Enhancing Farmers Productivity Through IoT and Machine Learning: A State-of-the-Art Review of Recent Trends in Africa

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Abstract. Agriculture is considered as the main source of food, employment and economic development in most African countries and beyond. In agricultural production, increasing quality and quantity of yield while reducing operating costs is key. To safeguard sustainability of the agricultural sector in Africa and globally, farmers need to overcome different challenges faced and efficiently use the available limited resources. Use of technology has proved to help farmers find solutions for different challenges and make maximum use of the available limited resources. Internet of Things and Machine Learning innovations are benefiting farmers to overcome different challenges and make good use of resources. In this paper, we present a wide-ranging review of recent studies devoted to applications of Internet of Things and Machine Learning in agricultural production in Africa. The studies reviewed focus on precision farming, animal and environmental condition monitoring, pests and crop disease detection and prediction, weather forecasting and classification, and prediction and estimation of soil properties.

Keywords: Internet of Things · Machine Learning · Innovations · Agriculture · Africa

1 Introduction

Crop and livestock farming (hereafter agriculture) is the major food contributor and key to Africa's prosperity and development. For instance, in Sub-Saharan Africa (SSA), agriculture accounts for over 30% of total Gross Domestic Product (GDP) and over 50% of export earnings. Gross Domestic Product is a standard monetary measure of the value of all the final goods and services produced in a

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definite time period by a country [1]. Large part of the agricultural production in Africa come from smallholder rainfed production [2,3].

There are several challenges facing the agriculture sector in Africa: climate change, total dependency on rainfall, poor irrigation infrastructure, small land holdings, poor agricultural extension services, limited access to finance, exorbitant prices of farm inputs, and many more [4–7]. Climate change is a major challenge facing the agriculture sector in Africa and countries across the globe. High dependence on rain-fed agriculture renders Africa more prone to climate change's negative consequences. Due to climate change, there is unreliable rainfall, rising temperatures, eruption of pests and diseases, rampant water scarcity, intense floods and prolonged droughts. Generally, these changes have major negative implications on food security in Africa [4,5]. Currently, large number of people continue to suffer from hunger globally and it is more visible in Africa. Realization of maximum crop yield depends on different crop production attributes like soil properties, rainfall, treatment of pests and diseases and fertilizer application. Timely and precise monitoring of these crop production attributes remain critical for informed decision making and realization of maximum crop yield [4,5].

Information and Communication Technologies (ICTs) have been used to solve real life problems in Agriculture. It is noted that ICTs have been used in timely and accurately remote and proximal sensing of crop production attributes. Information and Communication Technologies promote the transformation of agriculture for improved food production greatly [1]. In the subsequent sections a review of applications of technologies (Internet of Things and Machine Learning) in solving real life agricultural challenges in Africa is presented. The fields of Internet of Things (IoT) and Machine Learning (ML) have turn out to be key for solving different agriculture related challenges. The review discourses the application of IoT in precision farming, animal and environmental condition monitoring. Further, the review discourses the application of ML in pests and crop disease detection and prediction, weather forecasting and classification, and prediction and estimation of soil properties.

2 Use of Internet of Things in Agriculture

Internet of Things is widely used in several domains to help humans carry out day to day endeavors. Agriculture is one of the leading domains where IoT is widely used. Generally, IoT refers to the interconnection of different devices (sensors, smart phones, cameras, etc.) using a defined network architecture to collect and transmit data for monitoring, tracking, tracing, process control, etc. [8,9]. In the following sections we present the main areas where IoT has been used in the agriculture domain in Africa.

2.1 Precision Farming

Precision farming is one of the areas in the agriculture sector where IoT is mostly used. As highlighted in [8], precision farming is the "approach to farm management that uses ICTs for monitoring crop and animal status by observing and measuring variables such as soil condition and plant health to ensure that crops and soil receive exactly what they need for improved resource use, productivity, quality, profitability and sustainability of agricultural production".

In Nigeria, a study performed in [11] deployed a system through use of wireless sensors for optimum catfish production. The system assisted farmers to achieve optimum catfish growth by developing a feeding pattern based on the tracked water parameters: temperature, PH, conductivity and turbidity. Results of the study show that lower feed conversion ratio of 0.62 was achieved against 0.67 in the control pond. A system based on Android platform was developed for user interaction. In Malawi, WiPAM system was developed to automate the irrigation process by observing agricultural field soil moisture changes through use of a sensor. Soil moisture readings were then used by the irrigation controller to determine when to irrigate [12]. A study done in Zambia [13], authors proposed a low-cost automatic irrigation control system by reading soil moisture through use of sensors. Table 1 provides a summary of IoT studies in precision farming.

Table 1. Summary of IoT studies in precision farming

Reference	Objectives	Parameters	Sensors	Transmission protocol
[11]	Optimum catfish production in Nigeria	Water temperature, pH, Conductivity, and turbidity	Temperature, turbidity, electrical conductivity, and pH	GSM/GPRS
[12]	Automatic irrigation in Malawi	Soil moisture	Watermark 200SS	ZigBee
[13]	Automatic irrigation in Zambia	Soil moisture	Soil Hygrometer moisture-sensor	GSM/ZigBee

2.2 Animal and Environmental Condition Monitoring

Animal health, crop growth, high quality and quantity yield are meticulously associated with environmental conditions. Timely and accurate environment information is important for planning farming activities. For example, farmers can plan when to sow, apply fertilizer, apply pesticides, harvest and other farming activities to avoid yield losses. Information and Communication Technologies like Internet of Things are now being widely used to monitor different climatic conditions. Internet of Things sensors can monitor and provide precise real-time climatic condition data at reduced cost [14,15].

In Tunisia, [14] presents a wireless sensor network and cloud IoT based Decision Support System which notifies the farmer when Late Blight may first attack potatoes by sending an SMS. In this study a sensor network monitor and report information to the cloud server about temperature and humidity then SIMCAST model assess the risk of Late Blight appearance. In another study done in Nigeria [20], a system was developed to monitor crop field temperature, humidity and soil moisture using sensors. Sensed environment data was sent to the web server for further processing using Internet. Consequently, the system could automatically trigger irrigation. Web and mobile application were developed for monitoring and user interaction.

In Senegal, [21] proposed a system prototype based on low-cost LoRa IoT platform and IoT cloud platform to prevent cattle stealing in Africa. The system notifies the farmer by triggering an alarm if cows are out of the bounds or if the collar is disconnected or damaged through the Internet (IoT cloud) or if a farmer cannot access Internet, information is sent directly to the smartphone or tablet through WiFi or Bluetooth. Table 2 provide a summary of IoT studies for monitoring of environmental condition.

Table 2. Summary of IoT studies for monitoring of environmental condition

Reference	Objectives	Parameters	Sensors	Transmission protocol
[14]	Detect when Late Blight may first attack potatoes in Tunisia	Temperature and humidity	Wasmposte	Internet, ZigBee
[20]	Monitor crop field environmental condition in Nigeria	Temperature, humidity and soil moisture	DHT11, YL 69	Internet
[21]	Prevention of cattle stealing in Senegal	Proximity and disconnected or damaged neck collar	LoRa end-device	Internet, WiFi, Bluetooth

3 Use of Machine Learning in Agriculture

In agriculture and other domains, big data is being collected every day. The word "Big Data" denotes large heterogeneous volumes of data from various sources which can be structured, semi-structured and unstructured [22]. Big data can be rendered not useful unless if it is organized, analysed, and meaningful features are extracted for decision making.

Unfortunately, humans have limited analytical abilities. To safeguard sustainability of the agricultural sector in Africa and globally, farmers need to gain meaningful insights from big data. Use of technology can help farmers extract meaningful insights from big data for informed decision making. Machine Learning is the present technology which is enabling farmers to efficiently analyze and extract meaningful insights from big data [23–25]. Machine Learning is a subdivision of Artificial Intelligence that includes methods, or algorithms, for automatically identifying patterns from data [26]. The upsurge of Machine Learning technologies allows farmers to solve growing number of real-life challenges [26,27]. In the following sections we present the main areas where Machine Learning has been used in the agriculture domain in Africa.

3.1 Pests and Crop Disease Detection and Prediction

In agricultural production, increasing quality and quantity of crop yield while reducing operating costs is key. Crop pests and diseases potentially reduce quality and quantity of crop yield. Currently, the most widely used and adopted approach for crop disease detection in Africa is through necked eye observation by experienced farmers or experts [29,30]. However, relying on expert's necked eyes to detect crop diseases has many drawbacks: less accurate, time consuming, labor intensive and can only be done in limited areas. Use of technology can help smallholder farmers detect, identify and predict crop diseases early without expert intervention. Image processing and ML are the techniques which have been widely used and adopted for automatic crop disease detection, identification and prediction [29,31,32].

A study done by [31] developed a system for detection of banana pests and diseases using Deep Convolutional Neural Network (ResNet50, InceptionV2 and MobileNetV1). Dataset was gathered from the hotspots in Africa and India comprising of about 18,000 field images taken from different parts of the banana plant. Dataset classes were healthy plant, xanthomonas wilt, dried/old leaves, bunchy top disease, black sigatoka, yellow sigatoka, fusarium wilt and corm weevil. Dataset was split into training set (70%), validation set (20%) and testing set (10%) using simple random technique. Results attained demonstrates an accuracy between 70% and 99%.

In Tanzania, work done by [32] presents a Deep Learning technique to detect invasion of tomato leaf miner at early development stages. Convolutional Neural Network architectures: ResNet50, VGG16 and VGG19 were used to train classifiers on 2145 colored health and unhealth tomato images. Dataset was split into 10% for testing and 75:25, 80:20, and 85:25 ratios into training and validation respectively. Results show that VGG16 achieved highest accuracy of 91.9%. A study done by [33] in republic of Benin and DR Congo demonstrates use of Random Forest and Principal Component Analysis in classifying healthy and diseased banana plant images: banana bunchy top disease (BBTD) and xanthomonas wilt of banana (BXW). Dataset was collected from UAV-RGB aerial images (Sentinel 2, PlanetScope and WorldView-2) from DR Congo and republic of Benin banana fields. Results show accuracy of up to 99%. Table 3 provides a summary of pests and crop disease prediction and detection using Machine Learning.

3.2 Weather Forecasting and Classification

Weather forecasting is defined as foretelling the condition of the atmosphere for a specific location using principles of physics, statistics, empirical techniques and technology. It also includes changes on the surface of the earth produced by atmospheric circumstances. Humans have attempted to forecast weather condition informally by using intuition. Weather forecasting is very important for resource management in crop production: crop growth, fertilizer timing and delivery, pest and disease control and crop yield. Correct forecasting of weather is a complex process. Use of Machine Learning simplifies the process of weather forecasting [34].

Table 3. Summary of pests and crop disease prediction and detection

Reference	Objectives	Datasets	Machine Learning models/algorithms	Results
[31]	Automatic detection of banana pests and diseases in Benin	About 18,000 banana images	ResNet50, InceptionV2, MobileNetV1	Accuracy between 70 and 99%
[32]	Automatic detection of *tuta absoluta* in tomatoes in Tanzania	2,145 colored health and unhealth tomato images	ResNet50, VGG16 and VGG19	Accuracy of 91%
[33]	Automatic classification of health and diseased banana plant in Benin and DR Congo	Health and unhealth banana plant images	Random Forest and Principal Component Analysis	Accuracy of 99%

In South West Nigeria, [35] conducted a study to forecast drought events using Artificial Neural Network (ANN) calculated by Standardized Precipitation Index (SPI). Secondary data for Ijebu-Ode rainfall station was obtained from Nigeria Meteorological Agency. Dataset comprised of rainfall from 1975 to 2013, and maximum and minimum temperature, relative humidity, wind speed and sunshine from 1991 to 2012. The dataset was split into 75% and 25% for training and testing the network respectively. Results indicated 24 episodes of severe drought (-1.5 to -1.99), 44 episodes of moderate drought (-1.0 to -1.49) and 16 episodes of extreme drought (SPI below -2). In Ethiopia, a study by [36] was done to classify current and past drought based on Logistic Regression and Primal Estimated sub-Gradient Solver for SVM (Pegasos) using temperature, precipitation and El Niño data from 1953 to 1993. Results show 81.14% accuracy. In South Africa, a study by [37] was conducted to forecast rainfall rates utilizing Backpropagation Neural Network. The model was trained using 108,861 samples of rainfall data collected from 2013 to 2016 in South Africa. Testing and validation data was collected in South Africa from 2017 to 2018. Results of the model show Mean Square Error (MSE) of 6.017 and Correlation Coefficient of 0.8298. Table 4 provides a summary of weather forecasting and classification using Machine Learning.

3.3 Prediction and Estimation of Soil Properties

Soil is a very important resource for successful agricultural production. For example, soil hold water and nutrients which are essential for crop growth. Generally, without soil, it is difficult to grow crops. Performing soil analysis is vital for a farmer to know the properties of the soil. Consequently, a farmer can determine the crop and inputs suitable for the soil to realise maximum yields [38–40]. Accurate estimation and understanding of soil condition can help in soil management. Soil properties play a major role in crop yield variability. Traditional ways of soil analysis can be slow, costly and not suitable for vastly varied soil environments. Machine Learning techniques provide a reliable solution for estimation and prediction of soil

Table 4. Summary of weather prediction and classification

Reference	Objectives	Datasets	Machine Learning models/algorithms	Results
[35]	Predict drought events in South West Nigeria	Meteorological data for rainfall, relative humidity, maximum and minimum temperature, wind speed and sunshine	Artificial Neural Network	24 episodes of severe drought, 44 episodes of moderate drought 16 episodes of extreme drought
[36]	Classify current and past drought in Ethiopia	Meteorological data for temperature, precipitation and El Niño	Logistic Regression and Primal Estimated sub-Gradient Solver for SVM	Accuracy of 81.14%
[37]	Predict rainfall rates in South Africa	Meteorological data for rainfall	Backpropagation Neural Network	MSE of 6.017 and R^2 of 0.8298

properties [41,42]. This section of the review is about Machine Learning application on prediction and estimation of agricultural soil properties.

[43] conducted a study covering Sub-Saharan Africa at 250 m and 0–30 cm spatial and depth respectively for soil macro and micro nutrient content prediction. Ensemble model was developed using Random Forest and Gradient Boosting. The study targeted 15 nutrients: total phosphorus (P), potassium (K), manganese (Mn), organic carbon (C), magnesium (Mg), organic nitrogen (N), calcium (Ca), iron (Fe), boron (B), calcium (Ca), zinc (Zn), sodium (Na), copper (Cu), sulfur (S), extractable phosphorus (P) and aluminium (Al). In addition to remote sensing, soil samples were collected from 59,000 locations. Results show coefficient of determination (R^2) value of between 40 to 85%. Using two-scale ensemble Machine Learning, [44] performed a prediction of African soil nutrients at 30 m spatial resolution using soil samples data. Targeted nutrients are: total carbon, pH, extractable phosphorus (P), organic carbon (C), calcium (Ca), sodium (Na), total nitrogen (N), iron (Fe), Cation Exchange Capacity (eCEC), magnesium (Mg), zinc (Zn), potassium (K), sulfur (S), clay and sand, stone content, silt, bulk density and depth to bedrock (at 0, 20, and 50 cm depth). Varying results from best to poor show accuracy of soil pH at CCC = 0.9 and extractable phosphorus at CCC = 0.654. Overall, at continental scale, land surface temperature showed to be the most important variable for predicting soil chemical variability.

[45] conducted a study In South Africa for land degradation prediction using Random Forest by combining soil data and environmental data: rainfall, soil temperature, soil moisture, evapotranspiration, elevation, slope, aspect and albedo. Notable overall best results of the model are R^2 of 0.86, Root Mean Squared Error (RMSE) of 7.72% and Relative Root Mean Squared Error (RelRMSE) of 12.94%. Table 5 provides a summary of prediction and estimation of soil properties using Machine Learning.

Table 5. Summary of prediction and estimation of soil properties

Reference	Objectives	Datasets	Machine Learning models/algorithms	Results
[43]	Prediction of soil macro and micro nutrient content in Sub-Saharan Africa	Soil samples	Random Forest and Gradient Boosting	R^2 value of between 40 to 85%
[44]	Prediction of soil nutrient content in Africa	Soil samples	Two-scale ensemble	Accuracy levels from best to poor ranged from 0.900 to 0.654
[45]	Prediction of land degradation in South Africa	Soil samples and environmental data	Random Forest	Notable best results are R^2 of 0.86, $RMSE$ of 7.72% and $RelRMSE$ of 12.94%

4 Our Future Work

Weather information and services are more and more being needed by farmers to survive more capably with climate changeability and growing occurrence of extreme weather events like rising temperatures, floods and droughts. Weather forecasting help farmers plan their farming activities in advance and take preventive measures in case of expected adverse weather conditions. Rainfall is the main source of water for agricultural production. Most of the agricultural production in Africa come from rain-fed agriculture. On the other hand, crop diseases largely contribute to loss of yield quality and quantity. To avert loss of quality and quantity of crop yield due to crop diseases, early detection and prediction of crop diseases and its level of severity is important for right and timely intervention.

Therefore, our future work builds on the already existing studies by developing AI based model(s) adapted to the context of long-term rainfall forecasting and crop disease detection and prediction in the northern geographical part of Senegal. Rainfall forecasting will be done by using ML based on several atmospheric parameters like minimum temperature, maximum temperature and dew point temperature. The best performing model will be selected by evaluating performance metrics such as Mean Absolute Error and Root Mean Squared Error. While crop disease detection and prediction will be done by using image processing and ML based on global and local image features. The best performing model will be selected by evaluating performance metrics such as Precision, Recall, F1-score and Accuracy. An Expert Decision Support System will be developed to utilize the output from the models to provide a platform where farmers and researchers will have access to localized rainfall information, expert recommendations and insights for farmer decision support and action. Additionally, farmers and researchers will use this system to detect and predict crop diseases.

5 Conclusion

By using different IoT approaches and ML models/algorithms such as Deep Convolutional Neural Network, Random Forest, Artificial Neural Network, Logistic Regression, Support Vector Machine, Principal Component Analysis etc., researchers have demonstrated how IoT and ML are set to transform the agriculture sector. Internet of Things and Machine Learning innovations have demonstrated to offer enormous potential for enhancing agricultural productivity and development in developing countries by ensuring efficient use of resources. While Internet access and shortage of expertise are notable challenges in emerging and developing countries, falling prices of smartphones and IoT devices are the driving forces for hasty adoption of IoT and ML innovations. Due to the enormous economic potential of IoT and ML, we propose that governments and development partners in developing and emerging countries invest in the development of policies and ways to support IoT and ML innovations.

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References

1. Brandolini, A., Smeeding, T.M.: Income inequality in richer and OECD countries. In: The Oxford Handbook of Economic Inequality, pp. 71–100 (2009)
2. Warnatzsch, E.A., Reay, D.S.: Temperature and precipitation change in Malawi: evaluation of CORDEX-Africa climate simulations for climate change impact assessments and adaptation planning. Sci. Total Environ. **654**, 378–392 (2019). https://doi.org/10.1016/j.scitotenv.2018.11.098
3. Ngwira, A.R., Aune, J.B., Thierfelder, C.: DSSAT modelling of conservation agriculture maize response to climate change in Malawi. Soil Tillage Res. **143**, 85–94 (2014)
4. Aune, J.B., Coulibaly, A., Giller, K.E.: Precision farming for increased land and labour productivity in semi-arid West Africa. A review. Agronomy Sustain. Dev. **37**(3), 16 (2017). https://doi.org/10.1007/s13593-017-0424-z
5. Shah, M., Fischer, G., Van Velthuizen, H.T.: Food security and sustainable agriculture: the challenges of climate change in Sub-Saharan Africa (2009)
6. Ishengoma, F., Athuman, M.: Internet of things to improve agriculture in sub sahara Africa-a case study (2018). https://doi.org/10.31695/ijasre.2018.32739
7. El Baroudy, A.A.: Monitoring land degradation using remote sensing and GIS techniques in an area of the middle Nile Delta. Egypt. Catena **87**(2), 201–208 (2011). https://doi.org/10.1016/j.catena.2011.05.023
8. Patel, K.K., Patel, S.M.: Internet of things-IOT: definition, characteristics, architecture, enabling technologies, application and future challenges. Int. J. Eng. Sci. Comput. **6**(5) (2016). https://doi.org/10.4010/2016.1482
9. Ndubuaku, M., Okereafor, D.: Internet of things for Africa: challenges and opportunities. In: 2015 International Conference on Cyberspace Governance-CYBERABUJA2015, pp. 23–31 (2015)

10. Liakos, K.G., Busato, P., Moshou, D., Pearson, S., Bochtis, D.: Machine learning in agriculture: a review. Sensors **18**(8), 2674 (2018)
11. Bolaji, A.B., Olalekan, A.W., Olanrewaju, O.E.: Precision farming model for optimum catfish production. Am. J. Electr. Electron. Eng. **8**(2), 51–59 (2020). https://doi.org/10.12691/ajeee-8-2-2
12. Mafuta, M., Zennaro, M., Bagula, A., Ault, G., Gombachika, H., Chadza, T.: Successful deployment of a wireless sensor network for precision agriculture in Malawi. Int. J. Distrib. Sens. Networks **9**(5), 150703 (2013). https://doi.org/10.1155/2013/150703
13. Mulenga, R., Kalezhi, J., Musonda, S.K., Silavwe, S.: Applying Internet of Things in monitoring and control of an irrigation system for sustainable agriculture for small-scale farmers in rural communities. In: 2018 IEEE PES/IAS Power Africa, pp. 1–9. IEEE (2018)
14. Tiwari, M.M., Narang, D., Goel, P., Gadhwal, A., Gupta, A., Chawla, A.: Weather monitoring system using IoT and cloud computing. Weather **29**(12s), 2473–2479 (2020)
15. Marković, D., Koprivica, R., Pešović, U., Randić, S.: Application of IoT in monitoring and controlling agricultural production. Acta Agriculturae Serbica **20**(40), 145–153 (2015). https://doi.org/10.5937/AASer1540145M
16. Mondol, J.P., Mahmud, K.R., Kibria, M.G., Al Azad, A.K.: IoT based smart weather monitoring system for poultry farm. In: 2020 2nd International Conference on Advanced Information and Communication Technology (ICAICT), pp. 229–234. IEEE (2020)
17. Khoa, T.A., Man, M.M., Nguyen, T.Y., Nguyen, V., Nam, N.H.: Smart agriculture using IoT multi-sensors: a novel watering management system. J. Sens. Actuator Networks **8**(3), 45 (2019). https://doi.org/10.3390/jsan8030045
18. Islam, M.M.: Weather monitoring system using Internet of Things. Trends Tech. Sci. Res. **3**(3), 65–69 (2019). https://doi.org/10.19080/TTSR.2019.03.55561
19. Foughali, K., Fathallah, K., Frihida, A.: Using cloud IOT for disease prevention in precision agriculture. Procedia Comput. Sci. **130**, 575–582 (2018). https://doi.org/10.1016/j.procs.2018.04.106
20. Ogunti, E.: IoT based crop field monitoring and irrigation automation system. IJISET-Int. J. Innov. Sci. Eng. Technol. **6**(3) (2019)
21. Dieng, O., Diop, B., Thiare, O., Pham, C.: A study on IoT solutions for preventing cattle rustling in African context. In: ICC, pp. 1–153 (2017). https://doi.org/10.1145/3018896.3036396
22. Riahi, Y., Riahi, S.: Big data and big data analytics: concepts, types and technologies. Int. J. Res. Eng. **5**(9), 524–528 (2018). https://doi.org/10.21276/ijre.2018.5.9.5
23. Sharma, R., Kamble, S.S., Gunasekaran, A., Kumar, V., Kumar, A.: A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. Comput. Oper. Res. **119**, 104926 (2020). https://doi.org/10.1016/j.cor.2020.104926
24. Mishra, S., Mishra, D., Santra, G.H.: Applications of machine learning techniques in agricultural crop production: a review paper. Indian J. Sci. Technol. **9**(38), 1–14 (2016). https://doi.org/10.17485/ijst/2016/v9i38/95032
25. Taghizadeh-Mehrjardi, R., Nabiollahi, K., Rasoli, L., Kerry, R., Scholten, T.: Land suitability assessment and agricultural production sustainability using machine learning models. Agronomy **10**(4), 573 (2020)
26. Lehmann, J., Völker, J. (eds.): Perspectives on Ontology Learning, vol. 18. IOS Press, Amsterdam (2014)

27. Meshram, V., Patil, K., Hanchate, D.: Applications of machine learning in agriculture domain: a state-of-art survey. Mach. Learn. (ML) **29**(8), 5319–5343 (2020)
28. Jia, X., et al.: Mapping soil pollution by using drone image recognition and machine learning at an arsenic-contaminated agricultural field. Environ. Pollut. **270**, 116281 (2021). https://doi.org/10.1016/j.envpol.2020.116281
29. Azfar, S., et al.: Monitoring, detection and control techniques of agriculture pests and diseases using wireless sensor network: a review. Int. J. Adv. Comput. Sci. Appl. **9**, 424–433 (2018). https://doi.org/10.14569/IJACSA.2018.091260
30. Nyabako, T., Mvumi, B.M., Stathers, T., Mlambo, S., Mubayiwa, M.: Predicting Prostephanus truncatus (Horn)(Coleoptera: Bostrichidae) populations and associated grain damage in smallholder farmers' maize stores: a machine learning approach. J. Stored Prod. Res. **87**, 101592 (2020). https://doi.org/10.1016/j.jspr.2020.101592
31. Selvaraj, M.G., et al.: AI-powered banana diseases and pest detection. Plant Methods **15**(1), 1–11 (2019). https://doi.org/10.1186/s13007-019-0475-z
32. Mkonyi, L., et al.: Early identification of Tuta absoluta in tomato plants using deep learning. Sci. African **10**, e00590 (2020). https://doi.org/10.1016/j.sciaf.2020.e00590
33. Selvaraj, M.G., et al.: Detection of banana plants and their major diseases through aerial images and machine learning methods: a case study in DR Congo and Republic of Benin. ISPRS J. Photogrammetry Remote Sens. **169**, 110–124 (2020). https://doi.org/10.1016/j.isprsjprs.2020.08.025
34. Frisvold, G.B., Murugesan, A.: Use of weather information for agricultural decision making. Weather Climate Soc. **5**(1), 55–69 (2013). https://doi.org/10.1175/WCAS-D-12-00022.1
35. Oluwatobi, A., Gbenga, O., Oluwafunbi, F.: An artificial intelligence based drought predictions in part of the tropics. J. Urban Environ. Eng. **11**(2), 165–173 (2017). https://doi.org/10.4090/juee.2017.v11n2.165173
36. Richman, M.B., Leslie, L.M., Segele, Z.T.: Classifying drought in Ethiopia using machine learning. Procedia Comput. Sci. **95**, 229–236 (2016). https://doi.org/10.1016/j.procs.2016.09.319
37. Ahuna, M.N., Afullo, T.J., Alonge, A.A.: Rain attenuation prediction using artificial neural network for dynamic rain fade mitigation. SAIEE Africa Res. J. **110**(1), 11–18 (2019)
38. Tittonell, P., Shepherd, K.D., Vanlauwe, B., Giller, K.E.: Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya-An application of classification and regression tree analysis. Agric. Ecosyst. Environ. **123**(1–3), 137–150 (2008)
39. Stark, J.C., Porter, G.A.: Potato nutrient management in sustainable cropping systems. Am. J. Potato Res. **82**(4), 329–338 (2005). https://doi.org/10.1007/BF02871963
40. Gruhn, P., Goletti, F., Yudelman, M.: Integrated nutrient management, soil fertility, and sustainable agriculture: current issues and future challenges. Intl Food Policy Res Inst (2000)
41. Gibbons, J.M., et al.: Sustainable nutrient management at field, farm and regional level: soil testing, nutrient budgets and the trade-off between lime application and greenhouse gas emissions. Agric. Ecosyst. Environ. **188**, 48–56 (2014). https://doi.org/10.1016/j.agee.2014.02.016

42. Du Plessis, C., Van Zijl, G., Van Tol, J., Manyevere, A.: Machine learning digital soil mapping to inform gully erosion mitigation measures in the Eastern Cape. South Africa. Geoderma **368**, 114287 (2020). https://doi.org/10.1016/j.geoderma.2020.114287
43. Cooper, M.W., Hengl, T., Shepherd, K., Heuvelink, G.B.: Soil nutrient stocks in sub-saharan Africa: modeling soil nutrients using machine learning. In: AGU Fall Meeting Abstracts, vol. 2017, pp. B53F–2001 (2017)
44. Hengl, T., et al.: African Soil Properties and Nutrients Mapped at 30-m Spatial Resolution using Two-scale Ensemble Machine Learning (2020)
45. Nzuza, P., Ramoelo, A., Odindi, J., Kahinda, J.M., Madonsela, S.: Predicting land degradation using Sentinel-2 and environmental variables in the Lepellane catchment of the Greater Sekhukhune District, South Africa. Physics and Chemistry of the Earth, Parts A/B/C, p. 102931 (2020). https://doi.org/10.1016/j.pce.2020.102931