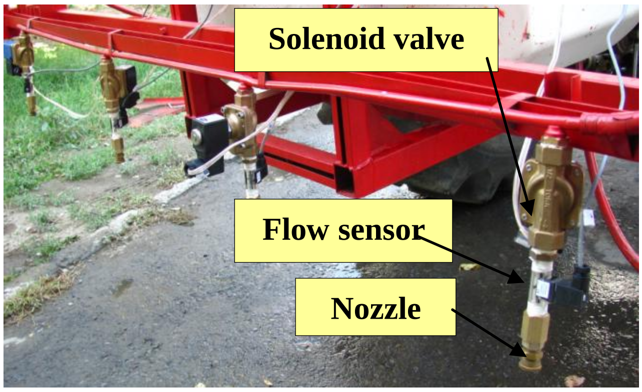

Figure 1 Position of solenoid valves, flow sensors and nozzles on the boom sprayer.

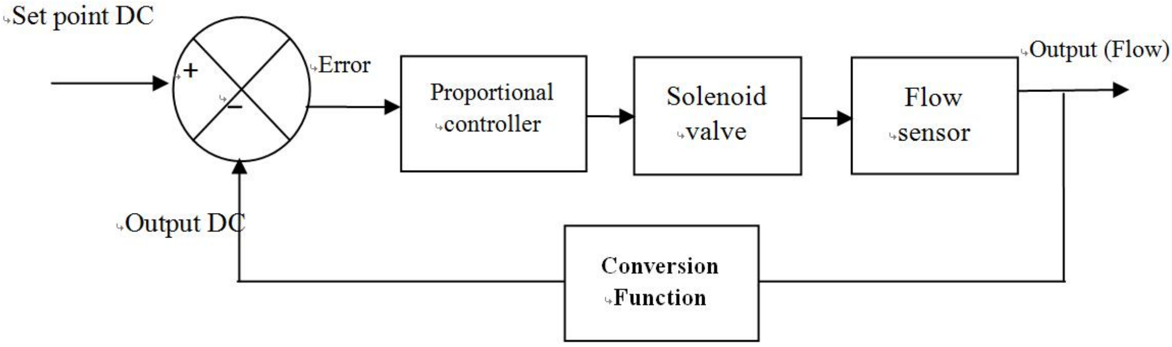

Figure 2 Block diagram of proportional close loop control system

2.2 The nitrogen fertilizer map:

The nitrogen fertilizer map was prepared based on ASTER satellite imagery. Research area was a corn farm with 23 ha. area in Pakdasht town in south of Tehran province in Iran. Plant sampling was carried out simultaneously by passing satellite sensor over the farm. A total of 53 pixels were selected by systematic randomized sampling method. Nitrogen content was determined by the Keldjahl method. Geometric correction was performed by RMS 0.2 pixels. To predict corn canopy nitrogen content, NDVI, MSAVI2, MCARI2 and MTVI2 indices were investigated. Results showed that MTVI2 had the highest correlation with coefficient of R^2=0.87. A supervised classification technique was performed to separate different nitrogen levels. The overall accuracy was 97.53% and kappa coefficient was 0.9669. Results of classification indicated that, there were three levels of nitrogen in farm: high nitrogen level (2.5%-3% nitrogen content), medium nitrogen level (2 %-2.5% nitrogen content) and low nitrogen level (1%-2% nitrogen content). Based on high nitrogen variability in farm, precision management of nitrogen fertilization application is necessary (Bagheri et al., 2011).

To evaluate performance of the variable rate system, ANN modeling was carried out by MATLAB software (The Mathworks, Inc., Natick, Mass.). To predict nozzles flow by ANN, 727 networks were tested and four types of ANN models, namely, linear, multilayer perceptron (MLP), radial basis function (RBF) and generalized regression neural networks (GRNN) were evaluated and trained using the experimental data. As the number of output and input layer's neuron was known (Q_{op} as input layer and Q_1 to Q_4 as output layers), for each ANN type is just identified the number of hidden layers and their neurons. To determine network architecture, 1 hidden layer and 10 neurons are assumed for each network and 50 epochs for evaluating training to compare primary convergence of each network. So, try and error algorithm is used to enhance the number of hidden neurons for each ANN types and their algorithms. Among 90 data collected for each nozzle, 45, 22 and 23 data were selected for training, verification during training and testing networks, respectively. After testing all models, seven networks with the lowest error were chosen among 727 networks.

RBF network structure used for evaluation of VR system is shown in Figure3. In this figure, Q_{op} is the optimum nozzle flow (map data). So, Q_1, Q_2, Q_3 and Q_4 are output solenoid valves flow.

The selected structure had one input, which corresponded to the optimum flow. Four neurons were selected after testing several arbitrary numbers of neurons for the hidden layers. So, the output layer had four neurons which represent nozzles flow values. The ANN models were developed by training the networks for certain epochs or until they converged to the sum of square error (SSE) goal for the target variable, which was nozzle flow.

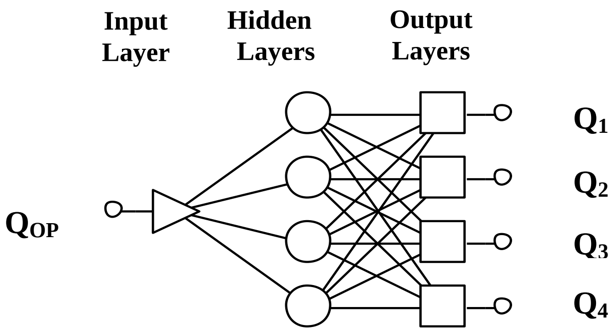

Figure 3 RBF network structure used for evaluation of the VRA system

To evaluate the capability of ANN model in prediction of nozzles flow the coefficient of determination (R^2) and coefficient of variation (CV) was calculated.

3. Results and discussion

3.1 ANN models for evaluation of the VRA system

Based on the result of train, verification, and test error and performance, 7 out of 727 networks were selected as the best models, which are shown in Table 1. In this table, different types of ANN models, namely, RBF, MLP, Linear and GRNN with different combination of hidden layers and training algorithms were showed. Selecting the best network is carried out based on verification error and verification performance. As it is shown in Table 1, RBF type verification error is lower than other models. Error analysis of RBF model for four nozzles is shown in Table 2. So, verification performance of RBF type is lower than MLP type. Linear model had lower verification performance in comparison with RBF model but the RBF type is preferred because this model is more flexible by using sigmoid function in comparison with linear functions. Results showed that more simple networks with lower number of layers could be a better network for prediction of nozzles flow. Notwithstanding, GRNN types designed with large number of hidden layers but they indicted higher verification error and performance in comparison with RBF type. It is because the low inference power of GRNN, which could be seen by comparing its errors with verification errors data. MLP showed higher verification error and performance. As, MLP works based on back propagation, it has good results when the system has a few input layers and one output layer but in this project the system was composed of one input and 4 output layers. Therefore, this model did not show good results.

Totally, RBF model with one input, four hidden and four output layers was selected as the best model by regression ratio of 0.2 (verification error from Table 1) and average correlation of 0.98 (from Table 2). Total error for train, validation and test of RBF type model was 34.7, 38.6 and 49.4, respectively. So, training, verification and test performance was 0.14, 0.20 and 0.17, respectively.

Table1 Suitable ANN models for evaluation of the VRA system

Rank	Type	Hidden	Hidden(2)	Training Error	Verification Error	Test Error	Training Performance	Verification Performance	Test Performance	Training*
1	**RBF**	**4**	**-**	**34.67**	**38.60**	**49.373**	**0.14**	**0.20**	**0.17**	**KM,KN,PI**
2	Linear	-	-	35.46	38.77	36.08	0.15	0.18	0.11	PI
3	GRNN	45	5	32.57	41.23	94.61	0.14	0.19	0.25	SS
4	GRNN	45	5	31.08	41.33	96.02	0.13	0.19	0.26	SS
5	GRNN	45	5	33.36	41.79	93.72	0.14	0.19	0.25	SS
6	RBF	3	-	38.90	44.91	41.48	0.16	0.19	0.13	KM,KN,PI
7	MLP	25	-	54.11	63.37	70.33	0.26	0.31	0.23	BP50,CG1b

Note: MLP (Multilayer Perceptron), RBF (Radial Basis Function), BP50: the network was trained with the Back Propagation for 50 epochs, KM: K-Means algorithm (Moody and Darkin, 1989; Bishop, 1995), KN: K-Nearest neighbor (Bishop, 1995) and PI:Pseudo-Invert algorithm, (Bishop, 1995; Press et. al., 1992; Golub and Kahan, 1965). CG: the conjugate gradient algorithm, b in CG51b means training process was stopped manually because of avoiding overtraining.

Table 2 Error Analyzing of the RBF model

	Q1			**Q2**			**Q3**			**Q4**		
Parameters	**Tr**	**Ve**	**Te**	**Tr**	**Ve**	**Te**	**Tr**	**Ve**	**Te**	**Tr**	**Ve**	**Te**
Data Mean	1192.1	1219.1	1066.0	1187.4	1201.2	1077.1	1191.0	1231.1	1051.7	1184.9	1219.8	1069.7
Data S.D.	227.4	210.3	305.9	233.2	228.8	319.6	226.1	223.8	321.8	225.6	226.7	321.7
Error Mean	0.0	10.5	-7.45	0.0	20.84	-35.93	0.0	-1.82	11.1	0.0	0.61	-22.5
Error S.D.	33.1	41.6	51.1	35.7	36.1	51. 7	35.6	34.3	39.8	35.6	38.5	37.9
Abs E. ean	26.5	35.1	38.9	29.7	35.1	45.2	29.5	26.6	34.0	30.6	33.2	36.1
S.D. Ratio	0.145	0.198	0.167	0.153	0.157	0.161	0.157	0.153	0.123	0.157	0.169	0.12
Correlation	0.989	0.980	0.988	0.988	0.988	0.989	0.987	0.991	0.992	0.987	0.990	0.993

So, Predicted nozzles flow data by RBF model versus the same set of measured data for all nozzles are shown in Figure 4.

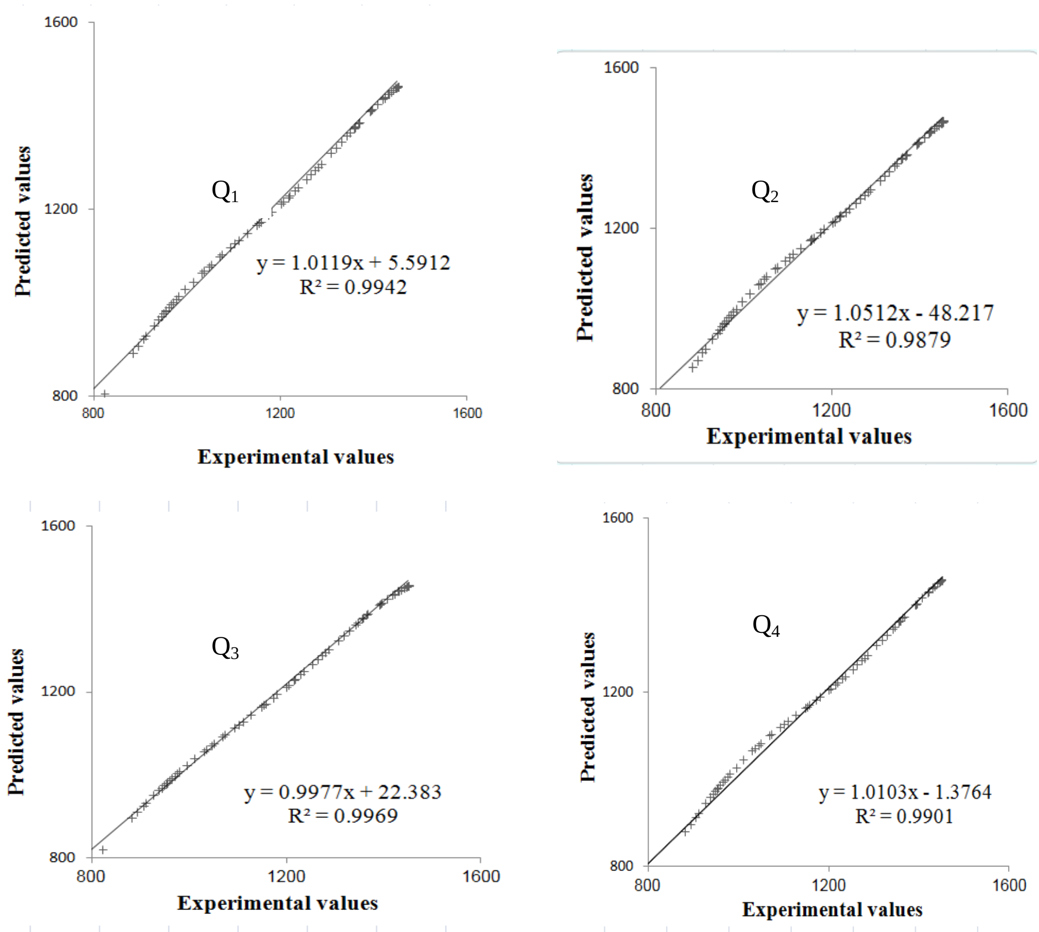

Figure 4 Comparison of experimental and predicted values by RBF model

Results of Figure 4 indicated that the relationship between predicted flow by RBF model and experimental data was closed to linear relationship (with R^2 of 0.99). In other words, linear regression models in Figure 2 shows that for four nozzles, there is high correlation and good agreement between predicted data by RBF model and experimental data. From the results, it is concluded that the RBF model is useful for estimation on nozzles output flow in the variable rate system.

So, average coefficient of variation for RBF model is indicated in Table 3.

Table 3 Average coefficient of variation (CV) for nozzles

Nozzle number	Neural network model
Q_1	17.97
Q_2	19.70
Q_3	19.02
Q_4	19.15
Average	18.96

According to Table 3, the average of CV by RBF was 18.96% which shows low scattering and low variation between data by RBF model.

From high correlation between data, it is concluded that RBF model is suitable enough for evaluation of the RBF system.

Therefore, According to the results, it is proposed using a close-loop intelligent control system based on RBF for prediction of nozzles flow and changing rate of application. In this approach, there is no need to install flow sensors in the close-loop control system to check system error, which leads to simplify system, reduce costs and encourage farmers to use these systems in practice.

4 Conclusions

Firstly, RBF model with one input, four hidden layers and four output layers showed less error between ten ANN selected models which was found to be able to predict the nozzles flow after it was trained adequately.

Secondly, RBF model resulted in average R^2 value of 0.99 between predicted and experimental data.

Thirdly, the average value of CV for RBF model was were 18.96%.

Lastly, based on the results, the nozzle flow predicted by ANN model was reliable to represent the spatial variability in pesticide or fertilizer distribution with reasonable accuracy**.**

References

Al-gaadi, K.A. and P.A. Ayers. 1999. Integration GIS and GPS into a spatially variable rate herbicide application system. *Applied Engineering in Agriculture* 15(4): 255-262.

Bagheri, N., H. Ahmadi, M. Omid, and S. K. Alavipanah. 2011. Preparing Nitrogen Variability Map for Corn Based on Satellite Imagery. *Iranian Journal of biosystem engineering* 42 (1): 111-103.

Bagheri, N., H. Ahmadi, S.K. Alavipanah, M. Omid, and K. Gerami. 2013. A Map-Based System for Variable Rate Liquid Nitrogen Fertilizer Application. *Journal of Agricultural Engineering Research* 13(4):97-108.

Bennur, P. J. and R.K. Taylor. 2009. Response time evaluation of real-time sensor based variable rate technology equipment. ASABE annual international meeting sponsored by ASABE, Reno, Nevada.

Bora, G.C., M.D. Schrock, D. L. Oard, J. J. Grimm, T. C. Kplb and J. J. Hggins. 2005. Reliability tests of pulse width modulation (PWM) valves for flow rate control of anhydrous ammonia. *Applied Engineering in Agriculture* 21(6): 955-960.

Carrara, M., A. Comparetti, P. Febo, and S. Orlando. 2004. Spatially variable rate herbicide application on durum wheat in Sicily. *Biosystems Engineering* 87(4): 387-392.

Chen, C. R. and H.S. Ramaswamy. 2002. Modeling and optimization of variable retort temperature (VRT) thermal processing using coupled neural networks and genetic algorithms. *Journal of Food Engineering* 53 (3): 209–220.

Fleming, K. L. and K.G. Westfall. 2000. Evaluating farmer definded management zone maps for variable rate fertilizer application. *Precision Agriculture* 2: 201-215.

Gopalapillai, S., L. Tian, and J. Zheng. 1999. Evaluation of a flow control system for site-specific herbicide application. *Journal of ASAE* 42(4): 863-870.

Hanna, H.M., P. M. Boyd, K. J. Baumgartner, J. L. Baker, and T.S. Colvin. 2006. Field application uniformity of impellicone and pulse-width-modulated Anhydrous Ammonia manifolds. *Applied Engineering in Agriculture* 22(3): 365-371.

Jeon, H.Y., H. Zhu, R. Derksen, E. Ozkan, and C. Krause. 2011. Evaluation of ultrasonic sensor for variable-rate spray applications. *Computers and Electronics in Agriculture* 7 (1): 213-221.

Juan, L.W**.** 2007. Decision-making Method for Variable-rate Fertilization Based on RBF Neural Network. *Journal of Anhui Agricultural Sciences*.

Kim, Y. J., H.J. Kim, K.H. Ryu, and J. K. Rhee. 2008. Fertiliser application performance of a variable-rate pneumatic granular applicator for rice production. *Journal of Biosystems Engineering* 100: 498-510.

Kasabov, N. K. 1996. Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering. Cambridge, Mass.: The MIT Press.

Koch, B., R. Khosla, W.M. Frasier, D.G. Westfall, and D. Inman. 2004. Economic Feasibility of Variable-Rate Nitrogen Application Utilizing Site-Specific Management Zones. *American Society of agronomy* 96:1572-1580.

Li, F., M. Gnyp, L. Jia, Y. Miao, Z. Yu, W. Koppe, G. Bareth, X. Chen, and F. Zhang. 2008. Estimating N status of winter wheat using a handheld spectrometer in the north China plain. *Journal of Field Crops Research* 106: 77-85.

Noh, H., Q. Zhang, S. Han, B. Shin, and D. Reum. 2005. Dynamic calibration and image segmentation methods for multispectral imaging crop nitrogen deficiency sensors. *The Information & Electrical technologies Division of ASAE*.

Rockwell, A.D. and P.D. Ayers. 1994. Variable rate sprayer development and evaluation. *Applied Engineering in Agriculture* 10(3): 327-333.

Schrock, M.D., J. J. Grimm, D.L. Oard, R.K. Taylor, T.C. Kolb, and J.D. Anderson. 2001. Performance of a multipoint pulse-width modulation metering system for ammonia. *Transactions of the ASAE* 44(2): 211-216.

Sui, R. and J. A. Thomasson. 2006. Ground-Based sensing system for cotton nitrogen status determination. *Transactions of ASABE* 49(6): 1983-1991.

Witten, I. H. and E. Frank. 2000. Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations. *San Diego, Cal.: Academic Press.*

Yang, C.C., S.O. Prasher, J.A. Landry, J. Perret, and H.S. Ramaswamy. 2000. Recognition of weeds with image processing and their use with fuzzy logic for precision farming. *Canadian Agricultural Engineering* 42(4): 195−200.

Yang, C.C., S.O. Prasher, J.A. Landry, and R. Kok. 2002. A vegetation localization algorithm for precision farming. *Biosystems Engineering* 81(2): 137−146.

Zaman, Q.U., T.J. Esau, A.W. Schumann, D.C. Percival, Y.K. Chang, S.M. Read, and A.A. Farooque. 2011. Development of prototype automated variable rate sprayer for real-time spot-application of agrochemicals in wild blueberry fields. *Computers and Electronics in Agriculture* 76 (2): 175-182.