**Supplementary Tables**

**Table S1**. Details on full-text articles evaluating modelling of banana fruit yield

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| **No** | **Authors** | **Title** | **Year** | **Country (cultivar/ sample size (n), if available)** | **Key findings** | **Independent variables** | **Dependent variables** | **Statistical methods** | **Equation/****Outcomes** | **Model Performance** |
| 1 | Olivares B.O., Araya-Alman M., Acevedo-Opazo C., Rey J.C., Cañete-Salinas P., Kurina F.G., Balzarini M., Lobo D., Navas-Cortés J.A., Landa B.B., Gómez J.A. | Relationship Between Soil Properties and Banana Productivity in the Two Main Cultivation Areas in Venezuela | 2020 | Venezuela | Olivares et al. (2020) developed a model to predict the banana Productivity Index (PI) in the two main cultivation areas in Venezuela using soil properties. The selected model compromised with Mg, penetration resistance, total microbial respiration, bulk density, and omnivorous free-living nematodes and explained the PI. | In total, 16 soil variables that accounted for the highest proportion of the variance of PI were selected in the random forest analysis including penetration resistance (PR), copper (Cu), magnesium (Mg), and soil pH from both soil horizons, while the variables omnivorous free-living nematodes (NVLomc), calcium carbonate (CaCO3), silt, total microbial respiration (TMRc), moisture index (W), soil bulk density (BD), and percentage of functional roots (% RF) were selected from data on soil horizon 1 only and potassium (K) from soil horizon 2. | PI was derived from the circumference of the pseudo-stem of the mother plant at 1 m in height (CircM, cm), the number of hands per bunch (Nhand, n), and the height of the succession plant (AltH, cm) according to the methodology proposed by Rosales et al. (2008). | Principal component analysis (PCA) was used to select variables best-presented PI index. The soil variables were selected through a random forest. A multiple linear regression model was performed, using the forward stepwise regression method to finalize the final model.  | PI=9.03+0.19(Mg\*)-8.78(PR\*)-0.40 (TMRc\*)-4.70(BD\*)+0.02(NVLomc\*)  | R2 of 0.55, a MAEof 0.8, and an RMSE of 1.0.  |
| 2 | Alcudia-Aguilar A., Martínez-Zurimendi P., Van Der Wal H., Castillo-Uzcang.M., Suáez-Sánchez J | Allometric estimation of the biomass of Musa spp. In homegardens of Tabasco,  | 2019 | Mexico (M. balbisiana) | Alcudia-Aguilar et al. (2019) produced a mathematical model for banana biomass using taxonomic data and dry weight of the above and below ground components in home gardens of Tabasco, Mexico. The results indicated that above-ground biomass (AGB) was strongly correlated with the diameter of pseudostem (DBH) and to a certain extent with height data.  | Pseudostem diameter (DBH) at a height of 30cm, height of the pseudostem (HF), and total height (HT) | Growth, Biomass | Simple linear regressionKopezky model (Segura and Andrade, 2008) | AGB= -0.0927+0.0203\*DBH2 | R2=0.88MSE=1.9PRESS=316.74CV=27.89  |
| 3 | Salvacion A.R, | Effect of climate on provincial-level banana yield in the Philippines | 2020 |  Philippine | This study assessed the effect of climate on banana yield using provincial-level yield data and different climatic variables. Linear trend analysis, multiple regression analysis were used to assess the effect of climate on provincial-level banana yield. Trend analysis showed that 71% of the banana producing area in the country experience significant yield trend while multiple regression analysis showed that only 10% of the banana producing areas is significantly affected by climate. | Annual rainfall, frequency of wet days, precipitation seasonality, annual mean temperature, temperature seasonality, and annual mean diurnal temperature range | Banana yield | Time series analysis, multiple regression  | Y=β0+β1X1+βnXn (Y is the yield and X is weather variables) | R2>0.5 |
| 4 | Rathod, S., & Mishra, G. C.  | Statistical Models for Forecasting Mango and Banana Yield of Karnataka, India | 2018 |  India | The yield of mango and banana of Karnataka have been chosen as study variables. Classes of linear and nonlinear, parametric, and non-parametric statistical models have been employed to forecast the yield of bananas. In most cases, the time series are not purely linear or nonlinear as they contain both linear and nonlinear components. To overcome this problem, the hybrid model with the combination of Autoregressive Integrated Moving Average (ARIMA) and Support Vector Regression model was performed. | Temperature, relative humidity, precipitation, wind speed, solar radiation, socioeconomics variables | Banana and mango yield | Regression model, weather indices, ARIMA, ANN, NLSVR and proposed hybrid methodology | Nonlinear support vector regression (f(x)=WTФ(x)+b | Adj-R2=0.94 |
| 5 | Hossain, M. M., Abdulla, F., & Majumder, A. K.  |  Forecasting of banana production in Bangladesh. | 2016 | Bangladesh | Identified the Auto-Regressive Integrated Moving Average (ARIMA) the model that could be used to forecast the production of bananas in Bangladesh over the period 1972 to 2013. The best selected ARIMA model to forecast the banana productions in Bangladesh is ARIMA (0,2,1).  |   | Banana yield | Time series analysis (ARIMA) | ARIMA (0,2,1) | RMSPE = 19.577, MPFE = 17.60806 and TIC = 0.103167 |
| 6 | Sharath, K. M.  | Pre-harvest forecasting models and trends in the production of banana (Musa spp.) in Kerala   | 2016 | India | The growth and yield characters of the banana Nendran cultivar were considered to predict yield. Correlation and Stepwise multiple linear regression studies were conducted to predict the yield (bunch weight). The results of the analysis revealed that the height of 4th and girth of 5th month can be effectively used as best predictor variables. However, sucker parameters and some leaves don’t take any role in the prediction of the total yield. | sucker weight, length, girth, and volume of suckers; fruit parameters such as number of fruits, the weight of the second hand, fruit length, fruit weight, fruit girth, and plant height, plant girth, number of leaves, and leaf area | Bunch weight | stepwise multiple regression | For the 4th month, Y=-0.47+0.033H3-0.08L4+0.01H4+0.07G4 ; For 5th month, Y= -1.37+ 0.025 H4 + 0.10 G5 | R2=0.55  |
| 7 | Zucoloto M., Lima J.S.S., Coelho R.I., Xavier A.C. | Regression models to estimate the mass of the bunch of banana tree cv. Prata Anã  | 2013 | Brazil (Prata Anã)  | Zucoloto et al. (2013) used multiple linear regression models to estimate the bunch weight (BW) of banana cv. Prata Anã using morphological characteristics such as the width of the third leaf (LF), number of leaves at a tree (NF), the diameter of the bunch (DC), and number of bananas per bunch (NB).  | Width of the third leaf (LF), number of leaves at a tree (NF), the diameter of the bunch (DC), and number of bananas per bunch (NB) | Bunch weight (BW) | Multiple linear regression | BW = -10.96 + 0.176\*(DC) + 0.0983\*(NB) + 0.0928\*(LF) + 0.2216\*(NC) | R2=0.58  |
| 8 | Jaiswal P., Jha S.N., Bharadwaj R. | Non-destructive quality prediction of banana using spectroscopy | 2012 | IndiaLudhiana (Musa acuminata) (cv:Grandnaine) | Jaiswal et al. (2011) employed spectroscopy and multiple linear regression model (MLR) to predict dry matter (DM) content, pH, total soluble solids (TSS), and acid-Brix ratio (ABR) for a banana at their maturity and/or ripening stage. | Wavelength | Dry matter (DM) | Partial least square (PLS) and multiple linear regression (MLR) |  Space is inadequate to indicate the equations | R=0.83  |
| 9 | Wairegi L.W.I., van Asten P.J.A., Tenywa M., Bekunda M. | Quantifying bunch weights of the East African Highland bananas (Musa spp. AAA-EA) using non-destructive field observations | 2009 | Uganda, East African Highland (Musa spp. AAA-EA, n=179)  | Wairegi et al. (2009) developed allometric relationships to estimate bunch weight, Bunch weights were estimated via log-transformed grith of pseudostem at the base and 1 m, number of hands, and number of fingers in the lower row of the second-lowest hand using the linear regression method.  | Log-transformed girth of pseudostem at base (PB) and 1m (PG1), number of hands (NH), and number of fingers (NF) in the lower row of the second lowest hand | Bunch weight (BW) | Multiple linear regression | ln (BW) = -6.8 + 0.75 ln (PB) + 1.05 (PG1)+0.57 ln( NH)+ 0.48 (NF) | R2 = 0.73  |
| 10 | Venugopalan R., Shamasundaran K.S. | Statistical model for evolving a crop-logging technique in banana | 2005 | India (cv. Robusta,n=200) | They developed a statistical model to identify the best yield indicators of bananas across different growth stages. Statistical models developed and validated showed that at 70 days after planting (DAP), the number of leaves and plant girth [Coefficient of Determination (R2) 88%] with optimum values as 8 leaves and 15.07 cm were the best yield indicators.  | Number of leaves, plant girth, plant height, leaf breadth and leaf length, number of fingers per bunch, and number of hands per bunch | Yield | Multiple linear regression |   Space is inadequate to indicate the equations | R2=0.81-0.99  |
| 11 | Villegas-Santa L., Castañeda-Sánchez D.A. | Multivariate analysis for modeling yield variability to define management zones in a banana agroecosystem | 2020 | Colombia (Cavendish AAA. West) | Villegas-Santa et al. (2020) identified the relationship between soil variables and crop performances of bananas using the multivariate statistical tool. Three clusters of sites were evaluated based on dry mean weight, pH, and Ca+Mg/K ratio of soils, and all these soil properties were highly correlated with banana yield. | Soil texture, surface penetration resistance, surface apparent density, structural stability indexes, wet and dry mean weight diameter, wet and dry structure index, wet and dry fine aggregates (< 0.5 mm), wet and dry extreme aggregates, moisture indexes, gravimetric moisture retention, pH, organic matter content, effective cation-exchange capacity, effective cation exchange capacity at pH 7, Ca, Mg, K, Al, Ca/Mg ratio, (Ca + Mg)/K ratio, P, S, Fe, Mn, Cu, Zn, B | Exported bunch weight, rejected bunch weight, bunch hands number, bunch fingers number, central finger width of the second hand, central finger width of a penultimate hand, central finger length of the second hand, central finger length of the penultimate hand, functional and not functional root | Principal Component Analysis | The most influential variables for banana yield were (Ca+Mg)/K ratio, the difference between the average size of wet and dry aggregates, and pH. | Not given  |
| 12 | Venugopalan R. | Yield prediction in banana (Musa x paradisiaca) (cv Grand Naine) by ANN models | 2015 | IndiaBengaluru (Musa x paradisiaca L) | Venugopalan (2015) used ANN models to predict the yield of banana (Musa x paradisiaca) (cv Grand Naine) and results showed that during 3rd month of crop growth: after sucker emergence and before inflorescence stage, plant girth (optimum value as 27 cm), and leaf breadth (optimum values as 35.5 cm); during the pulp development stage (7thmonth), plant height (optimum value as 82 cm) and 13 leaves; during starch accumulation stage (9th month) plant height (optimum value as 127 cm); leaf breadth (optimum value as 54 cm) were the significant crop logging biometrical traits having 82.3 to 92.1% power of predicting crop yield. They indicated that the ANN approach can be utilized to handle nonlinear relations among the biomedical traits in crop modeling research, for a realistic representation of nonlinearity. | Plant girth, and leaf breadth during pulp development stage, plant height, leaf breadth  | Yield | Artificial Neural Network (ANN) | Space is inadequate to indicate the equations | R2=0.82-0.92  |
| 13 | Soares J.D.R., Pasqual M., Lacerda W.S., Silva S.O., Donato S.L.R. | Utilization of artificial neural networks in the prediction of the bunches' weight in banana plants | 2013 |  BrazilGuanambi, Bahia [Tropical (YB42-21), an AAAB tetraploid hybrid] | Soares et al. (2013) estimated the effect of agronomic characters associated with the bunch weight of the banana plant in Guanambi, Bahia, using a cultivar called Tropical (YB42-21) hybrid. The artificial neural networks (ANNs) method was used to predict banana yield with high accuracy (R2=91%, MPE=1.40, and MSD=2.29). | The Weight of the rachis, length, and diameter of the stalk, Weight of the second hand, the total number of hands per bunch, number of fruits per bunch, the weight of the fruit, external length of the fruit, diameter or side calibration of fruit, and number of living leaves at harvest were considered as input layers.  | Bunch weight (BW) | Artificial Neural Network (ANN) | The model consisted of three layers, the first composed of ten neurons corresponding to the ten input variables, the second layer, the second layer is a hidden layer with ten neurons and the third layer is the output layer with one neuron, which provides the weight of the bunch. | R2=0.91, MSD=2.29, EMP%=1.4 |
| 14 | de Souza A.V., Bonini Neto A., Cabrera Piazentin J., Dainese Junior B.J., Perin Gomes E., dos Santos Batista Bonini C., Ferrari Putti F. | Artificial neural network modelling in the prediction of bananas’ harvest | 2019 | Brazil  | de Souza et al. (2019) developed an artificial neural network (RMSE =0.3% and R2=0.89) to find the relationship between climatic variables and banana bunch gestation period to predict the harvesting time.  | Climatic factors (main axis): Average temperature - AverageT (ºC); Minimum temperature - MinT (° C); Maximum temperature - MaxT (° C); Humidity - H (%); Precipitation (mm) and Photoperiod (h). | Bunch weight (BW) | ANN computational implementation in MATLAB |  ANN | RMSE =0.3% R2=0.89  |
| 15 | Tixier P., Malezieux E., Dorel M. | SIMBA-POP: A cohort population model for long-term simulation of banana crop harvest | 2004 | FranceFrench West Indies [Musa spp., AAA group, (cv. Cavendish Grande Naine)] | A new simulation model (SIMBA-POP) to predict non-synchronized phenological patterns and yield of banana cropping system using Cavendish Grande Naine (Musa spp., AAA group). The model was able to predict harvesting date and bunch yield with a precision of fewer than 3 weeks for 3 cropping cycles of banana. Due to flowering, harvesting, and sucker selection, the two linear chains of cohorts were used to develop the model that is featured by physiological age and dispersion of development-stage in banana population.  | Plant physiological parameters, weather conditions, soil properties, and crop management-related variables.  | Growth, development, and yield | SIMBA model |  Crop model | R2=0.98  |
| 16 | Ortiz-Ulloa J.A., Abril-González M.F., Pelaez-Samaniego M.R., Zalamea-Piedra T.S. | Biomass yield and carbon abatement potential of banana crops (Musa spp.) in Ecuador | 2020 | Ecuador | Ortiz-Ulloa et al. (2020) quantified the yearly residual biomass amount of banana monoculture system, carbon stock of banana mass, carbon sequestration by residual banana mass as well as develop a biomass prediction model for the banana crop in Ecuador. The Musa AAA Cavendish variety was used to obtain samples of pseudostem, leaves, rachis, and flowers from three provinces in Ecuador. The residue to product ratio of 3.79 has resulted in 2.65 Mt of annual biomass generation on a dry basis. It was estimated an average of 4.92±1.03 Mg/ha of the carbon stock of the standing biomass and 3.92 MtCO2 of sequestrated carbon of the residual biomass. | circumference at breast height (CBH) | Biomass | Simple linear regression model | Residual biomass = 0.0001(CBH)3 + 35.62 | R2=0.85, MAE=9.74  |
| 17 | Laskar S.Y., Sileshi G.W., Nath A.J., Das A.K. | Allometric models for above and below-ground biomass of wild Musa stands in tropical semi-evergreen forests | 2020 | IndiaCachar district of Barak Valley, Assam , M. balbisiana, n=156) | Laskar et al. (2020) used mathematical models to estimate biomass accumulation of wild Musa spp. The height-diameter (H-D models of Chapman-Richard, exponential, Gompertz, hyperbolic, Michaelis-Menten (saturation growth), power-law, Weibull, and Von Bertalanffy functions were used to predict missing heights from field measurement of plant diameter. The predictors of diameter (D), height(H), and combination of diameter and height of pseudostem were used to estimate total biomass estimation models via non-linear seemingly unrelated regression analysis. The Exponential and Gompertz functions were observed to be the two best models for describing the H-D relationship and the model containing D and H product was found to be the best model to estimate the total biomass. | Diameter (D), height (H), and combination of diameter and height of pseudostem  | Biomass | Non-linear seemingly unrelated regression analysis.  | Model 1: ln(a) þ bln(D); Model 2: ln(a) þ bln(Hp); Model 3: ln(a) þ bln(D2Hp); Model 4: ln(a) þ bln(D) þ gln(Hp). | R2=0.94, RMSE=0.317  |
| 18 | de Deus J.A.L., Neves J.C.L., Soares I., Alvarez V V.H., de Lima Neto A.J., de Albuquerque F.M.R., dos Santos L.L., Natale W. | Multivariate selection and classification of mathematical models to estimate dry matter partitioning in the fertigated Prata banana in Northeast Brazil | 2020 | Northeast Brazil (Prata banana, n=16) | de Deus et al. (2020) developed models to estimate dry matter partitioning in the banana mat. Models for the estimation of dry matter weight were generated for the different plant organs. Mean square residual (MSR), standard error of the estimate (Syx%), residual mean absolute deviation (MAD), coefficient of determination (R2), corrected Akaike information criterion (AICc), and Bayesian information criterion (BIC), in addition to cluster analysis was used for comparison and selection of the most appropriate model. The dry matter weight (DMw) of the organs comprising the mother plant and the daughter plant is best estimated as a function of DMw\_Mother and DMw\_Daughter respectively. | Dry matter weight (DMw) of the organs comprising the mother plant and the daughter plant  | Dry matter | Gaussian function | Ŷ = a / e((−(b–x)²) / (2 c²)) | R2=0.77, R=0.8  |
| 19 | Kuneepong P., Silayoi B., Apauthaipong T., Chutchwanchaiphan J. | Modelling banana yields to evaluate land use in Thailand | 2020 | Thailand | Kuneepong et al. (2020) used PLANTGRO- a generic system for predicting the growth of plants to study the performance of new banana varieties (Kasetsart 2) in Thailand. Data were collected from 4 farms with different climate and soil types and PLANTGRO was successfully used to simulate banana yields in Nakorn Sawan, Tak, and Rayong Provinces with planting periods. Integration of PLNTGRO and the Automated Land Evaluation System (ALES) was used to determine potential lands for new banana production in the Tak province. | Elevation, Cultivar, Irrigation practices | Yield | General linear model | 192.85+ 0.1(elevation)-14.22 (Cultivar)+3.316 (Without Irrigation) +212.2 (Irrigation) | Not given |
| 20 | Olivares B.O., Calero J., Rey J.C., Lobo D., Landa B.B., Gómez J.A. | Correlation of banana productivity levels and soil morphological properties using regularized optimal scaling regression | 2022 | Venezuela | Developed a regression model between the soil morphological variables of banana plantations and a Crop Productivity Index (PI). The study showed how soil quality is clearly related to productivity on commercial banana plantations.  | Biological activity (B), texture (T), dry consistence (DC), HCl and structure type (ST), Stickiness (Sti), Structure grade (SG), Root abundance (RA) | Productivity index (PI) | regularized optimal scaling regression/Categorical regression | PI = B (0.044), T (0.006), DC (0.001), ST (0.002), HCl (0.182), Sti (0.818), SG (0.478), RA (0.657) | R2 = 0.645, Boostrapped = 0.770 (0.169), crossvalidation =0.778 |
| 21 | Yeasin M., Singh K.N., Lama A., Gurung B. | Improved weather indices based Bayesian regression model for forecasting crop yield | 2021 |  India | To illustrate Bayesian models, production data of banana, mango and wheat yield data are taken under consideration and compared the traditional regression model with the Bayesian regression model and conclusively infer that the models estimated under Bayesian framework provided superior results as compared to the models. | Maximum and minimum temperature, morning and evening relative humidity, amount of rainfall for 23 years (from 1984 to 2007)  | Yield | Simple and Bayesian regression model  | y = β0+ β1x1+ β2x2 + ... + βkxk + ɛ | RMSE for simple regression = 223.14, RMSE for Bayesian regression = 216.87 |
| 22 | Guimarães B.V.C., Donato S.L.R., Aspiazú I., Azevedo A.M. | Yield prediction of ‘prata anã’ and ‘BRS platina’ banana plants by artificial neural networks [Predição da produtividade de bananeiras ‘Prata-Anã’ e ‘BRS Platina’ por redes neurais artificiais] | 2021 |  Brazil | This study aimed to evaluate the feasibility of predicting the yield of ‘Prata- Anã’ and ‘BRS Platina’ banana plants using artificial neural networks. The best adjustments were obtained with 2 and 3 neurons at the intermediate layer, respectively for ‘Prata-Anã’ and ‘BRS Platina’. The best adjustments were found for ‘Prata-Anã’ (R² = 0.99 for all the network compositions), while, for ‘BRS Platina’, the data adjustment enabled an R² with values between 0.97 and 1.00, approximately.  | Plant height; perimeter of the pseudostem at the ground level, at 30 cm and 100 cm; number of live leaves at harvest; stalk mass, length and diameter; number of hands and fruits; bunches and hands masses; hands average mass; and ratio between the stalk and bunch masses | Bunch weight (BW) |  Artificial neural networks | 2 and 3 neurons | R2 for Prata-Anã = 0.99, R2 for BRS Platina = 0.97 |
| 23 | Stevens B., Diels J., Brown A., Bayo S., Ndakidemi P.A., Swennen R. | Banana biomass estimation and yield forecasting from non-destructive measurements for two contrasting cultivars and water regimes | 2020 |  Tanzania |  Weighted least square regression models were built for (i) estimating aboveground vegetative dry biomass (ABGVD) and corm dry biomass (cormD) and (ii) forecasting bunch fresh weight (bunchF), for two banana cultivars, Mchare Huti-Green Bell (HG, AA) and Cavendish Grande Naine (GN, AAA), under two irrigation regimes. Pseudostem volume (Vpseudo) proved a good predictor for estimating ABGVD. Vpseudo at flowering predicted bunchF in FI plots correctly. Differences between FI and RF models were pronounced as 95%CI did not overlap. | Aboveground vegetative dry matter includes pseudostem (ABGVD), petiole and leaf dry matter. fresh bunch weight (BunchF); hand, number of hands ona bunch (N); finger, number of fingers on a bunch, phenology data | Growth and Yield | Weighted least square regression models |  ABVD= 0.33 + 6.02 × 10 × Vpseudo and bunch F= 0.13 + 2.24 × 10 -2 × Vpseudo | ABGVD (R2adj = 0.88-0.92; RRMSE = 0.14-0.19), predicted bunchF(R2adj = 0.70 for HG, R2adj = 0.43 for GN; RRMSE = 0.12-0.15 for HG and GN).  |
| 24 | Eyduran S.P., Akın M., Eyduran E., Çelik Ş., Ertürk Y.E., Ercişli S. | Forecasting Banana Harvest Area and Production in Turkey Using Time Series  | 2020 |  Turkey | Banana harvest area and production were modelled for the 2016–2025 period. Several Autoregressive Integrated Moving Average (ARIMA (0,1,1), ARIMA (1,1,0) and ARIMA (1,1,1)) and Exponential Smoothing (Holt, Brown and Damped) models were tested. Brown exponential smoothing model was determined as the most suitable. Banana production was predicted to show a substantial increase for the 2016–2025 period, from 291,667 to 482,093 t | Harvest area, production, time | Harvest area and production | ARIMA (0,1,1), ARIMA (1,1,0) and ARIMA (1,1,1)) and Brown Exponential Smoothing  |   |  R2 = 0.988, MAPE =19.052 |
| 25 | Khan T., Qiu J., Qureshi M.A.A., Iqbal M.S., Mehmood R., Hussain W. | Agricultural Fruit Prediction Using Deep Neural Networks | 2020 |  Pakistan | They implemented 3 different methods to predict the data for future fruit production using deep neural networks. The first method is Levenberg-Marquardt optimization (LM), which was 65.6% accurate; the second method is called scale conjugate gradient back propagation (SCG), which had an accuracy of 70.2%, and the third method, is Bayesian regularization back propagation (BR), which was 76.3% accurate.  | Time series analysis of fruit/ production data | Production | Levenberg-Marquardt optimization (LM), Bayesian regularization, scale conjugate gradient back propagation (SCG) |   | BR, accuracy= 75% |
| 26 | Rebortera M., Fajardo A. | Forecasting banana harvest yields using deep learning | 2019 |  Philippines | Recurrent neural network-long short term memory (RNN-LSTM) was used to estimate the banana production. The use of multiple LSTM layers joined together and the use of regularizatitechniquesque like dropout are suggested for exploration.  | Number of stems cut, the number of boxes produce/harvest yield, and box-stem ratio | Production | recurrent neural network-long short term memory (RNN-LSTM)  | Parameter (Epoch, Batchsize and Neurons) 1,1,50 | RMSE = 43.69 |
| 27 | Rebortera M.A., Fajardo A.C. | An enhanced deep learning approach in forecasting banana harvest yields | 2019 |  Philippines | Recurrent neural network-long short term memory (RNN-LSTM) was used to estimate the banana production. The use of multiple LSTM layers joined together and the use of regularization techniquesque like dropout are suggested for exploration.  | Number of stems cut, the number of boxes produce/harvest yield, and box-stem ratio | Production | recurrent neural network-long short term memory (RNN-LSTM)  | Parameter (Epoch, Batchsize and Neurons) 1,1,50 | RMSE = 43.69 |
| 28 | Bugaud C., Belleil T., Tixier P. | Modelling the effect of source/sink modifications on pulp dry weight of banana 'Cavendish' | 2015 |  France | An allometric relationship between the number of pulp cells, in fruit and fruit length at the end of cell division, was selected. A Michaelis-Menten relationship was used to simulate the cell filling rate in a bunch, with respect to the source/sink ratio during cell filling. Simulations of the different leaf-to-fruit ratio treatments showed good agreement with observed fruit growth data. The model was used to explore scenarios representing different cultivation practices and effects of climatic conditions. | RIE is radiation interception efficiency, RuE is radiation use efficiency (1.5 g/MJ), (Turner, 1990), SPAR is photosynthetically active radiation cumulated during the bunch filling period (in MJ/m 2 ), d is planting density (0.185 plant/m2 ) and TS is the thermal sum from inflorescence emergence to harvest | dry weight kinetics of the pulp during bunch filling | Non-linear regression | So=[RrExRuExSPAR]/[ dx(TS-350)] | RMSE = 2.36-4.5  |
| 29 | Soares J.D.R., Pasqual M., Lacerda W.S., Silva S.O., Donato S.L.R. | Comparison of techniques used in the prediction of yield in banana plants | 2014 |  Brazil | This study investigated the potential of using the culture's characteristics in predicting production responses by applying two techniques: artificial neural networks (ANNs) and multiple linear regression (MLR) in banana plants cv. Tropical. The neural network proved to be more accurate in forecasting the weight of the bunch in comparison to the multiple linear regressions in terms of the mean prediction-error. | Weight of the rachis; length of the stalk; diameter of the stalk; weight of the second hand; number of hands by bunch; number of fruits per bunch; weight of the fruit; length of the fruit; diameter of the fruit; number of living leaves | Bunch Weight | artificial neural networks and multipleregression analysis | ϒ=B+B1x1+B2x2….Bkxk+€ |  MPE=1.40, R2=91 |
| 30 | Negash M., Starr M., Kanninen M. | Allometric equations for biomass estimation of Enset grown in indigenous agroforestry systems in the Rift Valley escarpment of southern-eastern Ethiopia | 2013 |  Ethiopia | The objective of this study was to develop and evaluate allometric models for estimating above and belowground biomass and organic matter contents of enset. Basal diameter (d10) was the best predictor variable for total and all biomass components (Spearman r = 0. 775-0. 980, p &lt; 0. 01). The power model using d10 and height was found to be the best performing model for predicting total biomass. |  The diameter of the pseudostem was measured at a height of 10 cm (basal diameter, d10), at 30 cm (stump diameter, d30), at 130 cm (breast height, d130) and at 200 cm (boleheight diameter, d200), Pseudostem height (Hp) and total height (H), crown height (Hc) | Biomass | Allometric biomass models using linear (using untransformed and log-transformed, data) and nonlinear regression equations | Y=0.0007d102.7Ho.101 | R2 =0.91 |
| 31 | Robinson J.C., Human N.B. | Forecasting of banana harvest ('Williams') in the subtropics using seasonal variations in bunch development rate and bunch mass | 1988 |  South Africa | They developed a practical early forecasting technique for 'Williams' banana. Mean flower emergence to harvest interval and mean bunch mass were calculated for 24 flowering periods of 15 days each. It is proposed that with the estimated harvest spread and box/bunch adjustment factor, an earlier forecast can be made.  | Flower emergence to harvest interval (E-H), Number of new flowers counted at the end of the flowering period (N), Mean box (B), Box/bunch adjustment factor (a) | Yield (Y) | Multiple regression equation | Y = Y1 + Y2,..Y13 | Coefficient variation (CV) = 15% |
| 32 | Khan T., Sherazi H.H.R., Ali M., Letchmunan S., Butt U.M. | Deep learning-based growth prediction system: A use case of china agriculture | 2021 | China | This paper aims to reveal fruit production by focusing on the major crop production (from 1980 to 2050) taking into account various forms of data from fruit production (e.g., apples, bananas, citrus fruits, pears, and grapes). Five machine learning models (SP, LR, SVM, AdaBoost, MLP, and AGR-DL) have been employed as baseline. AGR-DL is capable to achive upto 95.56% precision. | Production data | Fruit production | Spatial Prediction, Deep neural networks -Agricultural Deep Learning (AGR-DL), Logistic Regression Model, Support Vector Machine (SVM), AdaBoost | spatial regression, maximum probability formula, Gaussian radial base function (RBF) kernel , AdaBoost algorithm | F1 score =87 - 94% |
| 33 | Salazar-Díaz R., Tixier P. | Individual-based analysis of interactions between plants: A statistical modelling approach applied to banana and cacao in heterogeneous multistrata agroecosystems in Talamanca, Costa Rica | 2021 |  Costa Rica | They analyzed the effect of the plant community in the neighborhood of each individual cacao tree and banana plant on their growth and yield parameters. They developed an individual-based analysis in two steps. First, they selected without a priori the distance at which the number of neighboring plants of a given functional group (banana plants, cacao trees, fruit trees, or wood trees) best explained the proportion of attainable yield (PAY) of cacao and banana plants. In a second step, they tested the significance of the abundances of the four groups of plants in a complete model that predicted the PAY of banana and cacao plants. Results suggest that it is possible to associate banana plants and cocoa trees to moderate densities of other plants without reducing their yield.  | Number of banana plants within a 2.6-m radius, number of cacao trees within a 2.9-m radius number of fruit trees within a 6.2-m radius, number of wood trees within a 7.8-m radius. Likelihood-ratio test, number of banana plants within a 3.9-m radius, number of cacao trees within a 5.5-m radius, number of fruit trees within a 3.9-m radius, number of wood trees within a 5.1-m radius. | proportion of attainable yield (PAY)  | linear mixed models, log-likelihood |   | bootstrap analysis, RRMSE=11.7%, R2 =0.6 |
| 34 | Wairegi L.W.I., van Asten P.J.A., Tenywa M., Bekunda M. | Abiotic constraints override biotic constraints in East African highland banana systems | 2010 | Uganda | They developed functional relationships between yield and those biophysical factors that correlated significantly (P ≤ 0.05) with yield in Spearman's test, or for those variables for which the upper boundary points in the scatter plot with yield suggested a functional relationship | Nematodes %, Weevils %, Soil pH, Soil organic matter (%), Total soil N (%), Clay (%), Rainfall, Mulch depth, Weeds, Population | Minimum predicted yield (Ymin) | quadratic or linear regression | Ymin= Min (Yx1, Yx2,….,Yxn) | R2 = 0.58 |

**Table S2**. Details on full-text articles evaluating modelling of banana crop growth

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **No** | **Authors** | **Title** | **Year** | **Country (cultivar/ sample size (n), if available)** | **Key findings** | **Independent variables** | **Dependent variables** | **Statistical methods** | **Equation/ Outcomes** | **Model Performances** |
| 1 | Donato L.T.F., Donato S.L.R., Brito C.F.B., Fonseca V.A., Gomes C.N., Filho V.A.R. | Estimating leaf area of Prata-type banana plants with lanceolate type leaves | 2020 |  Brazil (PrataAnã’ (AAB) & BRS Platina’ (AAAB), n1=212, n2=164) | Donato et L. (2020) developed modes for estimating leaf area of 'Prata-Ana' and BRS Plantina' banana plants with lanceolate leaf types. A simple and multiple linear regression equations were employed with variables of width (W), length (L), width/length ratio. The models of LA(Prata-Anã) -0.0133624+0.000489859\*\*L+0.00183182\*\*W and LA(Platina) = 0.00237026 + 0.00478116 W-0.0968020\*\* WLR were given precise results.  | width (W), length (L), width/length ratio (WLR) | Leaf Area | Multiple linear regression M2L2:O2L2:N2 | LA(Prata-Anã) -0.0133624+0.000489859\*\*L+0.00183182W and LA(Platina) = 0.00237026 + 0.00478116 W-0.0968020WLR | R2=0.96, R=0.98 |
| 2 | Vinson E.L., III, Coneva E.D., Kemble J.M., Woods F.M., Sibley J.L., Fonsah E.G., Perkins-Veazie P.M., Kessler J.R. | Prediction of flower emergence and evaluation of cropping potential in selected banana cultivars (Musa sp.) cultivated in subtropical conditions of coastal Alabama | 2018 | United States Alabama (Cavendish and non-Cavendish banana, n=13) | Vinson et al. (2018) developed a regression model to determine flower emergence and to assess vegetative and reproductive growth of Cavendish and non-Cavendish banana cultivars in subtropical conditions of coastal Alabama using the circumference of the pseudostem and the height-to-circumference ratio (HCR), and the number of days from planting to inflorescence emergence (DPE). | Height, circumference, height -to- circumference ratio (HCR) | Flower Emergence | Multiple linear regression | Medium tall banana (250 to 420 cm) :DPE = 7.06 – 9 · HCR and for tall banana (360 to 760 cm)=DPE = 700.1 – 3.8 · CM and DPE = 596.3 + 22.3 · HCR | No prediction |
| 3 | Demirsoy H. | Leaf area estimation in some species of fruit tree by using models as a non-destructive method | 2009 | Turkey | Demirsoy (2009) constructed models to leaf area of fruit trees including bananas. The analysis can be conducted with various subsets of the independent variables; for instance, leaf length (L), leaf width (W), L2, W2, and [L 2/W2] to develop the best model for predicting leaf area. | leaf length (L), leaf width (W), L2, W2 and [L 2/W2] | Leaf Area | Simple linear regression | Ardhapuri= – 0.0334 + 0.8402 LW Basrai =0.0266 + 0.7629 LW  | R2=0.96 and 0.98 |
| 4 | Nyombi K., Van Asten P.J.A., Leffelaar P.A., Corbeels M., Kaizzi C.K., Giller K.E. | Allometric growth relationships of East Africa highland bananas (Musa AAA-EAHB) cv. Kisansa and Mbwazirume | 2009 | Uganda (Musa AAA-EAHB cv. Kisansa and Mbwaziume) |  Individual leaf area was estimated as LA (m2) = length (m) × maximum lamina width (m) × 0.68. Total plant leaf area (TLA) was estimated as the product of the measured middle leaf area (MLA) and the number of functional leaves. MLA was estimated as MLA (m 2) = -0.404 + 0.381 height (m) + 0.411 girth (m). A light extinction coefficient (k = 0.7) was estimated from photosynthetically active radiation measurements in a 1.0 m grid over the entire day. The allometric relationship between aboveground biomass and girth (cm) during the vegetative phase followed a power function.  | length, width | Growth and yield |  Simple Linear regression | LA = length (m) × maximum lamina width × 0.68; MLA = -0.404 + 0.381 height + 0.411 girth; AGB = 0.325e0.036(girth)  | R2=0.99, R2=0.67 and R2=0.79 |
| 5 | Mekwatanakarn W., c D.W. | A simple model to estimate the rate of leaf production in bananas in the subtropics | 1989 | AustraliaGros Michel, Honduras | Mekwatanakarn and Mekwatanakarn (1989) developed a simple model to estimate the rate of leaf production in bananas in the subtropics using leaf emergence rate to temperature and ontogeny.  | Leaf emergence rate at T ° C; b = leaf emergence rate at optimumtemperature. P is the phyllochron (days leaf- 1 ) and n is leaf number | Leaf Area | Multiple linear regression | 1) a/b = 0.875--0.22429 T+0.01854 T2-0.000375 T3 2) P=3.585\_+ 0.309+ (0.1068+ 0.0122)n | R2=0.96 |
| 6 | Arantes A.D.M., Donato S.L.R., de Siqueira D.L., Amorim E.P., Rodrigues Filho V.A. | Chlorophyll index for real-time prediction of nutritional status of ‘prata’ banana [Índice de clorofila para predição do estado nutricional de bananeiras tipo prata em tempo real] | 2016 |  Brazil (Prata banana) | Arantes et al. (2016) used regression equations to find a correlation between chlorophyll index and leaf nutrient contents and predict the nutritional status of the 'Prata' banana. The selected models reliably estimate the leaf nutrient content of bananas. | chlorophyll index (CI) | N, P, K, S, Ca, Mg, B, Cu, Fe, Mn, Zn, Na | Multiple linear regression | N = -34.1489 + 1.75493 Chla, Zn = -84.8938 + 2.82298 Chl a | R2=0.84-0.97 |
| 7 | Allen R.N., Dettmann E.B., Johns G.G., Turner D.W. | Estimation of leaf emergence rates of bananas | 1988 | Australia | Allen et al. (1988) developed a model to estimate the leaf initiation rate (LIR) of 17 banana cultivars based on average monthly air temperature, day length, age of planting, plant density, and cultivar stature. The model was validated with an independent data set from South Africa and it gave a reliable prediction of LIR  | Mean monthly temperature (T), daylength (L), plantation age (A), and stature (H) | Leaf initiation rate | Multiple linear regression | LER = ko x exp[kl(T - Topt)2 + k2/A + k3/A2 + k4D + k5H] x (L/12)k6.  | R2>0.9 |
| 8 | Chaves, B., Cayón, G., & Jones, J. W.  | Modeling plantain (Musa AAB Simmonds) potential yield. | 2009 |  Dominico-Harton, Colombia | Leaf, stem, and corm dry matter were observed to increase in equal proportions during the vegetative stage. During the reproductive stage, only the stem was observed to increase its dry matter content (although not as much as in the vegetative stage), while leaves and corm were found to decrease it. A sensitivity analysis established Light use efficiency (LUE) as the most sensitive parameter. | Light extinction co-efficient, dry matter | growth  |  Crop model |   |   |
| 9 | Lamour J., Le Moguédec G., Naud O., Lechaudel M., Taylor J., Tisseyre B. | Evaluating the drivers of banana flowering cycle duration using a stochastic model and on-farm production data | 2020 | France (n=724) | Lamour et al. (2020) used a novel stochastic model to estimate the average time gap between two flowering events on the same banana plant (CD). The results indicated differences in CD with a median of 209 days± 24 days). There was a positive effect of elevation, cultivar, and irrigation vs. Julian days on model fitting and the CD estimation. | Elevation, cultivar, and irrigation  |   | General linear model | 192.85+ 0.1(elevation)-14.22 (Cultivar)+3.316 (Without Irrigation) +212.2 (Irrigation) |  Variance = 39.7 days |
| 10 | Tixier, P., Malézieux, E., Dorel, M., & Wery, J.  | SIMBA, a model for designing sustainable banana-based cropping systems.  | 2008 | France |   |   |   |  Crop models |  Space is inadequate to indicate the equations |   |
| 11 | Tixier P., Lavigne C., Alvarez S., Gauquier A., Blanchard M., Ripoche A., Achard R. | Model evaluation of cover crops, application to eleven species for banana cropping systems | 2011 |  France French West Indies ( n=11) | Tixier et al. (2011) developed the SIMBA-CC model to select cover crops for banana cover-cropping systems using 11 cover crop species, light interception traits, and values of optimal photosynthetically active radiation (PARopti). | Total radiation at step ‘t’ (Rg(t), Photosynthetically active radiation intercepted at step ‘t’ PARi(t), Biomass newly formed at step ‘t’ Dbiom(t), Leaf area index logistic factor LF(t), Leaf area index newly formed at step ‘t’ Dlai(t), Leaf area index at step ‘t’ LAI(t), Biomass at step ‘t’ BIOM(t), Nitrogen content in biomass at step ‘t’ N(t), Tissue senescence at step ‘t’ TS(t), Proportion of PAR p, Parameters of the biomass production as a function of PARi(t) (a; b) |   |   Crop models | Space is inadequate to indicate the equations |   |
| 12 | Tixier, P., Malézieux, E., & Dorel, M.  | SIMBA-POP: a cohort population model for long-term simulation of banana crop harvest.  | 2004 | France Cavendish Grande Naine, French West Indies |   | mean daily temperature | number of flowering plants and harvested plants |   Crop models | Space is inadequate to indicate the equations |   |
| 13 | Damour G., Ozier-Lafontaine H., Dorel M. | Simulation of the growth of banana (Musa spp.) cultivated on cover-crop with simplified indicators of soil water and nitrogen availability and integrated plant traits | 2012 | French West Indies (Cavendish group, cv Grande Naine) | Damour et al. (2012) modeled the growth of banana (Musa spp.) cultivated on cover-crop with simplified indicators of soil water and nitrogen availability and integrated plant traits. | Partitioning to sucker before flowering (Psk), partitioning to leaves withinthe vegetative parts (Pl), the thermal time interval between plantingand sucker selection (SDDr), specific leaf area (SLA), and bunch dry weight at flowering (BUN(flowering)) |   | one-way analyses of variance, a non-linear leastsquares optimization procedure, linear regressions. |  Space is inadequate to indicate the equations |   |
| 14 | Dorel M., Achard R., Tixier P. | SIMBA-N: Modeling nitrogen dynamics in banana populations in the wet tropical climate. Application to fertilization management in the Caribbean | 2008 | France (Musa spp., AAA group, cv. Cavendish Grande Naine; Vitropic SA) | Dorel (2008) designed the SIMBA-N model to simulate N dynamics in the banana cropping system. Model validation provides reliable results that can use in N fertilizer management in banana cultivation.  | Stock variables: Soil Mineral N at step t, Soil Organic N at step t, Banana N content at step t, Crop Residue N at step t, Mineral N of crop residues aged of i weeks at step tFlow variablesMineral N fertilized at step t, Mineral N leached at step t, Mineral N plant uptake at step t, Mineral N exported (bunch) at step t, N mineralized from residues at step t, N mineralized from soil organic matter at step, N humification at step t |   | ANOVA, SIMBA-N was developed using the STELLA® software Crop Model |  Space is inadequate to indicate the equations |   |
| 15 | Brisson N., Ozier-Lafontaine H., Dorel M. | Effects of soil management and water regime on banana growth between planting and flowering. Simulation  | 1998 | France French West Indies | Brisson et al. (1998) modelled the effects of soil and water management on banana growth between planting and flowering using the STICS model. |   |   |  Crop model |  Space is inadequate to indicate the equations |   |
| 16 | Revathi S., Sivakumaran N., Ramajayam D., Saraswathi M.S., Backiyarani S., Uma S. | Growth estimation during hardening phase of tissue-cultured banana plantlets using bootstrapped artificial neural network | 2019 | India | Revathi et al. (2019) developed a non-destructive model to estimate the plant growth rate of tissue cultures banana plantlets during the primary hardening phase using Bootstrapped Artificial Neural Network (BANN). Both non-destructive growth parameters like plant height, girth, number of leaves, leaf length, and leaf breadth, and destructive growth parameters like number of roots, longest root length, fresh and dry weight were measured periodically on selected plants of one week to nine weeks old. In addition to plant growth parameters, greenhouse temperature, radiation, and carbon dioxide concentration were also recorded daily. These sets of bootstrap samples were finally used as input to develop a neural model using a novel methodology of bootstrap re-sampling based artificial neural network (ANN) for studying the progress of plant ontogeny.  | Plant growth parameters suchas plant height (cm), girth (cm), number of leaves and roots,length of longest root (cm), leaf length (cm) and width (cm), greenhouse temperature,radiation and carbon dioxide concentration |   | Bootstrapped Artificial Neural Network (BANN) |  ANN model | Dry weight: RMSE= 1.18×10 , MAE=-7 7.74×10 and NSE = 99.15 and ; Leaf area: RMSE = 0.0802, MAE =0.0545 and NSE = 85.96 |
| 17 | Abdul Latif N.S., Anuar Mushoddad N.A.M., Mior Azmai N.S. | Agriculture Management Strategies Using Simple Logistic Growth Model | 2020 |  Malaysia | This paper explores the application of a simple logistic growth model for vegetative growth response of banana to foliar fertiliser. The model presented here quantitatively estimates the effectiveness of the procedure used.  | Time (week) (t), Carrying capacity (maximum growth (cm) (K), Constant (A), Growth rate (r),  | Pseudostem height, pseudostem girth and leaf area at time (Y) | Logistic function/ logistic regression | Y = K/ 1+Ae-rt | No validation is given |
| 18 | Mendes B.M.J., Filippi S.B., Demétrio C.G.B., Rodriguez A.P.M. | A statistical approach to study the dynamics of micropropagation rates, using banana (Musa spp.) as an example | 1999 | Brazil | To study multiplication rates over time, suckers of banana, Musa spp., cv. Maca, were collected in the field and the shoot apex introduced in vitro for micropropagation. The adjusted Poisson regression models for the number of shoots showed that the multiplication rate in this cultivar tends to decrease with time. Interpretation of the first and second derivatives of the regression model allowed determination of the maximum speed of multiplication and the time. | Number of shoots | Multiplication rate (Y) | Adjusted Poissonregression models | Yˆ= exp (-3.754+2843x-0.2312X2) | R2 = 0.98 |
| 19 | Potdar M.V., Pawar K.R. | Non-destructive leaf area estimation in banana | 1991 | India | A rapid, non-destructive and precise method for leaf area determination in 'Ardhapuri' and 'Basrai' cultivars of banana was developed from linear measurements. A strong correlation existed between leaf area (LA) and various combinations of leaf length (L) and width (W). LA can be predicted precisely with the regression models.  | Length (L), Width (W) | Leaf area (LA) | Simple linear regression models | LA= -0.0334+ (L× WX0.8402) for "Ardapuri" and LA=0.0266+ (LX W×0.7629) for 'Basrai" | R2 = 0.96-0.98 |
| 20 | GodfreyTaulya | East African highland bananas (Musa spp. AAA-EA) ‘worry’ more about potassium deficiency than drought stress | 2013 | Uganda | Taulya observed interaction of K and cumulative rainfall to drive dry matter production and yields. The total fresh mass of the leaves, petioles, pseudostem, corm and roots were taken on a digital scale (±0.1 g). The resulting data were subjected to regression analysis to determine allometric functions for estimating the fresh mass of the plants from the growth parameters in the drought stress pot trial. | The total fresh mass of the leaves, petioles, pseudostem, corm and roots | Total fresh mass per plant (Mt) | Multiple linear Regression analysis | Mt = (0.03873H+0.281L+3.169x10-6 Pv)-2.905 | R2 =0.59 |

**Table 3**. Full-text articles related to modelling of banana fiber

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **NO.** | **Authors** | **Title** | **Year** | **Country (cultivar/ sample size (n), if available)** | **Key findings** | **Related topic** |
| 1 | Chokshi S., Gohil P., Lalakiya A., Patel P., Parmar A. | Tensile strength prediction of natural fiber and natural fiber yarn: Strain rate variation upshot | 2020 | India | Chokshi et al. (2020) used mathematical models (eg., exponential, linear, logarithmic, polynomial, and power models)to predict the tensile strength at different strain rates. | Tensile strength 1) Low y = 0.325x2 + 2.165x + 61.625 2) y = 0.6321x2 1.0536x + 75.471 (R2=0.91-0.98) |
| 2 | Mwesigwa R., Mwasiagi J.I. | Use of regression models to study the factors affecting the tensile and compressive properties of banana bio-composites | 2019 | Uganda | Mwesigwa and Mwasiagi (2019) used regression models to study the factors affecting the tensile and compressive properties of banana bio-composites. | 1) Tensile strength (YT) 2) Elongation percentage (YE) 1) YT = 7:32 0:2107X1 þ 0:091X2 þ 0:001604X1X1 þ 0:000231X2X (R2=0.91-0.96) |
| 3 | Monzón M.D., Paz R., Verdaguer M., Suárez L., Badalló P., Ortega Z., Diaz N. | Experimental analysis and simulation of novel technical textile reinforced composite of banana fibre | 2019 | Spain (n=16) | Monzón et al. (2019) use a statistical approach to characterize mechanical properties of newly developed technical textile with a composite of banana fibre and compare the results with numerical simulation. | Fibre strength |
| 4 | Madhusudan S., Bhargava N.R.M.R., Madhukiran J. | Prediction of hygric strain coefficients for hybrid natural composites | 2018 | India | Madhusudan et al. (2018) used mathematical equations to predict hygric strain coefficients for hybrid natural composites of banana//pineapple. | Fibre strength |
| 5 | Mizera., Herák D., Hrab? P. | A mathematical model describing the drying curves of false banana´s fiber (Ensete ventricosum) | 2017 | Ethiopian region Hawasa (false banana (Ensete ventricosum) | Mizera et al. (2017) researched the analysis of drying curves of fibres of false banana (Ensete ventricosum) in the Ethiopian region Hawass. The basic mathematical model describes the dying behaviour of a false banana with statistically significant coefficients indicating the ability to use the model for future research. | Fibre strength |
| 6 | Venkateshwaran N., Elayaperumal A., Sathiya G.K. | Prediction of tensile properties of hybrid-natural fiber composites | 2012 | India (banana and sisal) | Venkateshwaran et al. (2012) Predicted tensile properties of hybrid-natural fibre composites | Fibre strength |
| 7 | Venkateshwaran N., Elayaperumal A. | Modeling and evaluation of tensile properties of randomly oriented banana/epoxy composite | 2011 | India | Venkateshwaran and Elayaperumal (2011) study the tensile properties of banana fibre. | Fibre strength |
| 8 | de Oliveira G.Q., do Nascimento R.A., Costa J.F., Santana E.B., Costa C.M.L., Ribeiro N.F.D.P. | Drying of Banana Pseudo-stem Fibers: Evaluation of Kinetic Models, Effective Diffusivity, Thermodynamic Properties, and Structural Characterization | 2020 | Brazil– EasternAmazon (EMBRAPA), Bazil (Musa paradisiaca L.)  | de Oliveira et al. (2020) developed nine mathematical models to study the drying behaviour, moisture diffusivity, activation energy, and thermodynamic properties of banana pseudo-stem fibre using thermogravimetric, morphological, and spectroscopic methods.  | Fibre strength |
| 9 | Rao, K. M. M., Rao, K. M., & Prasad, A. R. | Fabrication and testing of natural fibre composites: Vakka, sisal, bamboo and banana | 2010 | India | Rao et al. (2010) found that the mean tensile modulus of vakka fibre composite is higher than those of banana and sisal fibre composites and comparable to that of bamboo composite at highest volume fraction of fibre | Fibre strength |
| 10 | Chokshi S., Gohil P. | Effect of strain rate on tensile strength of natural fiber reinforced polyester composites | 2018 | India (Banana fiber, flax fiber, and bamboo fiber) | Chokshi and Gohil (2018) developed mathematical models to predict the tensile strength of the banana fibre. The linear relationships of exponential, linear, logarithmic, polynomial, and power models were used to study the behaviour of tensile strength and tensile strength increases with an increase in strain rate. | Fibre strength |
| 11 | Pujari S., Ramakrishna A., Padal K.T.B. | Comparison of ANN and Regression Analysis for Predicting the Water Absorption Behaviour of Jute and Banana Fiber ReinforcedEpoxy composites | 2017 | India [Jute and Banana (Musaulugurensiswarb),] | Pujari et al. (2017) compared ANN and Regression Analysis for Predicting the Water Absorption Behaviour of Jute and Banana Fibre ReinforcedEpoxy composites and indicated that ANN gives better results for physical properties of natural fibre composites of banana than the regression analysis.  | Fibre strength |
| 12 | Pujari S., Ramakrishna A., Balaram Padal K.T. | Prediction of Swelling Behaviour of Jute and Banana Fiber Composites by using ANN and Regression Analysis | 2017 | India | Pujari et al. (2017) predicted the swelling Behaviour of Jute and Banana Fibre Composites by using ANN and Regression Analysis and indicated that ANN performed better than regression analysis.  | Fibre strength |
| 13 | Sia, C. V., Fernando, L., Joseph, A., & Chua, S. N.  | Modified Weibull analysis on banana fiber strength prediction. | 2018 | Malaysia | To predict the tensile strength of the banana fibres, Weibull statistical analysis is used. This analysis has been conducted on oil palm fibre for strength prediction of banana fibres considering the variation of within fibre diameter variation. | Fibre strength  |
| 14 | Devireddy S.B.R., Biswas S. | Thermo-physical properties of short banana–jute fiber-reinforced epoxy-based hybrid composites | 2018 | India | Devireddy and Biswas (2018) developed a mathematical model to calculate thermal conductivity. The predicted thermal conductivity was in good agreement with the measured values with an acceptable range of 0–6.5% and 0–11% error. | Fibre strength |
| 15 | Veeramanipriya E., Umayal Sundari A.R., Asaithambi R. | Numerical modelling of drying kinetics of banana flowers using natural and forced convection dryers | 2019 | India (Musa acuminate colla  | Veeramanipriya et al. (2019) developed mathematical models to identify the drying kinetics of banana flowers for natural and forced convection solar dryers.  | Processing |
| 16 | Macedo L.L., Vimercati W.C., da Silva Araújo C., Saraiva S.H., Teixeira L.J.Q. | Effect of drying air temperature on drying kinetics and physicochemical characteristics of dried banana | 2020 | Brazil (Musa spp., cv Prata) | Macedo et al. (2020) evaluated the impact of dying air temperature on drying and physiochemical properties of dried bananas and predict moisture of dried samples as a function of drying time as well as dying temperature using mathematical models. | Processing |
| 17 | Patwari A.U., Bhuiyan S.A., Ahsan Q., Khan I.H., Rabbani N. | Prediction and optimization of compressive load of a green composite material from natural fiber using statistical approach | 2019 |  Bangladesh | A quadratic model has been proposed to predict the compressive load of the moulded green composite materials within five levels of the two process parameters. Statistical tools are used for best fitting of the developed quadratic model and desirability analysis is coupled with it in order to find out the optimum process condition for which maximum compressive load is achieved.  | Processing |
| 18 | Vijaya Bhaskar V., Srinivas K., Devireddy S.B.R. | A novel mathematical correlation for thermal conductivity of hybrid composites reinforced with natural fibers | 2019 |  India | A novel mathematical model to predict the transverse thermal conductivity of hybrid composites based on microstructural characteristics is developed. The estimations are validated with analytical methods existing in the literature, finite element analysis, and experimental results.  | Thermal conductivity |
| 19 | Mizera Č., Herák D., Hrabě P., Müller M., Kabutey A. | Effect of Length of False Banana Fibre (Ensete ventricosum) on Mechanical Behaviour under Tensile Loading | 2016 |  CzechRepublic | The effect of gauge length of false banana fibre on the tensile strength, volume energy, and modulus of elasticity under tensile loading was examined. Mathematical models describing the mechanical behaviour of the varying gauge lengths were presented.  | Mechanical behaviour |
| 20 | Zerihun Yemataw, Alemar Said ,Tesfaye Dejene,Walter Ocimati, David Amwonyaand Guy Blomme | Estimating Yield Components, Limiting Factors, and Yield Gapsof Enset in Ethiopia Using Easily Measurable Above-GroundPlant Traits | 2021 | Ethiopia | Allometric regression equations based on the above-ground traits significantly explained the variation in the yield traits. Based on the adjusted R2, model significance,model bias, and RMSE, leaf length, petiole length, and plant height were the best predictors for fibre yield. | Fibre Yield of false banana, R2 = 0.35 to 0.57% |
| 21 | MikiasYeshitila Haile | Regression Analysis to Estimate Enset (Enset Ventricosum (Welw.) Cheesman) Kocho Yield from Vegetative Linear Dimensions | 2014 | Ethiopia | Halie (2014) attempted to estimate enset fibre content from aboveground plant traits using a linear regression model, but even when fibre data was log transformed, he was unable to produce significant regression equations (R2 = 0.01) to estimate fibre yield. | Fibre Yield of false banana, R2 = 0.01 |