$$\frac{\partial^2 S^2(X_{i\alpha};\beta^0)}{\partial\beta^{0,j}\,\partial\beta^{0,k}} = \frac{1}{m_j m_k}\{S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}+m_j,\dots,\beta^{0,k}+m_k,\dots,\beta^{0,q}) - S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j},\dots,\beta^{0,k}+m_k,\dots,\beta^{q}) - S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}+m_j,\dots,\beta^{0,k},\dots,\beta^{0,q}) - S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,q})\}$$

For $j,k = 1,\dots,q$ and $i = 1,\dots,n$ (3)

The direct diagonal elements of B_0 on the other hand are evaluated as:

$$\frac{\partial^2 S^2(X_{i\alpha};\beta^0)}{(\partial\beta^{0,j})^2} = \frac{1}{m_j m_k}\{S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}+m_j,\dots,\beta^{0,q}) + S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}-m_j,\dots,\beta^{0,k},\dots,\beta^{0,q}) - 2S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,q})\}$$

For $j,k = 1,\dots,q$ and $i = 1,\dots,n$ (4)

β^1 is then obtained by differentiating the right hand side of equation (5) with respect to $\beta^1 - \beta^0$ and equating the result to zero to get:

$$\beta^1 = \beta^0 - B_0^{-1}A_0 \quad (5)$$

The iteration then continues from iteration 1 to 2 until the stopping criterion is met. In general the r^{th} iteration would be given by:

$$\beta^{r+1} = \beta^r - B_r^{-1}A_r \quad (6)$$

Incase during the iteration, the Hessian matrix B becomes non-singular, equation (6) is redefined as follows:

$$\beta^{r+1} = \beta^r - W_r B_r^{-1}A_r \quad (7)$$

Where W_r is the step length and is found such that:

$$S^2(X_{i\alpha};\beta^r - W_r B_r^{-1}A_r) < S^2(X_{i\alpha};\beta^r) \quad (8)$$

This is done using the step halving method in which W_r is first set to one and the function $S^2(X_{i\alpha};\beta^r - W_r B_r^{-1}A_r)$ tested for a decrease. If it fails W_r is decreased by ½ and the test carried out again. The process continues until a decrease in the function occurs. The final value of W_r is the required step length.

By letting the change in parameters $(\beta^{r+1} - \beta^r)$ be:

$$a_r = -W_r B_r^{-1}A_r$$

And

$$b_r = A^{r+1} + A^r \quad (9)$$

The Quasi Newton condition is then be given by:

$$B_{r+1}a_r = b_r \quad (10)$$

Note that the Quasi Newton condition is the ratio of the change in gradient to the change in parameters.

The Quasi Newton method solves equation (11) for B_{r+1} as:

$$B_{r+1} = B_r + \frac{b_r b_r^t}{b_r^t a_r} - \frac{B_r a_r a_r^t B_r}{a_r^t B_r a_r} \quad (11)$$

This continues until the termination criterion is satisfied. The termination criteria in this study included fixing the maximum number of iterations to be attained.

4. A comparison of the statistical accuracy of the calculations from the training, testing and validation phases was then done.

5. The fifth step then involved checking if the statistical accuracy from training, testing, and validation sets were comparable and if they were found not to be, the process was repeated starting with the third step otherwise, an ANN model with an acceptable structure for the desired model was created. Supervised learning was used to train the network because the program knows the outputs it will be trying to calculate, as opposed to unsupervised learning where the outputs are usually unknown.

3. Results and Discussion

As identified in the methodology, data for ANN modeling was divided into 3 categories with 50% for ANN drilling, 25% (67groups) for testing and another 25% for the validation process. Different trials were done in drilling to get the finest possible values for different number of hidden nodes and learning rates for the back propagation algorithm. The error parameter with respect to the number of iterations for various learning rates and number of hidden nodes was noted. At first the value of learning rate was varied keeping the number of hidden nodes constant. Then the number of hidden nodes was varied keeping learning rate constant. The optimal learning rate and number of hidden node were found to be 0.01 and 10NHN respectively. The results from training, testing and validation were compared to verify whether there was consistency in the model developed and summarized as shown in table 3.

Table 3: results from ANN training, testing and validation

		ANN Training			ANN Testing			ANN Validation		
		B	I	M	B	I	M	B	I	M
Original output	B	7	0	0	1	0	0	5	1	1
	I	0	49	0	2	25	1	0	26	0
	M	0	0	11	0	0	5	0	0	3

In general the performance measures from training, testing and validation of the neural networks model were summarized as in table 4.Results indicate a validation accuracy of 97%

Table 4: ANN Performance measures in training, testing and validation

		Testing			Validation		
		Accuracy	True Rate	Precision	Accuracy	True Rate	Precision
Expected output	Beginner	94.03%	1.0000	40%	97.06%	0.8462	100%
	Intermediate		0.9273	100%		1.0000	98%
	Mature		1.0000	90.9%		1.0000	85.71%

4. Conclusion

This paper offers empirical insight on how the performance of farmer groups can be evaluated through mathematical modelling. There exists a relationship between governance, management, leadership, capacity development and resilience and the performance of farmer groups. This findings advocate for greater recognition of the importance and application of statistical methods in the agricultural sector as well as a participatory approach in capacity building through the development of farmers. The model developed will be applied in the capacity needs assessment of farmer organization in determining their maturity levels.

References

[1] Asnaashari A, McBean EA, Shahrour I, Gharabaghi B. 2009. Prediction of watermain failure frequencies using multiple and Poisson regression. Water Science and Technology: Water Supply.

[2] Caudill M. 1988. Neural networks primer, Part III. AI Expert 3.

[3] Despagne F, Massart DL. 1998. Tutorial review: neural networks in multivariate calibration. The Analyst.

[4] Hajela P, Berke L. 1991. Neurobiological computational modes in structural analysis and design. Computers & Structures.

[5] Hecht-Nielsen R. 1989. Theory of the back-propagation neural network. Vol. 1 of Proceedings of the International Joint Conference on Neural Networks, 593–606. Washington, DC: IEEE TAB Neural Network Committee

[6] Maier HR, Dandy GC. 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications. Environmental Modelling and Software.

[7] Najjar YM, Basheer IA, Hajmeer MN. 1997. Computational neural networks for predictive microbiology: methodology. International Journal of Food Microbiology.

[8] Ragasa C. 2012. The Role of Rural Producer Organizations for Agricultural Service Provision in Fragile States Development Strategy and Governance Division. International Food Policy Research Institute.

[9] Ramdwar MN, Ganpat WG, Bridgemohan P. 2013. Exploring the Barriers and Opportunities to the Development of Farmers' Groups in Selected Caribbean Countries. International Journal of Rural Management.

[10] Salchenberger LM, Cinar EM, Lash NA. 1992. Neural networks: A new tool for predicting thrift failures. Journal of Decision Sciences

[11] Shahin MA, Jaksa MB, Maier HR. 2002. Artificial neural network based settlement prediction formula for shallow foundations on granular soils. Australian Geomechanics

[12] Shiferaw B, Hellin J, Muricho G. 2011. Improving market access and agricultural productivity growth in Africa: what role for producer organizations and collective action institutions? Food Security.

[13] Sonam T, Martwanna N. 2011. Performance of smallholder dairy farmers' groups in the East and West central regions of Bhutan: Members' perspective. Journal of Agricultural Extension and Rural Development.

[14] Taylor WA. 1998. Methods and Tools for Process Validation.Taylor Enterprices,Inc.

[15] Vogt WP. 1993. Dictionary of statistics and methodology: A nontechnical guide for the social sciences. Newbury Park,CA: Sage.