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ORIGINAL PAPER

Comparative evaluation of linear and nonlinear weather-based models for coconut yield prediction in the west coast of India

Bappa Das[1] · Bhakti Nair[1] · Vadivel Arunachalam[1] · K. Viswanatha Reddy[1] · Paramesh Venkatesh[1] · Debashis Chakraborty[3] · Sujeet Desai[1]

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Abstract

Coconut is a major plantation crop of coastal India. Accurate prediction of its yield is helpful for the farmers, industries and policymakers. Weather has profound impact on coconut fruit setting, and therefore, it greatly affects the yield. Annual coconut yield and monthly weather data for 2000–2015 were compiled for fourteen districts of the west coast of India. Weather indices were generated using monthly cumulative value for rainfall and monthly average value for other parameters like maximum and minimum temperature, relative humidity, wind speed and solar radiation. Different linear models like stepwise multiple linear regression (SMLR), principal component analysis together with SMLR (PCA-SMLR), least absolute shrinkage and selection operator (LASSO) and elastic net (ELNET) with nonlinear models namely artificial neural network (ANN) and PCA-ANN were employed to model the coconut yield using the monthly weather indices as inputs. The model's performance was evaluated using R^2, root mean square error (RMSE) and absolute percentage error (APE). The R^2 and RMSE of the models ranged between 0.45–0.99 and 18–3624 nuts ha^{-1} respectively during calibration while during validation the APE varied between 0.12 and 58.21. The overall average ranking of the models based these performance statistics were in the order of ELNET > LASSO > ANN > SMLR > PCA-SMLR > PCA-ANN. Results indicated that the ELNET model could be used for prediction of coconut yield for the region.

Keywords Weather · Coconut yield · Prediction model · Artificial neural network · Sparse regression models

Introduction

Coconut (*Cocos nucifera* L.) is mostly grown between the north and the south equator in humid tropics, spreading over more than 90 countries covering an area of about 12.9 Mha and with a production of nearly 61.2 billion nuts (Naresh Kumar and Aggarwal 2013). Major coconut growing countries are India, Malaysia, Sri Lanka and Philippines. Coconut plays a significant role in the economy of these countries. India has an annual production of 22.17 billion nuts over 2088.47 ha land with productivity of 10,614 nuts ha^{-1} (CDB 2016). It is the main source of income for the most resource-poor families of coastal India. Coconut palm normally produces one bunch per month, and each bunch requires 38 months for its full development (Peiris and Peries 1993; Ranasinghe et al. 2015). After opening of the inflorescence, a period of 11 months is generally required for complete development into nut (Pathmeswaran et al. 2018). Therefore, coconut yield is subject to variations in climatic condition, especially after opening of the inflorescence. Being a perennial crop, single generation of coconut experiences changes in different climatic factors like change in CO_2 concentration, temperature, rainfall for the next 50 years of its growth throughout its life, affecting the economic yield. In addition, coconut can majorly be grown in the areas with high rainfall and high humidity (Naresh Kumar et al. 2009a; Naresh Kumar and Aggarwal 2013).

Studies have been carried out to evaluate the effect of climate on coconut production (Aggarwal et al. 2006; Naresh

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✉ Bappa Das
bappa.iari.1989@gmail.com

1 Central Coastal Agricultural Research Institute, ICAR, Old Goa, Goa 403 402, India

2 Present address: Central Tobacco Research Institute, ICAR, Rajahmundry, Andhra Pradesh 533 105, India

3 Indian Agricultural Research Institute, ICAR, New Delhi 110 012, India

Kumar et al. 2009b). According to Ranasinghe et al. (2015), the final yield of coconut depends on the early fruit setting which can be affected due to hostile weather. Naresh Kumar et al. (2007) studied cumulative effect of dry spell and rainfall on coconut yield and concluded that dry spell occurrence in 1 year would affect coconut yield for subsequent years, and the effect could be stronger on the fourth year irrespective of the rainfall. According to Peiris and Peries (1993), rainfall in January and February months was most effective while a high-intensity rainfall in May–August months could have adverse effect on the coconut yield. Rainfall during November and December had significant adverse effect on coconut in Sri Lanka. Peiris et al. (2008) using multiple linear regression reported positive effect of rainfall during January–March in all agro-ecological regions (AERs) and July–September on coconut production in the wetter regions of Sri Lanka. Rainfall, relative humidity and temperature of previous year during February, June, July, September and December months influenced the coconut yield to a large extent (Peiris and Thattil 1998). Naresh Kumar et al. (2009b) developed coconut yield prediction models with good to excellent accuracy (R^2 = 0.591–0.997) using different weather variables and multiple regression analysis for different agroclimatic zones of India. Balakrishnan and Meena (2010) used advance regression model i.e. artificial neural network (ANN) to forecast the coconut yield for the Andaman–Nicobar region using the using yearly weather data. Jayashree et al. (2015) compared six different models namely multilayer perceptron, support vector machine, decision tree, Naïve Bayes, fuzzy cognitive map and data-driven nonlinear Hebbian in combination with fuzzy cognitive map using both soil and weather variables for coconut yield prediction. But the main problem of this study was that the predictions were qualitative in terms of high, medium and low. Though prediction of coconut yield by means of simple and advance regression models based on weather parameters has been studied previously (Peiris et al. 2008; Naresh Kumar et al. 2009b; Jayashree et al. 2015; Jayakumar et al. 2016), comparison of multiple statistical models received much lesser attention. On the other hand, multiple linear regression (MLR) technique can be accepted for a smaller dataset but its application is restricted when the number of predictors is greater than the number of samples (Balabin et al. 2011). To deal with such problem, feature selection in the form of stepwise MLR or penalized regressions, feature extraction in the form of principal component analysis (PCA) and combination of these two methods of data analysis like PCA-SMLR are advised (Das et al. 2018a). Feature selection techniques aim to reduce the number of variables by selecting a set of most important variables which best describes the dependent variable while feature extraction techniques like PCA derive some new variables (PCs) from the original variable while conserving the maximum variability present in the original dataset. On this background, the present study was undertaken with the objectives to develop and compare the performance of linear models like stepwise multiple linear regression (SMLR), principal component analysis (PCA) followed by SMLR, least absolute shrinkage and selection operator (LASSO) and elastic net (ELNET) with nonlinear regression model like artificial neural network (ANN) and PCA-ANN for district-wise coconut yield prediction models of the west coastal region of India.

Materials and methods

A total of fourteen districts from western coastal zone were selected for this study: Thane (19.29° N, 72.97° E), Raigad (18.51° N, 73.18° E), Ratnagiri (16.99° N, 73.31° E), North Goa (15.49° N, 73.83° E), South Goa (15.39° N, 73.84° E), Uttar Kannada (14.79° N, 74.68° E), Udupi (13.33° N, 74.74° E), Dakshina Kannada (12.84° N, 75.24° E), Alleppey (09.49° N, 76.33° E), Kozhikode (11.25° N, 75.78° E), Kannur (11.87° N, 75.37° E), Kottayam (9.59° N, 76.52° E), Kollam (9.01° N, 76.93° E) and Trivandrum (8.52° N, 76.94° E).

Daily data of four weather variables viz. daily maximum (Tmax, °C) and minimum temperatures (Tmin, °C), wind speed (m s^{-1}), relative humidity (RH, %) and rainfall (RAIN, mm) were obtained from the India Meteorological Department (IMD), Pune, during the year 2000 to 2015 (15 years). Solar radiation (SRAD, MJ m^{-2} day^{-1}) data were downloaded from the National Aeronautics and Space Administration's Prediction of Worldwide Energy Resources web portal (NASA POWER; https://power.larc.nasa.gov/data-access-viewer/) as for most the stations daily sunshine hours or solar radiation data was not available from IMD. So, there might be some physical inconsistencies in the inputs like rainy days with high solar radiation as solar radiation data was taken from another source. To check that, we have also calculated the solar radiation using the Hargreaves and Samani (1982) equation based on maximum and minimum temperature and extraterrestrial radiation (Ra). Then the relationship of monthly NASA Power solar radiation with monthly rainfall and Hargreaves and Samani (1982) equation-based monthly solar radiation with monthly rainfall was calculated. The results of the correlation analysis showed that NASA power solar radiation was better correlated with rainfall than Hargreaves and Samani (1982) equation-based solar radiation (Supplementary Table S1). The negative correlation for all the stations showed that the days with high rainfall were associated with low solar radiations. So, we have used the NASA power solar radiation for modelling the coconut yield. Daily data of Tmax, Tmin, wind, RH and SRAD were converted into their monthly average values, while the monthly sum for RAIN was taken. Yield data were collected from the Coconut Development Board for year 2000–2014 and were used for calibration while the yield data of 2015 was used for validation of the models. The coconut yield depends on meteorological as well as non-meteorological parameters like area under coconut production, application of irrigation, fertilizers and pesticides. The total non-meteorological parameters have been growing steadily and are difficult to quantify (Subash et al. 2013; Subash and Gangwar 2014). Therefore, linear de-trended coconut yield was used to develop weather indices (regressors) (Fig. 1).

Weather index approach

Earlier studies indicated that a joint effect of weather parameters was more successful for yield prediction than the individual weather parameter approach. Therefore, two types of weather indices i.e. simple and weighted (single, and interaction of two weather variables in every possible combination) (Ghosh et al. 2014) were computed using the following formula:

Simple weather indices

$$Z_{ij} = \sum_{m=1}^{n} X_{im} \tag{1}$$

$$Z_{ii'j} = \sum_{m=1}^{n} X_{im} X_{i'm} \tag{2}$$

Weighted weather indices

$$Z_{ij} = \sum_{m=1}^{n} r_{im}^{j} X_{im} \tag{3}$$

$$Z_{ii'j} = \sum_{m=1}^{n} r_{ii'm}^{j} X_{im} X_{i'm} \tag{4}$$

where

$X_{im}/X_{i'm}$	value of the ith/i'th weather variable under study in the mth month
$r^{j}_{im}/r^{j}_{ii'm}$	correlation coefficient of de-trended yield with ith weather variable or product of the ith and i'th weather variables in the mth month
n	month of prediction
p	number of weather variables used.

Use of weather variables to generate different weather indices is presented in Table 1.

Multivariate techniques

The details of multivariate techniques used in this study to develop coconut yield prediction model are described in the following sections:

Artificial neural network

Artificial neural network (ANN) is a nonlinear machine learning technique which mimics the working principle of the human brain. It consists of interconnected neurons or nodes arranged in three groups namely input (one), hidden (one or more) and output (one) layer. Each layer consists of neurons or nodes interconnected with each other. The number of neurons in the input and output layers is determined by the dataset used while the optimum number of hidden neurons should be optimized. In this investigation, the 42 weather indices and year were used as input variables while coconut yield was used as output variable and the number of neurons in the

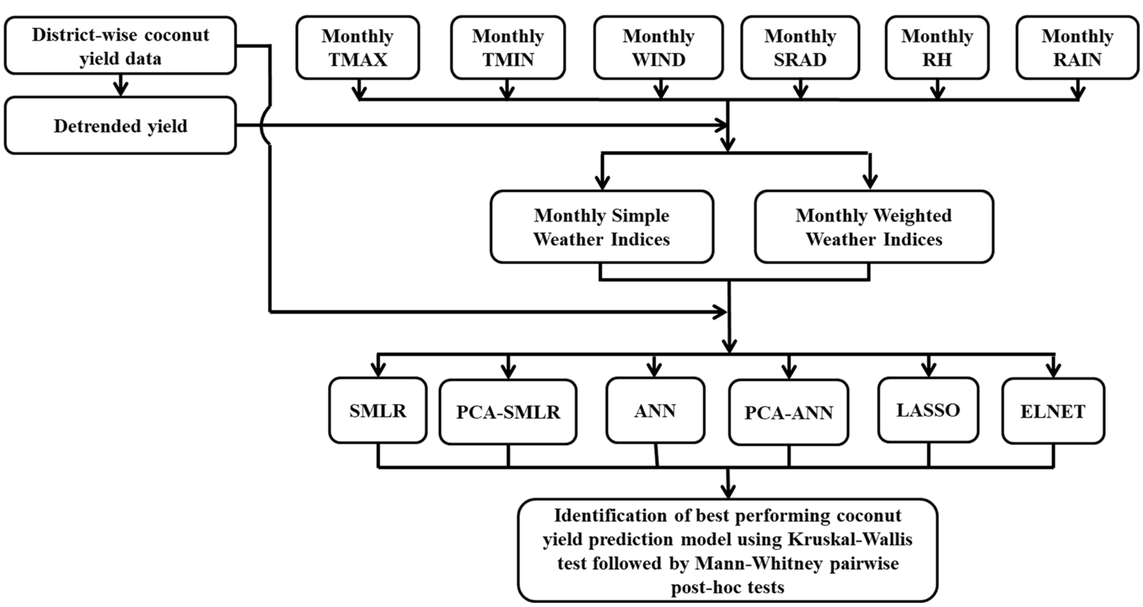

Fig. 1 Flowchart demonstrating steps in model development

Table 1 Simple and weighted weather indices

	Simple weather indices						Weighted weather indices					
	Tmax	Tmin	Wind	SRAD	RH	Rain	Tmax	Tmin	Wind	SRAD	RH	Rain
Tmax	Z10						Z11					
Tmin	Z120	Z20					Z121	Z21				
Wind	Z130	Z230	Z30				Z131	Z231	Z31			
SRAD	Z140	Z240	Z340	Z40			Z141	Z241	Z341	Z41		
RH	Z150	Z250	Z350	Z450	Z50		Z151	Z251	Z351	Z451	Z51	
Rain	Z160	Z260	Z360	Z460	Z560	Z60	Z161	Z261	Z361	Z461	Z561	Z61

hidden layer was tuned using 'caret' package with 10-fold cross-validation in R software (Kuhn 2008). The activation function for hidden and output layer used in the current study was hyperbolic tangent and identity, respectively.

Principal component analysis

A principal component analysis (PCA) was performed on all 42 weather indices for each district. According to the benchmarks set by Brejda et al. (2000), the principal components (PCs) with eigenvalues > 1 and which explained ~ 95% of the total variation in the dataset were considered. The main purpose of PCA is to construct a linear combination of the original variables that represent most of the variations present in the data set under investigation with reduced dimensionality and multicollinearity.

Stepwise multiple linear regression

Stepwise multiple linear regression (SMLR) is a linear feature selection technique in which a model is built by successively adding or removing variables based on the *p* value of *F* statistic at each step (Draper and Smith 1998). In the present study, for inclusion or removal of a weather index into the model, the *p* values were set at 0.05 and 0.10, respectively.

Principal components analysis-stepwise multiple linear regression and principal components analysis-artificial neural network

PCA followed by SMLR is the combination of feature extraction and selection method while PCA-ANN is feature extraction followed by nonlinear regression without any variable selection. To overcome the problem of multicollinearity, PC scores were used as predictor variables for SMLR and ANN to develop the coconut yield models.

Least absolute shrinkage and selection operator and elastic net

The least absolute shrinkage and selection operator (LASSO) and elastic net (ELNET) are two sparse regression methods used for handling the multicollinearity. These methods deal with multicollinearity by penalizing the magnitude of regression coefficients. The difference between LASSO and ELNET is that LASSO uses L1 regularization while ELNET uses both L1 and L2 regularization. LASSO and ELNET implementation have two parameters namely lambda and alpha which should be tuned to prevent overfitting. The optimal lambda values for LASSO and ELNET were selected through leave-one-out cross-validation (Piaskowski et al. 2016) while the alpha was set at 1 and 0.5 for LASSO and ELNET, respectively.

Model performance evaluation

For comparison of the models, statistical parameters like R^2 and root mean square error (RMSE) were used for calibration dataset using following formula:

$$R^2 = \left(\frac{\frac{1}{n}\sum_{i=1}^{n}\left(M_i - \overline{M}\right)\left(O_i - \overline{O}\right)}{\sigma_M \sigma_O} \right)^2 \quad (5)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - M_i\right)^2} \quad (6)$$

Absolute percentage error (APE) was used to test the model during validation.

$$\mathrm{APE}\ (\%) = \left| \frac{(M_i - O_i)}{O_i} \right| \times \frac{100}{n} \quad (7)$$

M_i: model output; $\overline{\mathrm{M}}$ and σ_M: mean and standard deviation of model output, respectively; O_i: observations; $\overline{\mathrm{O}}$ and σ_O: mean and standard deviation of observations, respectively. The models were ranked based on R^2 and RMSE values for calibration; APE of validation and average ranks across the districts were calculated to identify the best performing model.

Results

Coconut yield and climate of the study area

Descriptive statistics of coconut yield in the west coastal districts of India over the years 2000 to 2015 are presented in Supplementary Table S1. The yield varied between 2940 and 17,749 nuts ha^{-1} with a mean of 6953 nuts ha^{-1} (Supplementary Table S2). Coefficients of variation (CVs) ranged between 1.25 and 56.02%. The average maximum yield across the years was recorded in Raigad district (9885 nuts ha^{-1}) while the average minimum was in North Goa district (4965 nuts ha^{-1}). The assumptions of normality of the yield data for each district were tested using the Jarque–Bera test which was found nonsignificant ($p > 0.05$). The study area falls under hot humid ecoregion. The average monthly maximum temperature varied between 25.9 and 38.0 °C with a mean value of 31.7 °C while the average monthly minimum temperature ranged between 15.5 and 29.1 °C (Supplementary Table S3). Average monthly wind speed, solar radiation and RH were recorded as 3.9 m s^{-1} (1.4–10.0 m s^{-1}), 19.7 MJ m^{-2} (0.0–28.5 MJ m^{-2}) and 77.6% (40.1–92.8%), respectively with CVs of 37.1, 17.8 and 13.1%, respectively. The mean annual rainfall of the region was 2734.8 mm (1790.3–3636.7 mm) with a CV of 19.9%.

Stepwise multiple linear regression model

Coconut yield prediction models were evaluated using R^2 and root mean square error (RMSE) for calibration dataset (Table 2). The R^2 for SMLR was ranged between 0.57 (North Goa) to 0.98 (Kottayam). However, the RMSE varied between 25 nuts ha^{-1} (South Goa) and 1857 nuts ha^{-1} (Raigad). In case of SMLR model, all weather indices except Z50 for Thane, Z140 for Ratnagiri, Z240 for South Goa, Z450 and Z230 for Kottayam and Z120 for Trivandrum had positive influence on the coconut yield. Decoding of weather indices revealed that Tmin had the maximum influence on coconut yield followed by RH and wind speed. The absolute percentage error during validation (APEV) varied between 0.86% (North Goa) and 52.84% (Thane). Results indicated that the predictions were satisfactory for all locations except for Thane, Raigad, Ratnagiri, Udupi, Uttara Kannada and Trivandrum where the APEV was > 10%. To test the multicollinearity, variance inflation factor (VIF) was calculated for every independent variable selected through SMLR. The VIF values revealed no or moderate correlation except for Z130 and Z230 of Kottayam district.

Principal component analysis-stepwise multiple linear regression model

The number of PCs retained for various districts varied between 4 and 7 which were able to explain more than 90% variability present in the dataset (Table 3). The maximum R^2 was observed for Kottayam (0.98) with RMSE 58 nuts ha^{-1}, and minimum was recorded for Alleppey (0.53) with RMSE 551 nuts ha^{-1}. All the PCs had positive influence on coconut yield except PC5 and PC2 for North Goa and Udupi, respectively. The RMSE ranged between 38 nuts ha^{-1} (South Goa) and 2478 nuts ha^{-1} (Raigad). The APE during validation ranged between 0.17% (North Goa) and 57.73% (Raigad). The performance of the models was excellent during validation for North Goa, South Goa, Alleppey, Kannur, Kottayam, Kollam and Trivandrum districts with APEV < 10%. The main problem with PCA analysis is that it is not possible to identify the underlying predictor variable which is influencing the dependent variable. The multicollinearity as indicated by VIF values has been significantly reduced when principal components were used as regressors over SMLR. The reduction of multicollinearity was especially conspicuous for Kottayam district.

Artificial neural network and principal component analysis-artificial neural network model

For development of coconut yield prediction models using ANN, the Z variates were standardized by substracting mean from each case and dividing by the standard deviation while for PCA-ANN the PCA scores were standardized and used as regressors with time. Standardization was done to reduce the multicollinearity and making the input variables scale independent. The number of hidden neurons for ANN varied between 5 (Ratnagiri and North Goa) and 11 (Dakshina Kannada and Kannur) (Table 4). For PCA-ANN, the number of input neurons ranged between 5 and 8 depending on the number of PCs retained while the number of hidden neurons varied between 1 and 6 (Table 5). Coconut yield was taken as output neuron for both ANN and PCA-ANN. The R^2 and RMSE during model development varied between 0.46–0.95 and 19–3624 nuts ha^{-1} for ANN and 0.45–0.96 and 34–3024 nuts ha^{-1} for PCA-ANN. The APE during validation ranged between 0.19 and 54.23% and 0.27 and 58.21% for ANN and PCA-ANN, respectively. The validation of the models revealed that the performance of the models was good for Raigad, North Goa, South Goa, Alleppey, Kozhikode, Kannur, Kottayam and Kollam districts both for ANN and PCA-ANN. It is worth mentioning that PCA-ANN with much less number of input variable was able to provide comparable performance with ANN.

Table 2 Coconut yield prediction models for different districts of West Coast developed using SMLR

Districts	Predictor variables	Coefficient	VIF	R^2 ($p < 0.01$)	RMSE (nuts ha^{-1})	APEV (%)
Thane	Constant	93,609.52		0.87	1506	52.84
	Z351	16.84	1.002			
	Z50	− 1.90	1.002			
Raigad	Constant	− 9102.60		0.83	1857	40.81
	Z231	103.65	2.838			
	Z350	8.75	2.838			
Ratnagiri	Constant	1893.52		0.94	458	18.46
	Z151	7.55	1.289			
	Z231	92.70	1.224			
	Z361	1.22	1.446			
	Z140	− 2.41	1.278			
North Goa	Constant	6596.75		0.57	58	0.86
	Z121	0.84	1			
South Goa	Constant	5810.904		0.84	25	1.56
	Z121	1.906	2.552			
	Z41	0.799	1.768			
	Z240	− 0.096	1.797			
Uttara Kannada	Constant	11,133.452		0.94	371	20.36
	Z51	56.194	1.271			
	Z120	− 2.361	1.271			
Udupi	Constant	− 1268.249		0.90	468	21.44
	Z451	2.348	1			
Dakshina Kannada	Constant	37,313.764		0.83	1084	1.35
	Z451	10.004	1			
Alleppey	Constant	25,692.1		0.76	393	4.81
	Z11	275.271	1.702			
	Z241	5.195	1.702			
Kozhikode	Constant	9241.795		0.74	218	1.51
	Z341	42.976	1			
Kannur	Constant	15,633.704		0.69	218	1.94
	Z251	1.632				
	Z231	34.445				
Kottayam	Constant	5308.723		0.98	51	4.85
	Z241	10.456	1.92			
	Z450	− 0.276	2.724			
	Z231	34.269	2.091			
	Z130	3.332	90.008			
	Z230	− 3.728	100.329			
Kollam	Constant	8022.054		0.77	415	2.79
	Z51	60.242	1.251			
	Z161	0.123	1.251			
Trivandrum	Constant	− 8088.323		0.93	155	14.49
	Z121	24.675	2.067			
	Z261	0.138	1.464			
	Z120	− 1.801	1.566			

Least absolute shrinkage and selection operator and elastic net

The maximum R^2 was found for the Udupi district (0.99) with RMSE 152 nuts ha^{-1} and the minimum R^2 was recorded for North Goa district (0.73) with RMSE 48 nuts ha^{-1} (Table 6) for LASSO. Most of the Z variates had positive influence on coconut yield. Further investigation of the Z variates selected through LASSO unveiled that RH had impact on coconut yield to the maximum extent followed by the impacts of

Table 3 Coconut yield prediction models for different districts of West Coast developed using PCA-SMLR

Districts	No. of PCs	Predictor variable	Coefficient	VIF	R^2 ($p < 0.01$)	RMSE (nuts ha^{-1})	APEV (%)
Thane	6 (95.989)[$]	Constant	16,401.22		0.73	2255	49.83
		Time	− 887.905	1			
Raigad	7 (96.025)	Constant	17,026.385		0.70	2478	57.73
		Time	− 927.356	1			
Ratnagiri	7 (95.124)	Constant	8063.865		0.87	691	10.86
		PC4	1422.948	1.005			
		PC2	849.589	1			
		PC1	726.017	1.005			
North Goa	5 (95.685)	Constant	5082.715		0.64	53	0.17
		Time	− 14.178	1.102			
		PC5	− 64.622	1.102			
South Goa	6 (95.537)	Constant	4997.987		0.63	38	1.04
		PC4	36.193	1			
		PC2	36.339	1			
Uttara Kannada	6 (96.594)	Constant	6155.281		0.82	617	21.47
		PC1	1311.705	1			
Udupi	6 (96.212)	Constant	6435.343		0.93	392	12.98
		PC1	1603.061	1.137			
		PC2	− 709.198	1.137			
Dakshina Kannada	4 (92.843)	Constant	4165.994		0.89	1347	27.05
		PC2	2178.728	2.786			
		Time	426.98	2.786			
Alleppey	6 (94.872)	Constant	6049.104		0.53	551	1.76
		PC2	583.757	1			
Kozhikode	6 (94.636)	Constant	7076.143		0.66	248	11.78
		PC2	488.161	1.726			
		PC4	218.544	1.069			
		PC5	380.172	1.744			
Kannur	6 (93.227)	Constant	6636.035		0.54	263	5.49
		PC1	288.222	1			
Kottayam	7 (95.813)	Constant	4998.233		0.98	58	1.55
		PC6	280.335	1.042			
		PC2	184.091	1.007			
		PC7	194.074	1.008			
		Time	17.867	1.037			
Kollam	6 (94.159)	Constant	5816.392		0.77	420	2.52
		Time	126.755	1.056			
		PC4	454.771	1.056			
Trivandrum	6 (94.859)	Constant	6868.913		0.68	320	0.27
		Time	94.302	1.011			
		PC4	372.657	1.011			

[$] Values in parenthesis indicates percentage variability explained by respective number of PCs

Tmax and Tmin. Wind speed was the fourth most important variable affecting the yield. The APE of validation was less than 10 except for Thane (46.10%), Raigad (10.95%), Ratnagiri (16.29%), Uttara Kannada (17.28%) and Dakshina Kannada (34.96%) districts implying that these models can be used for predicting the coconut yield for west coastal region of India. For ELNET, the R^2 ranged between 0.74 and 0.99 (Table 7). The maximum RMSE was obtained in Raigad district (2155 nuts ha^{-1}) with R^2 of 0.82 and minimum RMSE was recorded in Kottayam district (23 nuts ha^{-1}) with R^2 of 0.99. The importance of different weather parameters based on frequency of inclusion was in the order: SRAD = RH > Tmax = Wind > Tmin > Rain. Inclusion of weighted weather indices was more frequent than simple weather indices during development of yield prediction models. APE for validation of ELNET model varied between 0.21% (North

Table 4 Coconut yield prediction models for different districts of West Coast developed using ANN

Districts	No. of hidden neurons	R^2 ($p < 0.01$)	RMSE (nuts ha^{-1})	APEV (%)
Thane	7	0.84	2227	31.17
Raigad	6	0.91	1293	16.17
Ratnagiri	5	0.78	1202	25.92
North Goa	5	0.46	66	0.39
South Goa	8	0.91	19	0.19
Uttara Kannada	6	0.87	735	21.07
Udupi	10	0.95	378	12.17
Dakshina Kannada	11	0.52	3624	54.23
Alleppey	9	0.89	279	3.59
Kozhikode	7	0.81	189	6.89
Kannur	11	0.84	158	2.49
Kottayam	7	0.94	49	3.93
Kollam	6	0.93	228	6.12
Trivandrum	10	0.77	317	17.15

Goa) and 33.98% (Thane). The performance of ELNET model was excellent with APEV of 9.92, 0.21, 0.80, 2.67, 2.09, 1.93, 1.66, 5.60, 0.73 and 1.36 for Raigad, North Goa, South Goa, Udupi, Alleppey, Kozhikode, Kannur, Kottayam, Kollam and Trivandrum, respectively.

Discussion

Impact of weather parameters on coconut yield

The coconut plantation requires a well-distributed rainfall (> 150 cm year^{-1}), mean temperature (27 °C ± 5 °C), sunshine of nearly 2000 h year^{-1} with a minimum of 120 h month^{-1} and 80–90% relative humidity for a good harvest (Naresh Kumar and Aggarwal 2013; Pathmeswaran et al. 2018). Instead of the mean temperature, maximum and minimum temperatures were used in this study as extreme temperatures might have larger effect on coconut production (Pathmeswaran et al. 2018). Vijayaraghavan et al. (1988) found that coconut yield was low to very low during northeast monsoon and winter season in Tamil Nadu coinciding with low to very low average minimum temperature. Coconut yield was higher between the southwest monsoon and summer season when the minimum temperature was high. Coconut yield was reduced when the mean minimum temperature fell below 21 °C (Thampan 1981). However, maximum temperature could adversely affect coconut production by affecting the pollen viability (Pathmeswaran et al. 2018). In this study, minimum temperature was found more important than maximum temperature for batter coconut harvest. Effect of solar radiation was on the rate of photosynthesis and transpiration (Krishnakumar

Table 5 Coconut yield prediction models for different districts of West Coast developed using PCA-ANN

Districts	Network architecture	R^2 ($p < 0.01$)	RMSE (nuts ha^{-1})	APEV (%)
Thane	7–3–1	0.70	3024	58.21
Raigad	7–2–1	0.91	1321	17.66
Ratnagiri	8–6–1	0.78	970	30.11
North Goa	6–3–1	0.77	44	0.27
South Goa	7–2–1	0.73	34	0.74
Uttara Kannada	7–3–1	0.87	558	19.74
Udupi	7–1–1	0.95	344	16.59
Dakshina Kannada	5–2–1	0.75	2857	6.25
Alleppey	7–1–1	0.45	663	3.63
Kozhikode	7–2–1	0.52	306	1.93
Kannur	7–1–1	0.67	318	4.69
Kottayam	8–6–1	0.96	77	8.78
Kollam	7–2–1	0.78	415	1.84
Trivandrum	7–1–1	0.66	363	14.22

Table 6 Coconut yield prediction models for different districts of West Coast developed using LASSO

Districts	Equation	R^2 ($p < 0.01$)	RMSE (nuts ha^{-1})	APEV (%)
Thane	$Y = 75{,}962.530 - (34.157 \times \text{time}) - (27.816 \times Z10) - (1.448 \times Z50) - (0.009 \times Z150) - (10.603 \times Z241) + (13.598 \times Z351) - (0.049 \times Z360) - (1.159 \times Z361)$	0.95	997	46.10
Raigad	$Y = -16{,}934.380 - (436.332 \times \text{time}) + (317.651 \times Z11) + (40.528 \times Z51) + (1.558 \times Z131) + (1.881 \times Z151) + (0.084 \times Z161) + (0.618 \times Z351)$	0.83	2073	10.95
Ratnagiri	$Y = -16{,}747.410 - (96.858 \times Z51) - (21.518 \times Z131) - (4.853 \times Z151) + (37.840 \times Z231) + (3.020 \times Z351) + (0.869 \times Z361)$	0.92	614	16.29
North Goa	$Y = 6393.649 - (96.858 \times Z51) - (21.518 \times Z131) - (4.853 \times Z151) + (37.840 \times Z231) + (3.020 \times Z351) + (0.869 \times Z361)$	0.73	48	0.31
South Goa	$Y = 5249.950 + (0.615 \times Z41) + (0.844 \times Z121) + (0.001 \times Z141) + (0.222 \times Z341) + (0.002 \times Z461)$	0.78	32	0.85
Uttara Kannada	$Y = 4544.312 + (1.658 \times Z41) + (24.060 \times Z51) - (0.432 \times Z120) + (0.022 \times Z141) - (1.052 \times Z240) + (5.998 \times Z341) + (1.182 \times Z350) + (0.346 \times Z450) + (0.013 \times Z460)$	0.97	244	17.28
Udupi	$Y = 5783.777 + (20.569 \times Z51) - (2.620 \times Z121) - (1.459 \times Z140) - (0.006 \times Z260) + (0.068 \times Z261) + (19.478 \times Z341) + (2.949 \times Z350) - (0.017 \times Z460)$	0.99	152	1.21
Dakshina Kannada	$Y = 48{,}925.170 + (257.981 \times \text{time}) - (69.137 \times Z10) + (0.365 \times Z50) - (2.380 \times Z120) - (7.124 \times Z121) + (0.003 \times Z150) + (0.240 \times Z261) + (3.581 \times Z351) + (0.285 \times Z361) + (3.361 \times Z451) + (0.058 \times Z461)$	0.9	541	34.96
Alleppey	$Y = 22{,}687.240 + (186.290 \times Z11) + (2.880 \times Z51) + (2.961 \times Z241) + (1.333 \times Z251) + (0.143 \times Z451)$	0.81	381	2.79
Kozhikode	$Y = 7078.168 + (55.578 \times Z21) + (28.490 \times Z341) + (0.024 \times Z461)$	0.81	202	2.50
Kannur	$Y = 14{,}304.470 + (1.902 \times Z121) + (0.011 \times Z161) + (9.529 \times Z231) + (0.493 \times Z251)$	0.81	210	0.12
Kottayam	$Y = 6223.758 + (33.540 \times \text{time}) + (30.405 \times Z11) + (7.531 \times Z51) + (26.398 \times Z231) + (7.295 \times Z241) - (0.103 \times Z250) + (0.546 \times Z340) + (0.014 \times Z361) - (0.149 \times Z450) + (0.513 \times Z451)$	0.99	18	5.08
Kollam	$Y = 10{,}034.780 + (13.768 \times \text{time}) + (22.680 \times Z51) + (0.259 \times Z151) + (0.083 \times Z161) + (2.137 \times Z241)$	0.8	433	1.20
Trivandrum	$Y = -385.092 - (1.522 \times \text{time}) + (10.990 \times Z121) + (0.516 \times Z140) + (0.215 \times Z151) + (0.014 \times Z160) + (0.053 \times Z161) + (2.506 \times Z241) - (0.104 \times Z250) + (0.683 \times Z251) + (0.046 \times Z261) - (0.252 \times Z350)$	0.99	69	1.04

Table 7 Coconut yield prediction models for different districts of West Coast developed using ELNET

Districts	Equation	R^2 ($p < 0.01$)	RMSE (Nuts ha^{-1})	APEV (%)
Thane	$Y = 35{,}378.122 - (120.687 \times \text{time}) + (55.294 \times Z51) - (1.015 \times Z130) + (2.727 \times Z131) + (0.640 \times Z231) + (4.499 \times Z241) - (0.413 \times Z250) + (1.607 \times Z251) - (0.574 \times Z350) + (3.509 \times Z351)$	0.93	1137	33.98
Raigad	$Y = 7916.946 - (88.043 \times \text{time}) + (102.769 \times Z11) + (0.277 \times Z31) + (6.339 \times Z131) + (8.060 \times Z231) + (3.097 \times Z351)$	0.82	2155	9.92
Ratnagiri	$Y = -7534.023 + (70.364 \times Z31) + (53.411 \times Z51) + (7.687 \times Z131) + (35.347 \times Z231) + (0.710 \times Z351) + (0.431 \times Z361) + (1.236 \times Z451)$	0.92	593	17.16
North Goa	$Y = 4969.030$	0.74	48	0.21
South Goa	$Y = 5146.226 + (0.188 \times Z41) + (0.004 \times Z61) + (0.409 \times Z121)$	0.79	32	0.80
Uttara Kannada	$Y = 1311.615 + (5.849 \times \text{time}) + (0.242 \times Z41) + (7.155 \times Z51) + (0.240 \times Z141) + (0.876 \times Z241) + (0.016 \times Z250) + (0.189 \times Z251) + (6.095 \times Z341) + (0.671 \times Z350) + (0.273 \times Z451)$	0.94	421	17.23
Udupi	$Y = 3105.540 + (6.772 \times \text{time}) + (0.702 \times Z41) + (0.030 \times Z50) + (6.964 \times Z51) - (0.055 \times Z140) + (0.702 \times Z141) + (0.029 \times Z150) + (0.186 \times Z151) + (0.851 \times Z241) + (6.659 \times Z341) + (0.920 \times Z350) + (0.248 \times Z451)$	0.99	109	2.67
Dakshina Kannada	$Y = 11{,}711.720 + (166.356 \times \text{time}) + (17.193 \times Z30) + (29.126 \times Z31) - (1.093 \times Z41) + (0.107 \times Z130) + (0.286 \times Z131) + (1.092 \times Z141) + (0.613 \times Z231) + (1.242 \times Z241) + (0.477 \times Z350) + (0.903 \times Z351) + (1.735 \times Z451) + (0.062 \times Z461)$	0.91	547	32.82
Alleppey	$Y = 17{,}442.970 + (99.666 \times Z11) + (0.374 \times Z41) + (8.425 \times Z51) + (0.298 \times Z121) + (0.378 \times Z141) + (1.729 \times Z241) + (0.771 \times Z251) + (0.023 \times Z451)$	0.82	378	2.09
Kozhikode	$Y = 6806.395 + (40.315 \times Z21) + (0.005 \times Z161) + (16.742 \times Z341) + (0.011 \times Z461)$	0.93	118	1.93
Kannur	$Y = 9300.920 + (0.167 \times Z41) + (0.591 \times Z121) + (0.169 \times Z141) + (0.207 \times Z251) + (0.002 \times Z461)$	0.84	177	1.66
Kottayam	$Y = 5899.956 + (27.873 \times \text{time}) + (12.628 \times Z11) + (0.845 \times Z40) - (0.011 \times Z50) + (0.510 \times Z121) + (0.997 \times Z131) + (0.880 \times Z141) - (0.007 \times Z150) + (18.445 \times Z231) - (0.071 \times Z240) + (0.527 \times Z340) + (0.614 \times Z341) + (0.726 \times Z351) + (0.064 \times Z361) - (0.088 \times Z450) + (0.653 \times Z451)$	0.99	23	5.60
Kollam	$Y = 9207.440 + (8.585 \times \text{time}) + (0.074 \times Z41) + (11.561 \times Z51) + (0.402 \times Z61) + (0.070 \times Z141) + (0.283 \times Z151) + (0.023 \times Z161) + (1.229 \times Z241) + (0.119 \times Z251) + (0.020 \times Z461) + (0.004 \times Z561)$	0.8	427	0.73
Trivandrum	$Y = 917.082 + (7.142 \times Z10) + (24.791 \times Z21) + (1.144 \times Z40) + (0.611 \times Z61) + (7.241 \times Z121) + (0.212 \times Z140) + (0.233 \times Z151) + (0.007 \times Z160) + (0.051 \times Z161) - (0.145 \times Z250) + (0.817 \times Z251) + (0.002 \times Z260) + (0.038 \times Z261) + (0.965 \times Z341) - (0.247 \times Z350) + (0.006 \times Z460)$	0.99	59	1.36

2011). Decrease in solar radiation during monsoon season compared with summer season led to a decrease in potential photosynthesis (Rao et al. 1995). Solar radiation during 29 and 30 months before harvesting also has positive influence on female flowers production (Coomans 1975). In the current study, solar radiation was the second most important variable affecting the coconut yield after RH. Higher RH reduces transpiration thereby affects the water and nutrient uptake by coconut plants. On the other hand, low ambient RH may reduce photosynthetic capacity by causing stomatal closure. The study area under the present study was having a high mean RH (77.6%, Supplementary Table S2) throughout the year which was having a greater impact on coconut production as indicated by highest frequency of occurrence in different models. Wind affects the coconut crop by affecting the evapotranspiration. Strong winds have depressing effect on coconut yield by causing mechanical damage to coconut plantation (Krishnakumar 2011). Heavy rainfall (> 355 mm month^{-1}) during south-west monsoon has harmful effect on coconut as it reduces the insolation and temperature and increases humidity (Abeywardena 1968). Rao (1982) observed that high rainfall during monsoon and no rainfall during pre- and post-monsoon adversely affected the coconut yield during subsequent years in Pilicode region of Kerala. Very high rainfall also reduces the final coconut yield by affecting pollination (Vijayaraghavan et al. 1988). On the other hand, reduced rainfall or drought may cause abortion of spadices and inflorescence primordial, reduction in female flowers, button shedding, immature nut fall and reduced nut size (Rao et al. 2005; Rethinam 2007). Nair and Unnithan (1988) reported that sunshine hours and evaporation had positive correlation with coconut yield while relative humidity had a negative correlation. Rainfall and number of rainy days were not having much influence. In our study, also the rainfall was the least important variable with lesser frequency of inclusion in the developed models. This may be due to the fact that the rainfall received in the region (1790.3–3636.7 mm, Supplementary Table S2) was more than the required rainfall for coconut production (1500 mm; Naresh Kumar and Aggarwal 2013; Pathmeswaran et al. 2018). Naresh Kumar et al. (2009b) found that relative humidity and temperature-based models are useful in prediction of coconut yield with the required accuracy limits. Carr (2011) reported that development of coconut yield forecasting models using climatic variables is difficult as there is a long-time gap between flower initiation and mature nut harvest. However, the current study used monthly weather-based indices and significant relations were obtained between weather parameters and coconut productivity. The biggest limitation of current study was the unavailability of long-term coconut yield data. It has been reported that increased sample size both temporally and spatially will improve the performance of predictive models (Cai et al. 2019). However, in the current study with fifteen years yield we cloud able to develop reliable models.

Inter-comparison of the models

Significant variations were obtained in the performance of the prediction models across the districts. Therefore, selection of a specific model based on its evaluation parameter might not be appropriate. So, models were ranked based on R^2 and RMSE of calibration and the APE of validation, and the average ranks were calculated for various models used to predict the coconut yield in west coastal region of India. Based on R^2 of calibration, ELNET (2.08) evolved as the best model followed by LASSO (2.23) and ANN (3.43). PCA-SMLR was found to be the least performing (5.00). With respect to RMSE, the order of performance was found to be: ELNET (2.36) > LASSO (2.64) > ANN (3.29) > SMLR (3.36) > PCA-ANN (4.50) > PCA-SMLR (4.86). Ranking based on APE during validation was found as ELNET (2.43) > LASSO (2.79) > PCA-SMLR (3.50) > ANN (4.00) = PCA-ANN (4.00) > SMLR (4.29). Overall, the performance of the models followed the order as: ELNET (2.32) > LASSO (2.63) > ANN (3.68) > SMLR (3.89) > PCA-SMLR (4.21) > PCA-ANN (4.27). Significant differences among the overall ranks were analysed using non-parametric Kruskal–Wallis test at $p < 0.001$. Furthermore, to identify the best model for the study region, Mann–Whitney pairwise post hoc tests followed by Bonferroni correction of p values was performed which identified the ELNET as the best model (Table 8). The performance of ANN and LASSO was found similar to ELNET while SMLR, PCA-SMLR and PCA-ANN did not perform at par with ELNET. Good performance of penalized regression models like ELNET and LASSO agrees with previous other studies which are due to reduction of overfitting and model complexity by shrinkage

Table 8 Multiple pairwise comparisons of the multivariate models using Mann–Whitney pairwise post-hoc tests followed by Bonferroni correction of p alues

	SMLR	PCA-SMLR	ANN	PCA-ANN	LASSO	ELNET
SMLR	–					
PCA-SMLR	1.000	–				
ANN	1.000	1.000	–			
PCA-ANN	1.000	1.000	1.000	–		
LASSO	0.060	0.080	0.760	0.015	–	
ELNET	0.004	0.004	0.075	0.002	1.000	–

and automatic variable selection simultaneously (Zou and Hastie 2005; Das et al. 2018a; Kumar et al. 2019). Slightly poor performance of LASSO as compared with ELNET may be due to selection of only one variable from a set of intercorrelated variables which may lead to loss of information. Balakrishnan and Meena (2010) reported that ANN was able to accurately predict the coconut yield using yearly weather data. But they have ignored impact of the intra-year variations of weather parameter on coconut yield. In the current study, monthly weather data were used for the development of the models. The better performance of ANN may be due to underlying nonlinear relationship of coconut yield with weather variables (Das et al. 2018b; Cai et al. 2019). The performance of PCA-SMLR and PCA-ANN was poor as compared with sole SMLR and ANN which may be due to exclusion of the components explaining less than 5% variance with the assumption that components with small variance have very little predictive power in the regression which may not be true always (Jolliffe 1982; Das et al. 2018a). On the other hand, PCA does not consider the dependent variable during transformation of input variables. Previous studies on coconut yield prediction mainly used simple linear regression models with specific monthly or seasonal climatological data (Peiris et al. 2008; Naresh Kumar et al. 2009b) ignoring the contribution of remaining months or seasons data. As coconut is a perennial crop, use of year-round monthly or seasonal data is better than using only specific monthly or seasonal data. This was achieved in the current study using the weather indices approach which may be the reason for achieving good prediction performances.

Conclusions

In this study, district-wise annual coconut yield prediction models were developed using six multivariate techniques with the monthly weather variables as inputs for the west coastal region of India. Relative humidity and solar radiation were the major weather variables with maximum impacts on the coconut yield. It is worth indicating here that the inclusion frequency of weighted weather indices was much higher than simple weather indices. The results of the present investigation revealed that reliable forecast of coconut yield can be obtained using ELNET model for the study region.

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