

A Survey on Support Vector Machines and Artificial Neural Network in Rainfall Forecasting

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Abstract: The Rain Fall Forecasting is very necessary for agriculture based countries. To increase the productivity of Crop, utilization of water and to avoid the problems of floods needs to know the Rain Fall prediction. In previous years the prediction was done by the statistical methods, but these methods not give the proper results. Now the researchers move from the traditional methods to classification methods. The classification method Artificial Neural Networks (ANN) and Support Vector Machines (SVM) yields accurate results in Rain Fall Forecasting. This paper gives the complete survey on (ANN) and SVM for Forecasting the Rain Fall. In this study clearly explains the issues involved in predicting the Rain Fall.

Keywords: Rainfall forecasting, Artificial Neural Networks, Support Vector Machines.

I. INTRODUCTION

Rainfall forecasting has been a difficult subject in hydrology due to the complexity of the physical processes involved and the variability of rainfall in space and time]. With the development of science and technology, in particular, the intelligent computing technology in the past few decades, many emerging techniques, such as artificial neural network (ANN), have been widely used in the rainfall forecasting and obtained good results. ANN are computerized intelligence systems that simulate the inductive power and behavior of the human brain. They have the ability to generalize and see through noise and distortion, to abstract essential characteristics in the presence of irrelevant data, and to provide a high degree of robustness and fault tolerance [6],[7]. Many experimental results demonstrate that the rainfall forecasting of ANN model outperformed multiple regression, moving average and exponent smoothing from the research literature. In addition, ANN approaches want of a strict theoretical support, effects of applications are strongly depended upon operator's experience. In the practical application, ANN often exhibits inconsistent and unpredictable performance on noisy data.

Recently, support vector regression (SVR), a novel neural network algorithm, was developed by Vapnik and his colleagues, which is a learning machine based on statistical learning theory, and which adheres to the principle of structural risk minimization seeking to minimize an upper bound of the generalization error, rather than minimize the training error (the principle followed by ANN). When using SVM, the main problems is confronted: how to choose the kernel function and how to set the best kernel parameters. The proper parameters setting can improve the SVM regression accuracy. Different kernel function and different parameter settings can cause significant differences in performance. Unfortunately, there are no analytical methods or strong heuristics that can guide the user in selecting an appropriate kernel function and good parameter values. In

order to overcome these drawbacks, a novel technique is introduced. The generic idea consists of three phases. First, an initial data set is transformed into several different training sets. Based on the different training sets, different kernel function of SVM and different parameter settings are then trained to formulate different regression forecasting.

Overview of Artificial Neural Network and Support Vector Machine is presented in below section-II and section-III. Literature survey of rainfall forecasting using ANN and SVM are discussed in section-IV and section-V respectively. A detailed analysis of issues involved in Rain Fall Forecasting is presented in section-VI. Strength of SVM over ANN has been discussed in section-VII. At Last we conclude this work.

II. OVERVIEW OF ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. It is composed of a huge number of highly interconnected processing elements (neurons) working in unison to solve specific problems. An ANN is configured for a particular application, such as pattern recognition or data classification, through a learning process. The artificial neuron is an information processing unit that is fundamental to the operation of a neural network. The artificial neural networks not only analyze the data but also learn from it for future predictions making them suitable for weather forecasting. Neural networks provide a methodology for solving many types of non-linear problems that are difficult to be solved through traditional techniques. Furthermore neural networks are capable of extracting the relationship between

inputs and outputs of a process without the physics being explicitly provided. Hence these characteristics of neural networks can be used for the prediction of the weather

processes [10]. The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.

III. OVERVIEW OF SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine is one of the important category of multi layer feed forward network. Like multi layer perceptrons and radial basis function networks, support vector machines can be used for pattern classification and nonlinear regression. Support Vector Machines (SVMs) developed by Vapnik and his co-workers has been used for supervised learning due to – (i) Better generalization performance than other NN models (ii) Solution of SVM is unique, optimal and absent from local minima as it uses linearly constrained quadratic programming problem (iii) Applicability to non-vectorial data (Strings and Graphs) and (iv) Few parameters are required for tuning the learning m/c. Kernel Methods are a set of algorithms from statistical learning which include the SVM for classification and regression, Kernel PCA, Kernel based clustering, feature selection, and dimensionality reduction etc. SVM is found to be a significant technique to solve many classifications problem in the last couple of years. Very few researchers of this field used this technique for rainfall prediction and got satisfactory result

IV. ANN LITERATURE SURVEY OF RAINFALL FORECASTING

There have been many researchers who have attempted rainfall forecasting. Approaches for rainfall forecasting can be divided into three categories based on time duration for which forecast is made: short-term (weekly), medium term (monthly), and long term (yearly). The works in [2],[3],[17],[20],[22],[24] have designed system for forecasting yearly data. The works in [4],[14],[15],[16],[17],[19],[23],[25],[27],[29],[30],[31],[32] have forecasted the monthly data, whereas the works in [17],[18],[30],[31] have forecasted the daily/weekly data. G.Geetha and R.Selvaraj [1] predicted monthly rainfall of Chennai using ANN. They suggested that for accurate prediction of peak values of rainfall more input parameters are required.

In [14], N.Philip and K.Joseph predicted monthly rainfall of Kerala region. They started with 12 input nodes (corresponding to rainfall of twelve months), 7 hidden nodes, and one output node. They found that ANN gives high accuracy with 48 input nodes (corresponding to 4 years rainfall data). J.Abbot and J.Marohasy [10] predicted monthly rainfall in Australia using Time Delay Recurrent Neural Network (TDRNN). They used input parameters such as monthly rainfall, climate indices, atmospheric temperature, and solar data (sunspot numbers and total solar irradiance). In [15], authors applied ANN for prediction average rainfall over Udipi district of Karnataka. They showed that Back Propagation Algorithm (BPA) was better than the layer recurrent and cascaded back propagation.

They concluded that as the number of hidden neurons increases in ANN, the MSE of a model decreases. In [16], authors applied ANN to predict the rainfall data of Thailand. They used FFNN technique for rainfall forecasting and achieved 96.9% accuracy on test data. K.Htike and O.Khalifa [17] designed four different Focused Time Delay Neural Networks (FTDNN) for rainfall forecasting using yearly, biannually, quarterly, and monthly rainfall data. The FTDNN model using yearly rainfall data set provided the most accurate results on training data set.

M.Sharma and J.Singh [18] predicted weekly rainfall in Pantnagar. They used meteorological parameters such as rainfall, maximum and minimum temperature, and relative humidity at 7.00 am and 2.00 PM. ANN technique achieved minimum prediction error and minimum mean difference compared to multiple linear regression model. V.Somvanshi et al. [3] compared the performance of ANN model with ARIMA technique for predicting rainfall of Hyderabad, INDIA region. They used four past rainfall observations as inputs to neural network model. They concluded that ANN model can be used as a forecasting tool to predict the rainfall, which out-performs the ARIMA model for forecasting the rainfall. N.Philip and K.Joseph in [19] predicted yearly rainfall in Kerala region. They used ABF neural network for rainfall forecasting. They concluded that ABFNN is better tool than the Fourier Analysis. G.Shrivastava et al. [20] designed BPN for Long Range Forecast of monsoon rainfall over small region of India. They concluded that BPN is suitable for identification of internal dynamics of high dynamic monsoon rainfall. R.Deshpande [21] found that for larger step ahead prediction the performance of Multilayer network is better than all other considered networks (Jordan Elman Neural Network, self organized feature map, and RNN), though initially they found that for small step ahead values Jordon Elman Network gave good results.

V. SVM LITERATURE SURVEY OF RAINFALL FORECASTING

The foundation of Support Vector Machines (SVM) was given by Vapnik, a Russian mathematician in the early 1960s (Vapnik 1995), based on the Structural Risk Minimization principle from statistical learning theory and gained popularity due to its many attractive features and promising empirical performance. SVM has been proved to be effective in classification by many researchers in many different fields such as electric and electrical engineering, civil engineering, mechanical engineering, medical, financial and others (Vapnik 1998). Recently, it has been extended to the domain of regression problems (Kecman 2001). In the river flow modeling field, Liong & Sivapragasam (2002) compared SVM with Artificial Neural Networks (ANN) and concluded that SVM's inherent properties give it an edge in overcoming some of the major problems in the application of ANN (Han et al.2006). Nonlinear modeling of river flows of the Bird Creek catchment in the USA with SVM was reported to have its limitations (Han & Yang 2001; Han et al. 2002). Dibike et al. (2001) presented some results showing that Radial Basis Function (RBF) is the best kernel function to be used in

SVM models. However, Bray (2002) found linear kernel outperformed other popular kernel functions (radial basis, polynomial, sigmoid). Bray & Han (2004) illustrated the difficulties in SVM identification for flood forecasting problems. It is clear that, due to its short history, there are still many knowledge gaps in applying SVM in flood forecasting and some conflicting results from different researchers are a good indication that this technique is still in its infancy and more exploratory work is necessary to improve our understanding of this potentially powerful tool from the machine learning community.

VI. ISSUES INVOLVED IN RAINFALL FORECASTING

Challenges in yearly, monthly, and weekly data are as follows. In yearly rainfall data, there is no simple method for determination of the rainfall parameters such as wind speed, humidity, and soil temperature etc. Too few or too many input parameters can affect either the learning or prediction capability of the network. User cannot use same model over long period of time because parameters are varying from day to day, month to month, or year to year. Therefore, new parameters cannot be fitted in the developed model. Forecasting of yearly data is dependent on a sampling interval of input data. In yearly data, if the training set is large then it provides good accuracy. Noises and distortion associated with the random fluctuations are possible in daily or weekly rainfall data. Therefore, daily or weekly rainfall data may not be accurately predicted.

Monthly predictions are better than weekly predictions when compared with actual rainfall data, and show a high correlation. Yearly rainfall data give more useful information than monthly or daily data. Challenges while applying different types of NN modeling for yearly, monthly, and weekly rainfall data are described as follows. In yearly rainfall prediction, average rainfall data is used as input to ANN. Therefore, ANN can easily predict approximate peak value of yearly rainfall data. However, an issue of minor peak detection occurs in the yearly rainfall prediction due to averaging of monthly rainfall data. These minor peak values can be predicted accurately using additional meteorological parameters. In monthly rainfall prediction, actual rainfall data almost meets with the predicted data except for the sharp peak values. Peak detection is major issue in weekly rainfall prediction. Weekly rainfall data contains approximately same range of rainfall (e.g., 6-15 mm) but also contains some peak values (e.g., 25 mm). Due to that average weekly rainfall can be predicted exactly, but peak values can be predicted approximately. Following problems could arise while applying ANN for rainfall forecasting. Zero rainfall is not possible in yearly rainfall prediction because yearly rainfall data includes average rainfall of all seasons. Negative prediction is a major issue in monthly and weekly rainfall data. The negative prediction problem occurs due to extrapolation ability of feed forward back propagation mechanism [11].

The selection of input parameters of ANN depends on the territory (region/state), topography of region (e.g., forests, mountain, and sea), amount and intensity of rainfall.

For yearly data, researchers have used input parameters such as maximum and minimum temperature, humidity, sea surface pressure. For monthly data, researchers [2, 4, 24, 25, 26, 27, 30, 31, 32, 33] have used input parameters such as maximum and minimum temperature, whereas others have used wind speed and relative humidity in addition to maximum temperature and minimum temperature. For weekly data, researchers [19] have used input parameters such as maximum temperature, minimum temperature, relative humidity (7 am, 2 pm), pan evaporation, bright sunshine, whereas others [2, 3, 4, 24, 25, 26, 27, 30, 31, 32, 33] used wind speed, relative humidity, maximum temperature, minimum temperature. Common challenges while applying different types of NN for modeling yearly, monthly and weekly rainfall data are described below:

1) Number of hidden layer and nodes: Main issue in design of NN is the selection of number of hidden layers [12, 13]. The hidden nodes of hidden layer allow neural network to capture the pattern in the data, and perform non linear mapping between input and output variables. Researchers have used one hidden layer for rainfall forecasting. But usage of one hidden layer may require large number of hidden nodes and due to that training ability of neural network gets minimized [12]. Many practitioners [4,14, 18, 25] have used two hidden layers for rainfall forecasting. NN architecture with two hidden layers provides better accuracy on training and test data compared to one hidden layer architecture. More than two hidden layers give same result as achieved with two hidden layers [12].

2) Training and test data : Many practitioners [21],[30] used 50% of data as training and remaining 50% of data as test data, whereas others [15] used 70% of data as training and remaining 30% of data as test data. Inappropriate division of data into training and test datasets will affect the selection of the optimal ANN structure and the forecasting performance of ANN.

3) Overfitting: ANN is prone to data over-fitting problem. This problem occurs due to over-fitting of model on training data or selection of large number of input parameters (dimensions). Over fitting problem can be reduced by using early stopping or regularization method.

4) Performance measures: There are number of performance measures such as mean absolute error, sum of squared error, root mean square error, and mean absolute percentage error used by researchers for evaluating performance of ANN. Some researchers have used more than two measures for checking accuracy, whereas others have used only one performance measure. Therefore, selection of appropriate performance measures is one of the main issues while forecasting rainfall data using ANN.

5) Training algorithm: The error is calculated by taking difference of predicted output and actual output. The synaptic weight can be updated to minimize the error by generating the predicted output as close to the actual output. To update the synaptic weights, different ANN back-propagation training algorithms such as conjugate gradient descent and Levenberg-Marquardt are available. There is no algorithm available which guarantees the global optimal solution for non linear optimization problem. Selection of good training algorithm is problem dependent.

6) **Selection of activation function:** Activation function provides non linear relationship between inputs and outputs. Selection of activation function is also problem dependent. The following 4 activation functions are commonly used by practitioners [2],[3],[12],[13],[18],[19],[20],[21],[22],[23],[24],[26],[27],[29],[33]: sigmoid, tanh, sine or cosine, and linear. Majority of practitioners have used the sigmoid function for rainfall forecasting. Different activation functions can be set for neurons of hidden layer and output layer.

VII. STRENGTHS OF SVM OVER ANN

This section presents a brief discussion of the advantages of SVM over ANN, particularly in terms of the nature of the model, arriving at the optimal architecture and dealing with multi-dimensional inputs. A more detailed discussion on comparison between SVM and ANN can be found in Liong & Sivapragasam (2000).

(a) SVM is not a black-box model: SVM is founded on principles from computational learning theory. Unlike ANN, where the final set of optimal weights and threshold of the trained network cannot be interpreted, the final values of Lagrange multipliers in SVM show the relative importance of the training patterns in arriving at the final decision. (b) Optimal architecture: arriving at the optimal architecture of the network is a time consuming and laborious task in ANN. In contrast, SVM gives the optimal architecture as a solution of quadratic optimization problem. (c) Multi-dimensional inputs: multi-dimensional input vectors result in more complicated ANN architecture with more number of tunable parameters. However, in SVM there is no increase in the number of tunable parameters with the size of input dimension. Since in dual representation, the dot product of two vectors can be easily estimated, SVM can handle multi-dimensional inputs more efficiently and easily than ANN.

VIII. CONCLUSION

This paper refers different Classification techniques like ANN and SVM are presented. ANN is applied for RFF on different parameters are discussed. This survey tells that ANN and SVM are suitable to predict rainfall than other forecasting techniques such as statistical and numerical techniques. In the survey we identify some issues in rainfall data. Support Vector Machines gives better performance on Rain Fall data. This study also deals with strength of SVM over ANN. In this paper we conclude that both play a major role in Rain fall prediction. Finally the SVM has great advantage in some areas with some limitations.

REFERENCES

[1] G. Geetha and R. S. Selvaraj, "Prediction of monthly rainfall in Chennai using Back Propagation Neural Network model," Int. J. of Eng. Sci. and Technology, vol. 3, no. 1, pp. 211-213, 2011.

[2] S. K. Nanda, D. P. Tripathy, S. K. Nayak, and S. Mohapatra, "Prediction of rainfall in India using Artificial Neural Network (ANN) models," Int. J. of Intell. Syst. and Applicat., vol. 5, no. 12, pp. 1-22, 2013.

[3] V. K. Somvanshi, O. P. Pandey, P. K. Agrawal, N.V.Kalanker1, M.Ravi Prakash, and Ramesh Chand,

"Modeling and prediction of rainfall using Artificial Neural Network and ARIMA techniques," J. Ind. Geophys.Union, vol. 10, no. 2, pp. 141-151, 2006.

[4] A. K. Sahai, M. K. Soman, and V. Satyan, "All India summer monsoon rainfall prediction using an Artificial Neural Network," Climate dynamics, vol. 16, no. 4, pp. 291-302, 2000.

[5] D. R. Nayak, A. Mahapatra, and P. Mishra, "A Survey on rainfall prediction using Artificial Neural Network," Int. J. of Comput. Applicat., vol. 72, no. 16, pp. 32-40, 2013.

[6] B. K. Rani and A. Govardhan, "Rainfall prediction using Data Mining techniques-A Survey," Comput. Sci. and Inform. Technology, pp. 23-30, 2013.

[7] Shoba G and Shobha G., "Rainfall prediction using Data Mining techniques: A Survey," Int. J. of Eng. and Comput. Sci., vol. 3, no. 5, pp. 6206-6211, 2014.

[8] R. S. Sangari and M. Balamurugan, "A Survey on rainfall prediction using Data Mining," Int. J. of Comput. Sci. and Mobile Applicat., vol. 2, no. 2, pp. 84-88, 2014.

[9] K. C. Luk, J. E. Ball, and A. Sharma, "An application of Artificial Neural Networks for rainfall forecasting," Mathematical and Comput. modelling, vol. 33, no. 6, pp. 683-693, 2001.

[10] J. Abbot and J. Marohasy, "Application of Artificial Neural Networks to rainfall forecasting in Queensland, Australia," Advances in Atmospheric Sci., vol. 29, no. 4, pp. 717-730, 2012.

[11] V. K. Dabhi and S. Chaudhary, "Hybrid Wavelet-Postfix-GP model for rainfall prediction of Anand region of India," Advances in Artificial Intell., pp. 1-11, 2014.

[12] G. Zhang, B. E. Patuwo, and M. Y. Hu, "Forecasting with Artificial Neural Networks: The state of the art," Int J. of forecasting, vol 14, no. 1, pp. 35-62, 1998.

[13] H. R. Maier and G. C. Dandy, "Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications," Environmental modelling & software, vol. 15, no. 1, pp. 101-124, 2000.

[14] N. S. Philip and K. B. Joseph, "A Neural Network tool for analyzing trends in rainfall," Comput. & Geosci., vol. 29, no. 2, pp. 215-223, 2003.

[15] A. Kumar, A. Kumar, R. Ranjan, and S. Kumar, "A rainfall prediction model using artificial neural network," Control and Syst. Graduate Research Colloq. (ICSGRC), pp. 82-87, 2012.

[16] N. Chantasut, C. Charoenjit, and C. Tanprasert, "Predictive mining of rainfall predictions using artificial neural networks for Chao Phraya River," 4th Int Conf. of the Asian Federation of Inform. Technology in Agriculture and the 2nd World Congr. on Comput. in Agriculture and Natural Resources, Bangkok, Thailand, pp. 117-122, 2004.

[17] K. K. Htike and O. O. Khalifa, "Rainfall forecasting models using Focused Time-Delay Neural Networks," Comput. and Commun. Eng.(ICCCE), Int. Conf. on IEEE, 2010.

[18] M. A. Sharma and J. B. Singh, "Comparative Study of rainfall forecasting models," New York Sci. J., pp. 115-120, 2011.

[19] N. S. Philip and K. B. Joseph, "On the predictability of rainfall in Kerala-An application of ABF neural network," Computational Science-ICCS, Springer Berlin Heidelberg, pp. 1-12, 2001.

[20] G. Shrivastava, S. Karmakar, and M. K. Kowar, "BPN model for longrange forecast of monsoon rainfall over a

- very small geographical region and its verification for 2012,” *Geofizika*, vol. 30, no. 2, pp. 155-172, 2013.
- [21] R. R. Deshpande, “On the rainfall time series prediction using Multilayer Perceptron Artificial Neural Network,” *Int. J. of Emerging Technology and Advanced Eng.*, vol. 2, no. 1, pp. 148-153, 2012.
- [22] P. Goswami and Srividya, “A novel Neural Network design for long range prediction of rainfall pattern,” *Current Sci.(Bangalore)*, vol. 70, no. 6, pp. 447-457, 1996.
- [23] P. Guhathakurta, “Long lead monsoon rainfall prediction for meteorological sub-divisions of India using deterministic Artificial Neural Network model,” *Meteorology and Atmospheric Physics* 101, pp. 93-108, 2008.
- [24] S. Chattopadhyay, “Anticipation of summer monsoon rainfall over India by Artificial Neural Network with Conjugate Gradient Descent Learning,” *arXiv preprint nlin/0611010*, pp. 2-14, 2006.
- [25] S. Chattopadhyay and M. Chattopadhyay, “A Soft Computing technique in rainfall forecasting,” *Int. Conf. on IT, HIT*, pp. 19-21, 2007.
- [26] S. Chattopadhyay and G. Chattopadhyay, “Comparative study among different neural net learning algorithms applied to rainfall time series,” *Meteorological applicat.*, vol. 15, no. 2, pp. 273-280, 2008.
- [27] S. Chattopadhyay, “Feed forward Artificial Neural Network model to predict the average summer-monsoon rainfall in India,” *Acta Geophysica*, vol. 55, no. 3, pp. 369-382, 2007.
- [28] S. Gadgil, M. Rajeevan, and R. Nanjundiah, “Monsoon prediction-Why yet another failure?,” *Current Sci.*, vol. 88, no. 9, pp. 1389-1400, 2005.
- [29] C. Venkatesanet, S. D. Raskar, S. S. Tambe, B. D. Kulkarni, and R. N. Keshavamurthy, “Prediction of all India summer monsoon rainfall using Error-Back-Propagation Neural Networks,” *Meteorology and Atmospheric Physics*, pp. 225-240, 1997.
- [30] C. L. Wu, K. W. Chau, and C. Fan, “Prediction of rainfall time series using Modular Artificial Neural Networks coupled with datapreprocessing techniques,” *J. of hydrology*, vol. 389, no. 1, pp. 146-167, 2010.
- [31] C. L. Wu and K. W. Chau, “Prediction of rainfall time series using modular soft computing methods,” *Eng. Applicat. of Artificial Intell.*, vol. 26, no. 3, pp. 997-1007, 2013.
- [32] Priya, Shilpi, Vashistha, and V. Singh, “Time Series Analysis of Forecasting Indian Rainfall,” *Int. J. of Innovations & Advancement in Comput. Sci.*, vol. 3, no. 1, pp. 66-69, 2014.
- [33] A. R. Naik and S. K. Pathan, “Indian monsoon rainfall Classification And Prediction using Robust Back Propagation Artificial Neural Network,” *Int. J. of Emerging Technology and Advanced Eng.*, vol. 3, no. 11, pp. 99-101, 2013.
- [34] S. S. Chinchorkar, V. B. Vaidya, and V. Pandey, “Long range forecast of South-West monsoon rainfall for 2013 for different regions of Gujarat,” *Int. Daily J. for Climate Change, Global Warming and Sustainability*, vol. 2, no. 2, pp. 6-9, 2013.
- [35] S. S. Chinchorkar, V. B. Vaidya, and V. Pandey, “Forecasting seasonal rainfall in different locations of Maharashtra,” *J. of Agrometeorology*, vol. 14, pp. 386-389, 2012.
- [36] .ASCE Task Committee. 2000a Artificial neural networks in hydrology-1: preliminary concepts. *J. Hydrol. Engng* 5(2), 115–123.
- [37] .ASCE Task Committee. 2000b Artificial neural networks in hydrology-2: hydrologic applications. *J. Hydrol. Engng* 5(2), 124–137.
- [38] .Babovic, V., Keijzer, M. & Bundzel, M. 2000 From global to local modelling: a case study in error correction of deterministic models. *Hydroinformatics’2000*, Iowa Institute of Hydraulic Research, Iowa, USA (CD-ROM).
- [39] .Cao, L. & Soofi, A. S. 1999 Nonlinear deterministic forecasting of daily dollar exchange rates. *Int. J. Forecast.* 15, 421–430.
- [40] .Cristianini, N. & Shawe-Taylor, J. 2000 *An Introduction to Support Vector Machines*. Cambridge University Press, Cambridge, UK.