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Agrometeorological Yield Modelling for Different Crops in Germany Principal Component Analysis

URMIL VERMA[1] AND WOLFGANG KOEHLER[2]

[1]*Department of Mathematics & Statistics, CCS Haryana Agricultural University, Hisar, Haryana, India*
[2]*Interdisciplinary Research Center, Giessen, Germany*
E-mail : Vermas21@hotmail.com

Abstract

Reliable, accurate and timely information on types of crop grown and their acreages, crop yield and crop growth conditions are vital components for planning efficient management of natural resources. This involves formulating and implementing appropriate prices of agricultural commodities and import/export of these commodities from time to time. Forecasts can be formed in many different ways. The method chosen depends on the purpose and importance of the forecasts as well as the costs of alternative forecasting methods. Keeping in view the importance of the subject matter, an attempt was made to develop agrometeorological yield models for different crops in Germany using principal component analysis. Yield data for maize, rapeseed, sugarbeet, winter barley and winter wheat from Marienborn (Germany) were dealt for the development of crop models.

Key words : Agrometeorological parameter, Fortnightly categorization, Principal component, Eigen root, Eigen vector.

Forecasts can be formed in many different ways. The method chosen depends on the purpose and importance of the forecasts as well as the costs of alternative forecasting metods. Various organizations in India and abroad are engaged in developing methodology for pre-harvest forecasting of crop yield using various approaches. With the advent of Remote Sensing technology during 1970s, its great potential in the field of agriculture have opened new vistas of improving the agricultural statistics system all over the world. The approach using weather parameters is normally based on time series data. Box and Jenkins (1) used time series models for forecasting yield where the variation in yield during different years is explained using historical data through trend analysis and presented the well-known technique of auto-regressive integrated moving averages (ARIMA). Jain et al. (2), Mahajan and Prasad (3) and Verma and Grover (4) have used principal component technique for crop yield forecasting. Keeping in view the importance of the subject matter, an attempt was made to develop agrometeorological yield models for different crops in Germany using principal component approach.

Study Area and Data Used

Daily agrometeorological data on maximum temperature, minimum temperature and rainfall (January 1980—March 2003) for Nidderau - Windecken (Germany) were converted to fortnightly meteorological data base for finding out the functional relationship with yield data of various crops from Marienborn (Germany).Yield data of maize, rapeseed, sugarbeet, winter barley and winter wheat crops from Marienborn were dealt to find out the suitable regression models.

Marienborn

Maize. The crop growth period was from second fortnight of April to November first fortnight, dividing the total period into 14 fortnights with relation to average maximum temperature, average minimum temperature and accumulated rainfall.

Rapeseed . The crop growth period covered August second fortnight to July second fortnight, dividing the period into 23 fortnights again in relation to average maximum temperature, average minimum temperature and accumulated rainfall.

Sugarbeet. The crop growth period was from second fortnight of March to November first fortnight, dividing the total period into 16 fortnights for the same agromet variables.

Winter Barley. The crop growth period covering

September second fortnight to July second fortnight divided the total period into 21 fortnights considering the same climate variables.

Winter Wheat. The growth period being October second fortnight to August first fortnight divided the total period into 20 fortnights in relation to the same meteorological parameters.

Agro-climate variables i. e. average maximum temperature, average minimum temperature, accumulated rainfall along with trend predicted yield (for trend analysis, time (year) as an independent variable was regressed against the yield to get the trend equation of the form Y_t=a+bt; where Y_t = yield, a= intercept, b= slope and t=year) were used to develop suitable yield models of different crops in Marienborn using principal component technique.

Extraction of Principal Components

The procedure consists of finding the eigen roots and eigen vectors of the correlation matrix of p explanatory variables. The variance of Y_i, the i[th] principal component is the i-th characteristic root λ_i of the correlation matrix R ; λ_s are obtained by solving the equation $|R - \lambda I| = 0$, for each λ_i, the corresponding characteristic vector v is obtained by solving the determinantal equation $| R - \lambda I |$ v = 0, (λ_1, v_1), (λ_2, v_2),...(λ_p, v_p) are the eigen values and eigen vector pairs of R with $\lambda_1 \geq \lambda_2 \geq ....\geq \lambda_p$. The purpose of PC analysis is to determine new variables, called principal components which carry most of the information present in original variables in term of variance. Varimax method due to Velicer (5), was used to rotate principal component solutions.

The mth PC, Y_m is a weighted linear combination of original variables i.e.X's

$$Y_m = 1'_m X = l_{ml} X_1 + 1_{m2} X_2 + ...+1_{mp} X_p,$$

where $1_{ml}, l_{m2},....l_{mp}$ are the weights to be chosen subject to constraint

$$l'_m l_m = 1 \qquad \text{(Normalization)}$$
$$1'_m 1_k = 0 \ (m \neq k) \qquad \text{(Orthogonality)}$$

The PC's are uncorrelated with each other and their variances are equal to the eigen values λ_1, λ_2,... λ_p.

Results and Discussion

Principal component method was used for extraction of components which consists of finding the eigen values and eigen vectors. The utility of principal components (PCs) depending upon the part of variability it accounts for. It was found that the first twelve PCs (42 agromet parameters) for maize, first thirteen PCs (69 agromet parameters) for rapeseed, first thirteen PCs (48 agromet parameters) for sugarbeet, first thirteen PCs (63 agromet parameters) for winter barley and first thirteen PCs (60 agromet parameters) for winter wheat crops, accounted for about 90% of total variation present in the original data (each crop being dealt separately). While the remaining PCs showed a smaller amount i. e. less than 10% of the total variation, hence these components were not considered to be of much practical significance. Principal component analysis has been performed independently for each crop considered under the study. Eigen values, sum of squared loadings and rotated sum of squared loadings were obtained using SPSS package. Agromet variables displaying higher loadings were further used to obtain the suitable crop yield models as mentioned below.

Maize Model (Fortnightly Categorization of Meteorological Data)

$$\text{Yield}_{est} = 13.11+0.61\ ppt_{14} - 0.26\ ppt_{13} + 2.33 tmx_3 + 3.27 tmn_1 + 2.65 tmn_2 - 2.89\ tmn_4$$

R^2 = .894, Adj. R^2 = .854, n= 22, SEOE = 6.36

where Yield_{est} = Model predicted yield
tmx_3 = Average maximum temperature of 3[rd] fortnight
tmn_4 = Average minimum temperature of 4[th] fortnight
tmn_2 = Average minimum temperature of 2[nd] fortnight
tmn_1 = Average minimum temperature of 1[st] fortnight
ppt_{14} = Accumulated rainfall of 14[th] fortnight
ppt_{13} = Accumulated rainfall of 13[th] fortnight
R^2 = Coefficient of determination
SEOE = Standard error of estimate
n = Total no. of data points

Rapeseed Model (Fortnightly Categorization of Meteorological Data)

$Yield_{est} = 7.83 + 2.84\ tmx_{16} - 0.84\ tmx_{14} - 1.65\ tmn_6 + 0.63\ tmn_{11}$

$R^2 = .89$, Adj. $R^2 = .85$, n = 22, SEOE = 1.77

where tmx_{16} = Average maximum temperature of 16th fortnight

tmx_{14} = Average maximum temperature of 14th fortnight

tmn_{11} = Average minimum temperature of 11th fortnight

tmn_6 = Average minimum temperature of 6th fortnight

Sugarbeet Model (Fortnightly Categorization of Meteorological Data)

$Yield_{est} = 563.49 + 21.73\ tmx_7 - 5.53\ tmx_{13} - 39.60\ tmn_7 - 17.71\ tmn_8 + 20.79\ tmn_{13} + 1.53\ ppt_4 + 1.14\ ppt_6$

$R^2 = .824$, Adj. $R^2 = .736$, n = 22, SEOE = 29.86

where tmx_{13} = Average maximum temperature of 13th fortnight

tmx_7 = Average maximum temperature of 7th fortnight

tmn_{13} = Average minimum temperature of 13th fortnight

tmn_7 = Average minimum temperature of 7th fortnight

tmn_6 = Average minimum temperature of 6th fortnight

ppt_6 = Accumulated rainfall of 6th fortnight

ppt_4 = Accumulated rainfall of 4th fortnight

Winter Barley Model (Fortnightly Categorization of Meteorological Data)

Where $Yield_{est} = 224.63 - 9.27\ tmx_9 + 2.56\ tmx_{12} - 1.28\ tmx_{18} + 2.18\ tmx_{19} + 8.88\ tmn_9 - 7.01\ tmn_{19} - 6.28\ tmn_{20} + 0.33\ ppt_8$

$R^2 = .73$, Adj. $R^2 = .49$, n = 22, SEOE = 6.599

where tmx_{19} = Average maximum temperature of 19th fortnight

tmx_{18} = Average maximum temperature of 18th fortnight

tmx_{12} = Average maximum temperature of 12th fortnight

tmx_9 = Average maximum temperature of 9th fortnight

tmn_{20} = Average minimum temperature of 20th fortnight

tmn_{19} = Average minimum temperature of 19th fortnight

tmn_9 = Average minimum temperature of 9th fortnight

ppt_8 = Accumulated rainfall of 8th fortnight

Winter Wheat Model (Fortnightly Categorization of Meteorological Data)

$Yield_{est} = 104.24 + 11.12\ tmx_5 - 10.44\ tmn_5 + 3.22\ tmn_{10} + 2.09\ tmn_{13} - 2.57\ tmn_{17} - 6.08\ tmn_{16} + 0.17\ ppt_{19}$

$R^2 = .824$, Adj. $R^2 = .729$, n = 22, SEOE = 4.60

where tmx_5 = Average maximum temperature of 5th fortnight

tmn_{17} = Average minimum temperature of 17th fortnight

tmn_{16} = Average minimum temperature of 16th fortnight

tmn_{13} = Average minimum temperature of 13th fortnight

tmn_{10} = Average minimum temperature of 10th fortnight

tmn_5 = Average minimum temperature of 5th fortnight

ppt_{19} = Accumulated rainfall of 19th fortnight

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