Recommendation of fertilizers for pearl millet using statistical and machine learning approaches

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Abstract

To recommend the fertilizer required for pearl millet plant nutrition using static and machine learning approaches has been studied. Recommended dose of fertilizers for pearl millet is reported 60:30:30 kg N: P_2O_5: K_2O ha^{-1}. Half quantity of N and full quantity of P and K are applied as basal by broad casting and the remaining half of N is applied after 20-25 days of sowing. Fertilizers recommendation is also influenced by climatic factors. The addition of S, Mn and Zn is the ratio 20:10:2.5 kg ha^{-1} improves the yield of pearl millet. The sustainable production of crop requires the knowledge of an economically optimal fertilizer rate (EOFR). Alternatively machine learning model maybe developed to predict the EOFR for pearl millet as the various soil physical, chemical parameters and climatic factors have an effect on the fertilizers rate. A machine learning based model using intelligent algorithms would help in obtaining the EOFR for particular site following any one of the approach viz., multiple linear regression, ridge regression, support vector machine, random forest, extreme gradient boosting. Interaction among the EOFR and the soil and climatic parameters can be both linear and nonlinear to develop the prediction equation and compare their accuracies.

Introduction

Pearl millet (*Pennisetum glaucum*) is cultivated in more than nine million hectare of land in India. The production has been historically favored in the climate of semiarid tropics because of its high productivity and short growing season under dry and high-temperature conditions. It is primarily grown for food, dry fodder, poultry and cattle feed, and alcohol extraction. However, due to awareness about consuming healthy food, the pearl millet might be increasingly preferred as it is a rich source of iron, zinc, magnesium, copper, manganese, potassium and phosphorous with mature kernels rich in vitamin A (Gopalan et al. 2003), low glycemic index, and high fiber content (Kam et al. 2016). All India Coordinated Pearl Millet Improvement Project (AICPMIP) administered by the Indian Council of Agricultural Research (ICAR) caries out the Pearl millet improvement research in India, which resulted in a total of 115 improved cultivars in the last few decades (Yadav et al. 2012). Moreover, using the various climate change scenarios for RCP (representative concentration pathways), it has been shown that there is an increase in the yield for cultivars with drought and heat tolerant traits at the dry and warm sites (Singh et al., 2017; Ullah et al., 2019).

The traditional fertilizer practice for pearl millet in India is 60:30 kg N: P_2O_5, while the recommended dose of fertilizers for pearl millet is reported as 60: 30: 30 kg N: P_2O_5:K_2O ha^{-1}. Half quantity of N and full quantities of P and K are usually applied as basal by broadcasting and the remaining half of N is applied after 20–25 days of sowing (Meena et al. 2016). In addition to this, there is a state recommended dose for fertilizer depending on the area and climate. A number of studies have been carried out on the effect of integrated fertilizer use on the crop and soil. Recently, various studies are being conducted for the adoption of micro dosing of fertilizer, which is developed in the 1990s by the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) for the purpose of low cost agriculture intensification. Coulibaly et al. (2019) reported the effect of fertilizer micro dosing in Mali and concluded that for a rainfall regime with 400 to 700 mm fertilizer dose of 0.4 g NPK hill^{-1} (i.e., 4 kg NPK ha^{-1}) performed better, while for regimes with annual rainfall of around 700 to 1000 mm, 0.8 g NPK hill^{-1} (20 kg NPK ha^{-1}) is required with an additional 1 g urea hill^{-1} (25 kg urea ha^{-1}) as top dressing. An elaborate experiment with five micro doses of fertilizer is also been carried out in western Niger to observe that 0.5 g NPK hill^{-1} provided the best economic production of pearl millet (Aune et al. 2020). The different recommended micro doses of fertilizers for different rainfall regimes indicate that fertilizer recommendation is influenced by the climatic factors. In addition to the micro-dosing of fertilizers, several studies have also reported the effect of addition of micronutrients other than NPK on the pearl millet yield. Kumar and Singh (2019) reported that the addition of S, Mn, and Zn in the ratio: 20:10:2.5 improved the yield of pearl millet significantly as compared to the recommended dose. In addition, Kadam et al. (2019) using 8 treatments, reported that the application of 120 kg N + 45 kg P + 45kg K + 20 kg Zn per ha recorded the maximum grain and fodder yield. In the recent testing of bio-fortified hybrid of pearl millet, it has also been reported that it is necessary to maintain sufficient amount of Fe and Zn levels in soil for the expression of full genetic potential of the crop and to ensure successful micronutrients accumulation in the grain (Govindaraj et al. 2019). These studies suggest the necessity of a complete soil macro and micro nutrients assessment for the cultivation of pearl millets.

Another widely used fertilizer recommendation system for pearl millet is the soil test crop response (STCR) based approach that uses soil testing of nutrients to recommend a fertilizer dose. The inductive cum targeted yield model based fertilizer prescription equations for a particular yield target of T q ha^{-1}is calculated as:

$$F = T \times NR/ CF – CS \times STV/ CF – CO \times M/ CF$$

where, F in Kg ha^{-1} is the recommended fertilizer dose; NR is the nutrient requirement of N, P_2O_5 (P x 2.29) or K_2O (K x 1.21) for 100 kg of economic produce; CS is the contribution from soil nutrients in fraction; CF is the contribution from fertilizer nutrients in fraction; CO is the contribution from organic nutrients in fraction; STV is the soil available nutrients of N, P2O5 (P x 2.29) or K2O (K x 1.21) determined through soil analysis and M is the Nutrient content in organic matter N, P2O5 (P x 2.29) or K2O (K x 1.21) determined through organic matter analysis.

Several researchers (Kanchana et al. 2020; Kumar et al. 2020; Udaykumar et al. 2019) have carried out the validation of the STCR method for pearl millet fertilizer recommendation and reported a significant improvement of yield and soil fertility. Kumar et al. (2020), however, reported an improvement of the soil such as organic carbon, microbial biomass carbon, available NPK and micronutrients with addition in 15 t ha^{-1} of farmyard manure in rabi and kharif both at surface and subsurface soils.

From previous studies on Pearl millet fertilizer recommendation it has been observed that there is a variation among the recommendation doses as it depends on a number of crop (cultivar), soil, and climatic factors. In addition, it has been studied long back (Christianson et al., 1990) using regular dose of N^{15} fertilizer in pearl millet that there is a 25%-53% N loses. Therefore, the sustainable production of the crop requires the knowledge of an economically optimal fertilizer rate (EOFR). Even the widely adopted inductive cum targeted yield model based fertilizer prescription uses the knowledge of economic produce. The calculation of EOFR would require an elaborate process, involving on-farm research trials with different fertilizer rates, measuring yield parameters and an end of season calculation using the grain and fertilizer prices and, therefore, is unknown at the time of fertilizer application. Alternately, a machine-learning model may be developed predicting the EOFR for pearl millet as the various soil physical, chemical parameters, and climatic factors would have an effect on the fertilizer rate and, therefore, would act as predictors. Several studies are conducted to estimate the economically optimal N and P rates (Hong et al. 2007; Jiang et al. 2019) partly because the post harvest residual N and P causes major pollution of water resources. It has been shown that using economically optimal N rates (EONR) for corn reduces the residual nitrates in soil (Hong et al., 2007). In addition, a substantial profit has been demonstrated with applying only EONR (Bullock and Bullock 1994), therefore, it has been anticipated that adopting the EOFR for the entire fertilizer requirement for pearl millet would be of a great benefit to the farmers. Fertilizers EOFR For effective use of fertilizers EOFR is proposed rather than EONR because in India generally urea is used in more quantity compared to other fertilizers for the macro and micro-nutrients. Also in India urea is sold at subsidized rate. This has caused imbalance in nutrient use affecting soil fertility and declined the crop response ratio (Gulati and Banerjee 2019). Therefore, modeling of EOFR and a fertilizer recommendation system based on it would be a step forward towards achieving a sustainable agricultural production.

The modeling of EOFR as a function of soil, crop, and climate parameters is also required because it has been reported that the optimal N fertilizer rate shows a significant variable within a particular field (Scharf et al., 2005). Ransom et al. (2020) used several modeling approaches to model economically optimal N rates for corn N management and reported the improvement of N recommendation tools using the modeled optimal rate. Ullah et al. (2020) obtained the optimal level of N for pearl millet quite different from the recommended economic level of N for their study area and concluded that economically optimum rate of N should be determined according to the soil and climate of an area for the sustainable production of hybrid pearl millet. A machine learning based model using intelligent algorithms would help in obtaining the EOFR for a particular site. The EOFR can be further utilized to guide the fertilizer recommendation for a season using the residual levels of nutrient in the field of experiment.

1. Measurement of Economically optimal fertilizer rate

For the calculation of the total economically optimal fertilizer rate for any crop, we have to determine the economically optimal nutrient rate for each of the nutrients that a particular crop would require throughout its life cycle. The yield response function of a crop for several rates of a particular nutrient starting from 0 (no fertilizer applied) to a value that is high enough that the particular nutrient would not limit yield is typically used for the calculation of EOFR (Jaynes 2011). Most of the published literature used four to ten rates of nutrient for the analysis. A quadratic function is then fitted to the nutrient rate vs. yield curve given as:

$$Y = a + bx + cx^2 + \varepsilon \tag{1}$$

where, Y is yield (kg ha^{-1}), x is nutrient fertilizer rate (kg ha^{-1}), a, b, and c are fitting parameters, and ε is the error which is normally distributed with zero mean and a finite variance. The economically optimal nutrient rate is then defined as the point where the return to the increase in yield just equals the cost of the increase in nutrient input. As a quadratic equation is fitted to the yield response function, the first derivative of the fitted response function equal to the price ratio of nutrient fertilizer to grain gives the economically optimal rate for that particular nutrient. From Eq. [1], the economically optimal nutrient rate for a particular nutrient can be calculated as follows:

$$r = b + 2cx$$

$$\text{i.e., } x^* = \frac{r-b}{2c} \tag{2}$$

where, r is the particular nutrient fertilizer:grain price ratio and x^* is the economically optimal nutrient rate for the particular nutrient. Therefore, the yield response not only depends on the rate of nutrient applied, but also on the cost of fertilizer and the price of harvested grain. The EOFR is then calculated by adding the x* obtained for each nutrient that is required for a particular crop:

$$\text{EOFR} = \sum_{i=1}^{n} x_i^* \tag{3}$$

where, *n* is the number of nutrients that is required for a particular crop. For pearl millet, *n* would be 7 as we have to find the economically optimal nutrient rate for 7 nutrients before calculating the EOFR for the crop.

2. **Modeling algorithms proposed to predict the economically optimized fertilizer rate based on soil and weather parameters**

The present study reviews the machine learning algorithms that are being used for agricultural production and recommendation and proposes the following five models to compare the prediction accuracy for the estimated EOFR. The machine learning algorithms learn the behavior of the underlying nutrient response from the input data to predict the target variable. As the interaction among the EOFR and the soil and climatic parameters can be both linear and nonlinear, it is recommended to use both linear and nonlinear models to develop the prediction equation and compare their accuracies. Qin et al. (2018) used multiple linear regression (MLR), ridge regression (RR), least absolute shrinkage and selection operator (LASSO) regression, and gradient boost regression trees to model the EONR for corn and observed that the RR outperformed all other approaches. Shahhosseini et al. (2019) evaluated the potential of four machinelearning algorithms of LASSO Regression, RR, random forests, and Extreme Gradient Boosting for the prediction of maize yield and nitrate loss. We are, therefore, proposing MLR, RR, support vector machine (SVR), random forest (RF), and extreme gradient boosting for the development of the model and briefly discussed each of these approaches in the following sections.

Multiple Linear Regressions

Multiple linear regression (MLR) is a statistical technique that uses several explanatory variables to predict the outcome of a response variable (Moore et al., 1993). It fits an observed dependent data set e.g, EOFR using a linear combination of independent variables e.g., soil and weather parameters. If we consider a response Y, predictors (x_1, x_2, …,x_p), the MLR has the form:

$$f(x) = \beta_o + \sum_{j=1}^{P} x_j \beta_j \qquad [4]$$

Where, βo is the intercept and βi s are the coefficients of the predictors.

The MLR equations are extensively being used for yield prediction for a particular crop and a particular region. Ramesh and Vardhan (2015) used MLR approaches combined with density based clustering to predict the future crop yield in Godavari district of Andhra Pradesh, India.

Ridge Regression

Ridge Regression is a shrinkage method for MLR. It is a technique for analyzing multi-co-linearity in regression data. By adding a degree of bias to the regression estimates, ridge regression reduces the standard errors. It shrinks the coefficients of the MLR by imposing the following constraint:

$$\widehat{\beta}^R = \arg\min_\beta \sum_{i=1}^{N} (Y_i - (\beta_o + \sum_{j=1}^{p} x_j \beta_j))2 \text{ subject to} \sum_{j=1}^{p} \beta_j^2 \leq C \qquad [5]$$

As RR is very efficient in dealing with the mulricollinearity in the predictors, it is exensively used in predicting grain yield from spectral data (Hernandez et al., 2019).

Support Vector Machine

Support Vector Machine (SVM) is a novel machine-learning tool that has been originated from Statistical Learning Theory developed by Vapnik in 1995 (Corrina and Vapnik, 1995). SVM works on the principle of structural risk minimization seeking to minimize an upper bound of the generalization error, rather than minimize the training error. With the introduction of Vapnik's ε-insensitive loss function, SVM has been extended to solve nonlinear regression estimation problems (Drucker et al. 1997).

Selection of optimal SVM parameters is the important step in SVM design. For the PTF developed in this study, we have considered a RBF kernel function and used Genetic algorithm (GA) to optimize regularization parameter, bandwidth of the RBF kernel function and radius of a tube of ε-insensitive loss function ε. The SVM has been recently used for the prediction of rice yield in Maharashtra, India (Gandhi et al., 2016).

Random Forests

Random forests (RF) follows a bagging algorithm. In Bagging, successive models do not depend on earlier models and each model is independently constructed using a bootstrap sample of the observation dataset (Breiman, 2001). Breiman (2001) proposed random forests, which add an additional layer of randomness to bagging. In addition to constructing each tree using a different bootstrap sample of the data, random forests change how the classification or regression trees are constructed. In a random forest, each node is split using the best among a subset of predictors randomly chosen at that node. It works by Variance reduction through averaging, however, the bias remains unaltered. Random forest has been extensively used for the prediction of various crop yield parameters and has been reported to provide accurate predictions (Everingham et al., 2016)

Extreme Gradient Boosting

XGB (extreme gradient boosting) algorithm is a boosting algorithm. Boosting is based on the theorem (Schapire 1990): "The Strength of Weak Learnability". It is an ensembling technique where we build many independent models and combine them using model averaging technique. The observations in boosting algorithm are not chosen based on the bootstrap process, but based on the error. The observations are chosen in a sequential manner. Each new model is a fit on a modified version of the original data set and each subsequent model aims to reduce the errors of the previous model. Therefore, the observations have an unequal probability of appearing in subsequent models and ones with the highest error appear most.

If we consider a response Y, predictors (x_1, x_2, …,x_p) and a loss function L (Y, f), The gradient boosting algorithm (Friedman 2000) is given as:

1. $F_o(x) = \arg\min_{\rho} \sum_{i=1}^{N} L(Y_i, \rho)$
2. For m =1 to M, do

   a. $\tilde{Y}_i = -\left[\frac{\partial L(Y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}, i = 1, \ldots, N$

b. $a_m = \arg\min_{a,\beta} \sum_{i=1}^{N} \left[\tilde{Y}_i - \beta h(x_i; a) \right]^2$

c. $\rho_m = \arg\min_{\rho} \sum_{i=1}^{N} L(Y_i, F_{m-1}(x_i) + \rho_m h(x_i; a_m))$

d. $F_m(x) = F_{m-1}(x) + \nu . \rho_m h(x; a_m)$

3. End For Loop

End Algorithm

where, ν is a shrinkage factor, if we consider the *h(x,a)* to be a tree, *a* would parameterize the split, ρ is the learning rate. The regression tree *h(x,a)*is the weal learner in the algorithm and fits to the residuals of step 1. A negative gradient shows the downhill direction of the loss function. The Loss function must be differentiable for example, squared error or absolute error.

3. A case study with collated data from literature

In the present study, an extensive literature review and reported data on pearl millet is collated to access the feasibility of introducing an EOFR based fertilizer recommendation system.

1. Collation of data from literature

Experimental data for the proposed recommendation system would require an extensive design, data collection, and time and would be considered depending on the observations obtained in this study using collated data from literature. Therefore, papers that included the yield response function for pearl millet for at least 4 doses of a fertilizer have been collated. All the available soil properties and weather parameters that have been reported along with the yield response functions are also saved.

2. Available soil properties for the reported data

Reported data from the study conducted by Thivierge et al. (2015) is taken as the first example data for the present study. The study was conducted in two experimental sites with different temperature regimes in Canada. The reported soil properties included the values for Sand, Clay, SOC, CEC, pH and BD and are provided in Table 1. The second data for this report is extracted from the study of Akponikpè et al. (2010) conducted in the 500–600 mm rainfall area of the Sahelian zone of Nigeria. The third data set is obtained from the study of Singh and Thakare (1986) for the savanna region of Nigeria. The soil properties are including pH, SOC, CEC, Sand, Silt, and Clay. The fourth dataset is taken from the study of Maman et al. (2017). The primary objective of this paper was to observe the pearl millet and cowpea intercrop response to applied nutrients, however, for our present study we have only collated data for sole crop of pearl millet and for on farm trials. The soil properties for the experimental site in Mali is given in table 1 which includes elevation, SOC, Sand, Silt, Clay, pH.

4. Yield response for pearl millet

The yield response curve for the various doses of N as reported by Thivierge et al. (2008) is shown in Fig. 1. The equations fitted to the yield response curve for the two locations of the study are given as:

$$Y = 1299 + 10.29x - 0.038x^2 \quad (R^2: 0.99)$$

and

$$Y=804.2+10.31x-0.048x^2 \quad (R^2:0.94)$$

The yield response curve for the various doses of N as reported by Akponikpè et al. (2010) is shown in Fig. 1. The equations fitted to the yield response curve for the location is given as:

$$Y=419.6+9.020x-0.063x^2 \quad (R^2:0.50)$$

The yield response curve for the various doses of N as reported by Singh and Thakare (1986) for five varieties and for Samaru, Nigeria is given as:

$$Y=637.1+19.42x-0.114x^2 \quad (R^2:0.93)$$

$$Y=1105+37.54x-0.331x^2 \quad (R^2:0.93)$$

$$Y=1057+32.22x-0.274x^2 \quad (R^2:0.93)$$

$$Y=1285+24.74-0.171x^2 \quad (R^2:0.95)$$

$$Y=1074+20.05x-0.148x^2 \quad (R^2:0.94)$$

The yield response curve for the various doses of N as reported by Singh and Thakare (1986) for five varieties and for Kano, Nigeria are given as:

$$Y=1328+17.31x-0.057x^2 \quad (R^2:0.93)$$

$$Y=1268+10.51x-0.022x^2 \quad (R^2:0.99)$$

$$Y=1288+10.91x-0.057x^2 \quad (R^2:0.99)$$

$$Y=1174+31.25x-0.148x^2 \quad (R^2:0.95)$$

$$Y=1142+12.57x-0.045x^2 \quad (R^2:0.99)$$

As the objective of this study is to observe the differences in EOFR as a function of soil parameters, we are not considering the variation in the economically optimal N rate because of different varieties. Therefore, for the data of Singh and Thakare (1986), we averaged the coefficients of the fitted quadratic equations to the five yield response curves in order to calculate the required economically optimal N rate.

The yield response function of pearl millet for various P and N rates, respectively, as given by Maman et al. (2017) are given as:

$$Y=1047-5.047x+0.368x^2 \quad (R^2:0.95)\ (P\ rates)$$

$$Y=1209+11.75x-0.135x^2 \quad (R^2:0.95)\ (N\ rates)$$

Using the quadratic equations fitted to the yield response curves, we calculated the economically optimal N rates. The fixed price of Urea is taken as 5.6 INR per kg and for traditional pearl millet is taken as 55 INR per kg. The calculated economically optimal N rates using Eq. 2 are shown in Table 2. As we could find yield response curve for various P rates for only one data, we are not including the same for our analysis.

As observed from Table 2, the EONR varies from 43 kg ha^{-1} to 133 kg ha^{-1} indicating that the soil and climate of a particular location to have an influence on the profit that might be obtained growing pearl millet. However, the pearl millet data are reported from various sources and might obviously have varietal differences, which is overlooked in this study. The entire study is conducted to propose a method to improve the sustainable pearl millet production.

As we could only collate 6 suitable data on pearl millet yield from the literature, therefore, it is not feasible to develop a model. It is not feasible to conclude any relationship from the figures because of the less number of data, however, the variation of EONR as a function of the soil properties indicates that a machine learning approach might have these responses and would be able to predict the EONR.

5. A proposed fertilizer recommendation system based on the modeled EOFR values

With the recent development in technologies, many sensors are already developed and some are in the developmental phases that would provide a quantification of the nutrients of soil in a real time. If we have a model to predict the EOFR, we may use this sensor detected nutrient values to recommend a fertilizer rates for crop for a sustainable and economic production. For example, in the present study we have calculated that the EONR for a region with SOC as high as 2.68, an acidic pH of 5.25, and a % sand and % clay contents of 64.4 and 20.3, respectively, is requiring only 43 kg ha^{-1} of N for a sustainable growth. If the N in the soil is detected as 20 kg ha^{-1} (for instance), providing only 23 kg ha-1 of N through fertilizer would be enough instead of the recommended dose of around 60 kg ha^{-1} of N. It is to be noted that we have used only the rate of chemical fertilizer to calculate the EONR. If an organic source of fertilizer is used, we have to consider the rate accordingly. A flowchart is shown in Fig. 1 for the proposed fertilizer recommendation system.

6. Conclusion

The analysis carried out with collated data clearly shows that the EOFR is influenced by the soil properties. As the data are reported for various climatic regimes, it is also very much clear that the climatic parameters would also have an effect on the EOFR. In addition, the fertilizer system based on EOFR is very much required for a sustainable agricultural production for pearl millet and also may be for other crops.

A comprehensive fertilizer recommendation system based on EOFR would require experimental trials with the concerned crop (pearl millet for example) to be carried out. The steps are: 1. calculate yield response curves for pearl millet for the essential nutrients for two growth season and for at least three different climatic regimes. A literature review supports that N, P, K, Zn, Fe, S, and Mn are essential for the growth of Pearl millet. 2. Use a number of datamining algorithms to predict the EOFR for pearl millet using soil physical parameters, EC, pH, water retention parameters, crop parameters, and climatic factors as predictors. 3. Measure the residual values of N, P, K, Zn, Fe, S, and Mn using a rapid nutrient sensing technology to provide a real time fertilizer recommendation system for pearl millet using the EOFR.

Table 1: Soil properties for sites growing pearl millet with different nutrient rates (collated from literature)

Soil Properties and water retention parameters						References
Sand (%)	Clay (%)	SOC (%)	CEC meq/100g	pH	BD gcc^{-1}	
62	17	1.54	13.8	6.5	1.4	Thivierge et al., 2015
56	21	1.79	16.65	6.6	1.24	Thivierge et al., 2015
-	-	0.19	-	5.4	1.65	Akponikpè et al., 2010
58	9	0.35	2.97	5.5	-	Singh and Thakare (1986)
83	5	0.23	1.11	4.9	-	Singh and Thakare (1986)
64.4	203	2.68	-	5.25	-	Maman et al., 2017

SOC, soil organic carbon; CEC, cation exchange capacity; BD, bulk density.

Table 2: Economically optimal N rates for the various pearl millet yields calculated from the quadratic function fitted to the yield response curves

r	*b*	*c*	EONR (kg h^{-1})	Reference
0.121	10.29	-0.038	133.80	Thivierge et al., 2015
	10.31	-0.048	106.13	Thivierge et al., 2015
	9.032	-0.063	70.72	Akponikpè et al., 2010
	26.754	-0.207	64.33	Singh and Thakare (1986)
	16.546	-0.065	126.34	Singh and Thakare (1986)
	11.75	-0.135	43.07	Maman et al., 2017

r is the ratio of the cost of fertilizer to the cost of pearl millet grain, *b* and *c* are the coefficients of the quadratic equation fitted to the yield response curve of pearl millet for different N rate in Kg $ha^{-1}$and EONR is the economically optimal N rate.

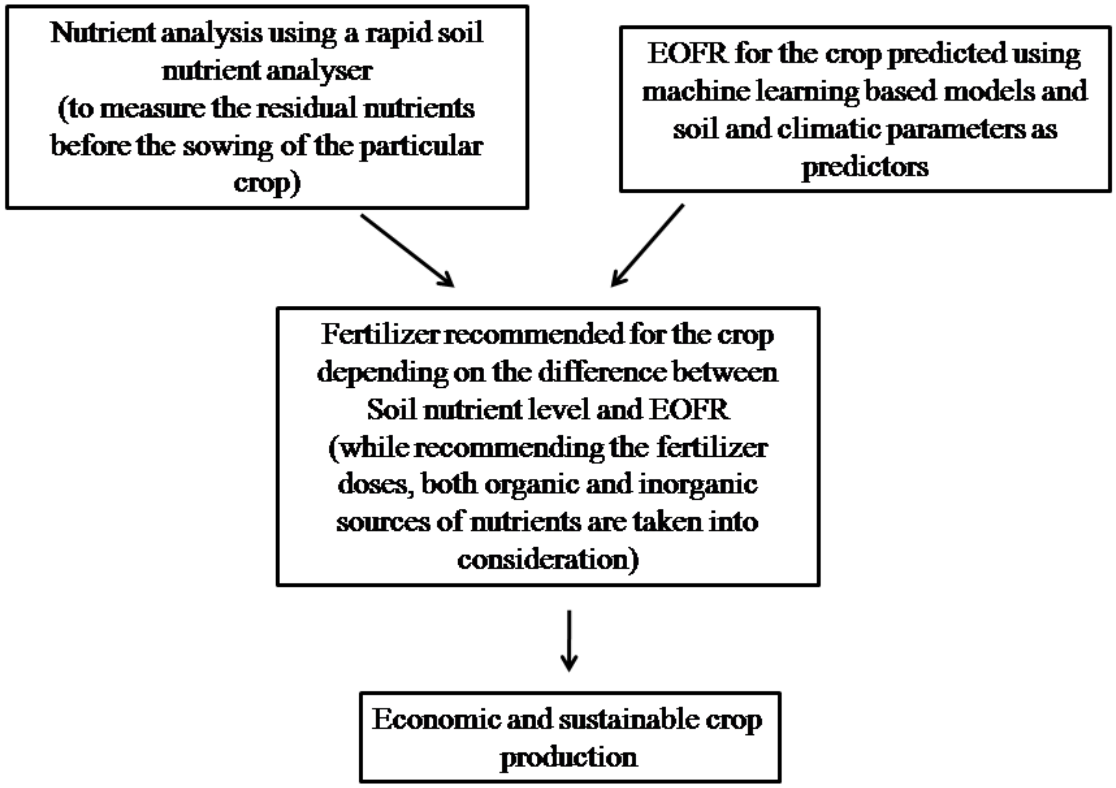

Fig. 1. A flow chart showing the different components of the proposed fertilizer recommendation system based on economically optimal fertilizer rate (EOFR) for a sustainable crop production.

REFERENCES

Akponikpè, P. B. I., B. Gérard, K. Michels and C. Bieldersa. 2010. Use of the APSIM model in long term simulation to support decision making regarding nitrogen management for pearl millet in the Sahel. *European Journal of Agronomy* 32: 144-154.

Aune, J. B., Naroua, I., S. Issaka, A. K. Saidou, I. A. Rachida, M. S. Souley. 2020. Effects of Fertilizer Micro-Dosing on Grain Yield of Cereals and Legumes in Western Niger, West Africa. *Journal of Environment and Agricultural Science* 22: 20-25.

Breiman, L. 2001. Random Forests. *Machine Learning* 45:5–32.

Bullock, D. S. and D. G. Bullock. 1994. Calculation of Optimal Nitrogen Fertilizer Rates. *Agronomy Journal*: 86: 921-923.

Christianson, C.B., A. Bationo and J. Henao. 1990. Fate and efficiency of N fertilizers applied to pearl millet in Niger. *Plant Soil* 125: 221–231.

Corinna, C., V. Vapnik (1995). "Support-Vector Networks". *Machine Learning*. 20:273-297. doi:10.1007/BF00994018.

Coulibaly, A., K. Woumou J. B. Aune. 2019. Sustainable Intensification of Sorghum and Pearl Millet Production by Seed Priming, Seed Treatment and Fertilizer Microdosing under Different Rainfall Regimes in Mali. *Agronomy* 9: 664. doi.org/10.3390/agronomy9100664

Drucker, H., J. C. B. Christopher, J. C. Burges, L. Kaufman, V. Vapnik. 1997. Support vector regression machines. *Advances in Neural Information Processing Systems* 28:779-784

Everingham, Y., J. Sexton, D. Skocaj and G. Inman-Bamber 2016. Accurate prediction of sugarcane yield using a random forest algorithm. *Agronomy for sustainable development* 36: 27. doi.org/10.1007/s13593-016-0364-z

Friedman, J. H. 2000. Greedy Function Approximation: A Gradient Boosting Machine. *Annals of Statistics* 29(5). doi:10.1214/aos/1013203451

Gandhi, N., L. J. Armstrong, O. Petkar and A. K. Tripathy. 2016. Rice crop yield prediction in India using support vector machines. 13th International Joint Conference on Computer Science and Software Engineering (JCSSE), Khon Kaen, 2016, pp. 1-5, doi: 10.1109/ JCSSE. 2016. 7748856.

Gopalan C, B. V. R. Sastri, S. C. Balasubramanian. 2003. *Nutritive value of Indian Foods.* National Institute of Nutrition, Hyderabad (India).

Govindaraj, M., A. Kanatti, K. N. Rai and T. Satyanarayana. 2019. Does Soil Micronutrient Variability in Test Locations Influence Performance of Biofortified Pearl Millet in India? *Better Crops South Asia* 11: 31-35.

Gulati, A., P. Banerjee. 2015. Rationalising Fertiliser Subsidy in India: Key Issues and Policy Options. Indian Council for Research on International Economic Relations, New Delhi (India).

Hernandez, J., G. A. Lobos, I. Matus, A. D. Pozo, P. Silva and M. Galleguillos. 2019. Using Ridge Regression Models to Estimate Grain Yield from Field Spectral Data in Bread Wheat (*Triticum aestivum* L.) Grown under three Water Regimes. *Remote Sens*ing 7: 2109-2126.

Hong, N., P. Scharf, J. G. Davis, N. R. Kitchen, K. A. Sudduth. 2007. Economically Optimal Nitrogen Rate Reduces Soil Residual Nitrate. *Journal of Environmental Quality* 36:354-362.

Jaynes, Dan B. 2011. Confidence bands for measured economically optimal nitrogen rates. *Precision Agric*ulture12:196–213 DOI 10.1007/s11119-010-9168-3

Jiang, W., L. Xiaohu, W. Xiukang, Y. Lihui and Y. Yin. 2019. Improving Phosphorus Use Efficiency and Optimizing Phosphorus Application Rates for Maize in the Northeast Plain of China for Sustainable Agriculture. *Sustainability* 11: 4799. doi.org/10.3390/su11174799

Kadam, S. B., S. B. Pawar and J. S. Rajeshwar. 2019. Impact of Integrated Nutrient Management on Growth, Yield of Summer Pearl Millet. *Trends in Biosciences* 12: 1-4.

Kam, J., S. Puranik, R. Yadav, H. R. Manwaring, S. Pierre, R. K. Srivastava, and R. S. Yadav. 2016. Dietary interventions for type 2 diabetes: How millet comes to help. *Frontier in Plant Science* 7: 1454. doi: 10.3389/fpls.2016.01454

Kanchana, B., R. Santhi, S. Maragatham and C. N. Chandrasekhar. 2020. Validation of Inductive cum Targeted Yield Model based Fertilizer Prescription Equations for Pearl millet (var. CO 10) on Inceptisol. *Madras Agricultural Journal* 107: 1-6 doi:10.29321/MAJ 2020.000353

Kumar, V. and V. Singh. 2019. Effect of site-specific nutrient management on yield and nutrient uptake in pearl millet (*Pennisetum glaucum*)-wheat (*Triticum aestivum*) cropping sequence. *Annals of Plant and Soil Research* 21: 1-6.

Kumar, V., V. Goyal and P. Dey. 2020. Impact of STCR based long term integrated management practices on soil chemical properties and yield attributing parameters of wheat and pearl millet in semi-arid North-West India. *International Journal of Chemical Studies* 8: 1320-1328. doi.org/10.22271/chemi.2020.v8.i4l.9783

Maman, N., Mohamed Dicko, Gonda Abdou, Zoumana Kouyate, and Charles Wortmann Nutrition. 2017. Pearl Millet and Cowpea Intercrop Response to Applied Nutrients in West Africa. *Agronomy Journal* 109: 2333-2342.

Meena, M. D., P. K. Joshi, H. S. Jat, A. R. Chinchmalatpure, B. Narjary, P. Sheoran, D. K. Sharma. 2016. Changes in biological and chemical properties of saline soil amended with municipal solid waste compost and chemical fertilizers in a mustard–pearl millet cropping system. *Catena* 140: 1-8.

Moore, I. D., P. E. Gessler, G. A. Nielsen and G. A. 1993. Peterson, Soil attributes presduction using terrain analysis. *Soil Science Society of American Journal* 57: 443-452.

Qin, Z., D. B. Myers, C. J. Ransom, N. R. Kitchen, S. Liang, J. J. Camberato, P. R. Carter, R. B. Ferguson, F. G. Fernandez, D. W. Franzen, C. A.M. Laboski, B. D. Malone, E. D. Nafziger, J. E. Sawyer and J. F. Shanahan. 2018. Application of Machine Learning Methodologies for Predicting Corn Economic Optimal Nitrogen Rate. *Agronomy Journal* 110: 2596-2607.

Ramesh, D., and V. Vardhan 2015. Analysis of crop yield prediction using data mining techniques. *International Journal of Research in Engineering and Technology* 4(01):470-473.doi:10.15623/ijret.2015.0401071

Ransom, C. J., N. R. Kitchen, J. J. Camberato, P. R. Carter, R. B. Ferguson, F. G. Fernández, D. W. Franzen, C. A. M. Laboski, E. D. Nafziger, J. E. Sawyer, P. C. Scharf, J. F. Shanahan. 2020. Corn nitrogen rate recommendation tools' performance across eight US midwest corn belt states. *Agronomy Journal* 112: 470-492.

Scharf, P., N. R. Kitchen, K. A. Sudduth, J. G. Davis, V. C. Hubbard and J. A. Lory. 2005. Field-Scale Variability in Optimal Nitrogen Fertilizer Rate for Corn. *Agronomy Journal* 97: 452-461.

Schapire, R. E. 1990. Strength of weak learniability. *Machine Learning* 5: 197-227.

Shahhosseini, M., R. A. Martinez-Feria, G. Hu, and S. V. Archontoulis. 2019. Maize yield and nitrate loss prediction with machine learning algorithms. *Environmental Research Letters* 14: 1-11.

Singh P., K. J. Boote, M. D. M. Kadiyala, S. Nedumaran, S. K. Gupta, K. Srinivas, and M.C.S. Bantilan. 2017. An assessment of yield gains under climate change due to genetic modification of pearl millet. *Science of the Total Environment* 601: 1226-1237.

Singh, L. and R. B. Thakare. 1986. Yield response and nitrogen uptake of pearl millet (*Pennisetum americanum* (L.) Leeke) cultivars to nitrogen application in the savanna region of Nigeria. *Fertilizer research* 10:113–118.

Thivierge, M. N., M. H. Chantigny, G. Bélanger, P. Seguin, A. Bertrand and A. Vanasse. 2015. Response to Nitrogen of Sweet Pearl Millet and Sweet Sorghum Grown for Ethanol in Eastern Canada. *Bioenergy Research* 8:807–820.

Udayakumar, S., R. Santhi, P. Dey, S. Meena and S. Maragatham. 2019. Validation of soil test and yield target based fertilizer prescription model developed for pearl millet on Inceptisol. *Research on Crops* 20: 266-274. doi10.31830/2348-7542.2019.039.

Ullah, A., I. Ahmad, A. Ahmad, T. Khaliq , U. Saeed, M. Habib-Ur-Rahman, J. Hussain, S. Ullah, G. Hoogenboom. 2019. Assessing climate change impacts on pearl millet under arid and semi-arid environments using CSM-CERES-Millet model. *Environmental Science and Pollution Research* 26: 6745-6757.

Yadav, O. P., K. N. Rai, B. S. Rajpurohit, C. T. Hash, R. S. Mahala, S. K. Gupta, H. S. Shetty, H. R. Bishnoi, M. S. Rathore, A. Kumar, S. Sehgal and K. L. Raghvani. 2012. Twenty-five Years of Pearl Millet Improvement in India. Indian Council of Agricultural Research, Jodhpur, Rajasthan.