Water Optimization in Digital Farming

Pascal Francois Faye[1][a], Jeanne Ana Awa Faye[2] and Mariane Senghor[1]
[1]*Dept. Mathematics and Computer Sciences,*
University Sine Saloum El Hadj Ibrahima NIASS (USSEIN), Kaolack, Senegal
[2]*Institut de Management Public et Gouvernance Territoriale,*
University Aix-Marseille, Marseille, France

Keywords: Water Optimization, Internet of Things, Data Analysis, Artificial Intelligence, Crop Similarities.

Abstract: In Senegal, agriculture is subsistence and highly dependent on soil, climate, and raining season. Food crops take up to 46% of the total land and make up 15% of the Gross Domestic Product (GDP), ensuring between 70% and 75% employment. In this work, we propose methods to understand through a sensor network, the effects of the required irrigation system on six soil types (ferruginous tropical - sandy - loamy - clay - humus-bearing - clay and loamy) depending to crop production like : - the time interval for infiltration or evaporation of the irrigation water according to the type of soil - the speed of spreading of water in both directions (lateral and depth) - the set up of four soil's amendments (peanut shells, livestock manure, poultry manure and plant mixture) methods for optimized water in crop production. We, also, propose an agricultural calendar for a good distribution of the farms' activities over time after finding the relationship between eighteen crop production and soil amendments. Our results show the effectiveness of our solution to help water optimization in agriculture. This means that, taking into account these data, it is possible to understand crop dependencies, anticipate agro-ecological phenomena and crop water stress that affect the yield of crops.

1 INTRODUCTION

In order to continuously feed humanity, in computer sciences it has several advances on sensor network, robot automation, computer vision and artificial intelligence for prediction, decision making, etc. However, due to the demographic pressure on cities, climate change and soil degradation, several research questions are done in order to face with the gradual abandonment of land and to find solutions or advice with the reduction of agricultural perimeters. This is one of the big issues in the peanut basin of Senegal(cf. figure 1). Computer vision recognition has been increasingly applied to numerous fields of agriculture with the advancement of computer graphics and image processing technology. The development of sensor technologies for smart agriculture, such as soil and air all-in-one sensors which provide temperature and humidity parameters, etc., enhance data collection and processing for decision making in agriculture. Usually, the data is transferred from the sensor to the sink node for data collection and the server for processing and decision making. In addition, the use of robots in agriculture that uses a variety of sensors to sense the dynamic of the agricultural environment and then picks the target using this knowledge and a decision-making algorithm based on artificial intelligence help farms in order to manage their field (ploughing, sowing, harvesting, pest attack, etc.).

In this work we tackle through sensors, the effects of soil type and the required irrigation system depending to crop production through - the time interval for infiltration or evaporation of irrigation water depending on the type of soil - the speed of spreading of water in both directions (lateral and depth) - the soil amendment methods for optimized water in crop production. This, to propose an agricultural calendar for a good distribution of the farms' activities over time and find the relationship between crop production and soils. Thus, to lead to a better planning of the agricultural calendar for a good distribution of activities over time. This in order to take into account climate changes, soil degradation, etc. for improving the farms' crops and to overcome the seasonality of the agriculture in the peanut basin of Senegal.

In the rest of this paper, section 2 presents our research problem, section 3 highlights our objectives and section 4 discusses related works. Section 5

[a] https://orcid.org/0000-0002-2078-5891

Faye, P., Faye, J. and Senghor, M.
Water Optimization in Digital Farming.
DOI: 10.5220/0013057400003822

In *Proceedings of the 21st International Conference on Informatics in Control, Automation and Robotics (ICINCO 2024) - Volume 1*, pages 472-479
ISBN: 978-989-758-717-7; ISSN: 2184-2809

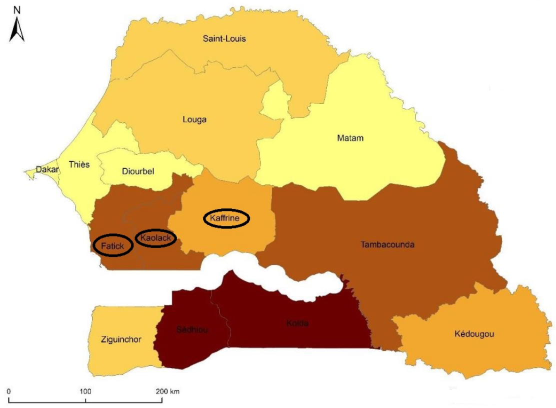

Figure 1: Peanut basin of Senegal (ANSD, 2024).

presents some preliminaries and methodologies. Section 6 highlights the results before the conclusion in the section 7.

2 RESEARCH PROBLEM

An agriculture that deals with the environment, the climate change and the soil degradation has become an imperative if we aim to make farmer and agriculture sustainable. A better understanding of the farm's environment is needed to make the right varietal choices and crop options. This is not to mention the rise in temperatures, which leads to increased evaporation or evapotranspiration, which influences yields and the seasonality of the agriculture. In addition, water is a critical resource that needed to optimize for an efficient crop production. That is why, this work focus on methods to understand, the time interval for water infiltration or evaporation depending on the soil type and amendment. This, in order to propose a better agricultural calendar for a good distribution of the farms' activities over time and find the relationship between crops and soil activities in the peanut basin of Senegal (cf. figure 1). Indeed, we highlight on the figure 2, the dependencies between month, from 2000s to 2023s regarding the agroclimatology parameters (Surface Pressure, Temperature, Humidity, Wind Speed, Surface Soil Wetness, Profile Soil Moisture, Root Zone Soil Wetness, Precipitation, Photosynthetically Active Radiation). Each square shows the correlation (a measure of dependencies). Values closer to zero means there is no linear trend between the months. Close to 1 the months are more positively correlated, and stronger is the relationship. The legend on the right side help to interpret correlations.

The results show a strong correlation between the months in the peanut basin. It is therefore possible to

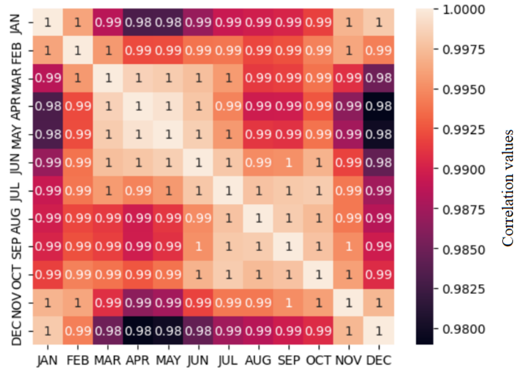

Figure 2: The result of our data correlation from 2000s to 2023s in the peanut basin.

refine cropping calendars to avoid seasonality in agriculture, taking into account other soil-related parameters.

3 OUTLINE OF OBJECTIVES

Knowledge of climate change and its effects on the various sectors of the national economy is a major challenge for the country's developers. Various initiatives are therefore being developed to better identify the implications of climate variability in the agriculture sector. However, while a causal relationship has clearly been established between the vulnerability of the agriculture sectors and a set of parameters like: the climate, the challenge of accurate information, the sharing and pooling efforts (Faye et al., 2022). This calls for a review of existing frameworks, but it should also help to find ways of collaborating, sharing and other one in order to provide better support for decision-making, particularly for grassroots users such as producers. Supporting farmers to better manage the risks associated with climate variability is now a major necessity (Faye et al., 2024a)(Faye et al., 2024b). All economic activities which promote food security and suitable agriculture must incorporate the risks of climate change, soil types and water quantity and water quality into their planning. The aims of this work are:

1. to understand the time interval for infiltration or evaporation of irrigation water depending on the type of soil.
2. to calculate the speed of spreading water in both directions (lateral and depth).
3. to set up several soil amendment methods for optimized crop production.
4. to help with water optimization that is adapted to variations of agrometeology parameters during

the annual seasons.

5. to find similarities between different crops in order to propose an annual soil occupation management strategy.

In this way, farmers can make decisions about the technical itineraries for their crops and the dates set for the cropping calendars (ploughing dates, sowing dates, fertiliser application dates, irrigation hours and other inputs), which can enable precision farming. This work combines the:

1. laws of probability to model the dynamics and unpredictable events;
2. Machine learning (ML) models to find the better decision making;

This combination delivers a solution that addresses well the dynamism and uncertainty challenges targeted in this work.

4 STATE OF THE ART

In (Sellam and Poovammal, 2010), they research the environmental parameters that affect the crop yield and related parameters through a multivariate Regression Analysis. A sample of environmental factors considers a period of 10 years. The System is applied to find the relationship between explanatory variables like annual rainfull,area under cultivation, food price index and hence the crop yield as a response variable and R^2 value clearly shows that, the yield is especially hooked into annual rainfall,area under cultivation and food price index are the opposite two factors that are influencing the crop yield. This research is often enhanced by considering other factors like minimum support price, cost price index, wholesale price index, etc. and their relationship with crop yield. In (Zhang et al., 2010), the authors show that NDVI (Normalized Difference Vegetation Index) and precipitation are the most important predictors for corn yield in Iowa. In (Zingade et al., 2018), the authors have presented an android based application and an internet site that uses Machine learning methods to predict the foremost profitable crop in the current weather and soil conditions and with current environmental conditions. This system helps the farmer with a sort of option for the crops that will be cultivated, which will be helping them over the long run. In (Sun et al., 2022) they improved a density peak cluster segmentation algorithm for RGB (Red Green Blue) images with the help of a gradient field of depth images to locate and recognize target fruit during the process of green apple harvesting or yield estimation. Specifically, the image depth information is adopted to analyse the gradient field of the target image. Usually, smart agriculture produces enormous quantities of multidimensional time series data. However, due to the technological's limitations, data loss and misrepresentation are frequent problems with the smart agriculture's IOT devices. In order to solve the issues in (Cheng et al., 2022), authors propose a anomaly detection model that can handle these multidimensional time series data. Meanwhile, a multi-objective strategy based on supervised machine learning was utilized in (Uyeh et al., 2022) to identify the ideal number of sensors and installation locations in a protected cultivation system. A machine learning tree-based model in the form of a gradient boosting technique was specifically adapted to observed (temperature and humidity) and derived circumstances (dew point temperature, humidity ratio, enthalpy, and specific volume). Time series forecasting was used for feature variables. In (Maia et al., 2022), sensor data analysis over two irrigation seasons in three cotton fields from two cotton-growing regions of Australia revealed a connection between soil matric potential and cumulative crop evapotranspiration (ETcn) derived from satellite measurements between irrigation events. They explore the distributed averaging issues of agriculture picking multi-robot systems under directed communication topologies by utilizing the sampled data. A distributed protocol based on nearest-neighbor information is presented using the principles of algebraic graph theory and matrix theory.

In contrast to our work, these works do not propose a cropping calender in order to minimize the risk depending to climate change, pest migration and other agrometeorological information and soils parameters like ours. In addition, we aim to enhance productivity and sustainability in the peanut basin of Senegal by taking into account the water optimization and cropping calendar. This, because in Senegal, there are different types of farms and various levels of complexities in terms of organization. We have on the one hand, family farms with limited levels of organizations, financial capabilities and standard procedures. On the other hand, there are some farms working on fruits and vegetables exportation with better organizations and procedures. In (Faye et al., 2023), a set of results in this peanut basin shown the crop yield relative to the raining season and to the temperature. In (Faye et al., 2024a), authors propose an Agriculture Information and Management System based on some Machine Learning Algorithm (ML) and Internet Of Things device that ensures data collection and control as well as a data monitoring system via a web platform for decision-making support in a real-world agricultural environments. (Faye et al., 2024b) provides a set of mechanisms that uses a set of trust database of agro-climatic parameters and a set of artificial intelligence algorithm in order to assess agricultural calendar for a good distribution of the farm's activities and to find the relationship between crops. In the continuity of their work, we take into account soils' types and water optimization.

The next section provides the methodology of this work.

5 METHODOLOGY

Our study is motivated by the environmental and climate challenges that make difficult the prediction on crop yield, crop diseases and pests in the peanut basin of Senegal (Fatick, Kaolack and Kaffrine) (cf. Figure 1). The peanut basin of Senegal has a set of different climatic characteristics (Faye et al., 2023). Many challenges are observable due to changes in land degradation, soil salinization, temperature, random rainfall, etc. We conducted a two years study that has shown the correlation relationship (Figure 3) between a set of climatic parameters of the peanut basin by using our dataset from our sensor network (figure 4).

We follow information on the agriculture requirements for planning work, forecasting the development risks of certain climate-related diseases, monitoring the water balance of soils, monitoring of temperatures in connection with the plant development schedule. The functioning of the crop, the soil and the water system depends mainly on:

- PS : Surface Pressure (kPa)
- T2M : Temperature at 2 Meters (C)
- QV2M : Specific Humidity at 2 Meters (g/kg)
- WS2M : Wind Speed at 2 Meters (m/s)
- GWETTOP : Surface Soil Wetness (1)
- GWETPROF : Profile Soil Moisture (1)
- GWETROOT : Root Zone Soil Wetness (1)
- PRECTOTCORR : Precipitation Corrected (mm/day)
- PAR : Photosynthetically Active Radiation (W/m$\hat{2}$)

In figure 3, we have plotted changes in soil parameters between 2002 and 2023 in order to complement the correlation relationships provided by the figure 2. It shows, between 2022 and 2023, the different relationships and differences between the various agroclimatic soil parameters that can influence plants apart from soil nutrients.

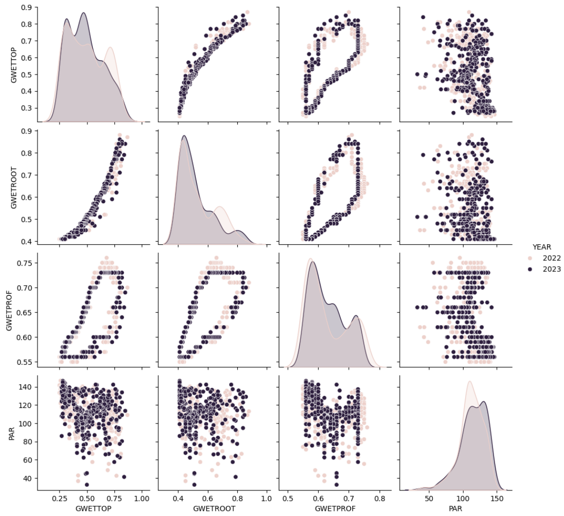

Figure 3: Our data clustering between 2022 and 2023 using DecisionTreeClassifier.

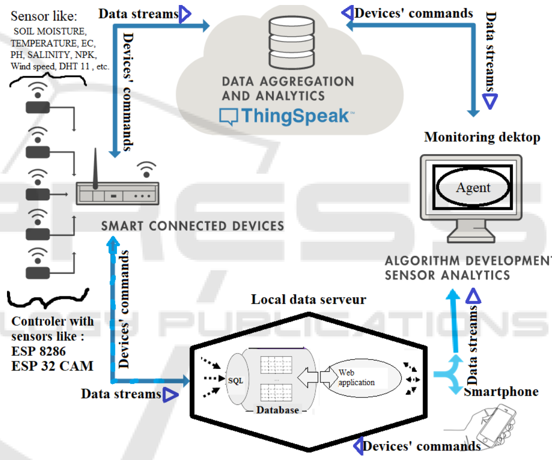

Figure 4: Our sensors network topology for local climate and soil data.

This, in order to study the set of real-time interactions between atmospheric phenomena and all of agronomic parameters, to deal with the real needs of farmers in order to avoid the seasonality of their activities without to guarantee a good crop yield. Our sensor network topology is shown in figure 4.

The data are collected via sensors (e.g. soil moisture, NPK, DHT11, temperature, etc.) with their controller cards (ESP 8266, ESP CAM, ARDUINO UNO) which create a mesh network of field sensors that will serve as a medium for transmitting data from sensors. Different cards transmit their data through the access points of the network. The data are sent simultaneously to the ThingSpeak platform and on our local server via HTTPS (Hypertext Transfer Protocol Secure) and SQL (Structured Query Language) requests. In our local server, it has a web application for data visualization to support decision making. ThingSpeak is a cloud IoT analytics platform service that allows to aggregate, visualize, and analyze live data streams. Data are sent to ThingSpeak from our devices, to create instant visualization. All data from our local server or from ThingSpeak are aggregated by our agent platform. An agent is a device or an application which can sense the environment compute some processes and provide results or acts on its environment. Our agent concept which extract, organize, aggregate and interpret sensor data based on our machine learning models is constrained by the parameters: $\{Rs, Hs, \vartheta^t, U, L_{Net}\}$. Rs is its resource(s) and Hs is its *history set* which consists of a set of previous decisions. A *view* ϑ^t is the set of sensors in its neighborhood with whom it can directly communicate at time t. U is its private utility function. L_{Net} defines the dependence level between the received data in a given sensors network (Net). The utility function U of the agent is the score used in order to help to improve the learning rate $U = \frac{errors\_rate}{good\_decision}$.

In the next section, we conduce a set of experiments with a set of soil types in order to optimize crop production and water infiltration in the peanut basin (see, figure 5). Choosing the right soil and crop is important but must take into account water quantity and water quality. That's why choosing the right watering system for the soil and crop, affects soil health and plant growth. Hence, the importance of maintaining appropriate humidity, saving water by meeting the specific needs of crops and preserving soil structure. A good watering system also helps to maximise crop yields and maintain a favourable environment for optimum development. By precisely adjusting irrigation to the specific soil conditions, it is possible to avoid wasting water while promoting optimum crop growth. The system also specifies the amount of water required in real time for each crop, based on agro-ecological parameters and the physicochemical parameters of the soil. The figure 5 shows the experimental set-up that we repeated for each type of soil, depending to the amendments and sensors' position. We apply the same compaction effect (weight of a person), the same quantity of water and the same composition: 75% soil and 25% soil amendment. We placed the sensors at a distance of 5 cm, with a width of 50 cm and a depth of 30 cm, based on the root systems of the crops that we consider in this work. Each sensor can measure humidity, NPK (nitrogen, phosphorus, potassium), pH (potential of hydrogen) and EC (Electro Conductivity), which allows us to determine the infiltration rates.

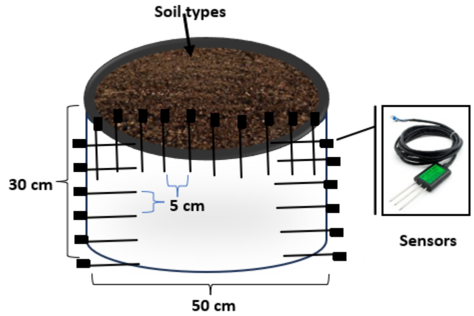

Figure 5: During our experimental set-up, we repeated for each type of soil and amendments the same sensors' position.

6 OUTCOMES

We have done our study by taking into account these sets of parameters.
Dates (month/day/year): From 06/01/2024 to 07/31/2024.
Location: Latitude 14.347943, Longitude -16.410459.
The agroclimatic parameters collected are:

- PS = Surface Pressure (kPa).
- QV2M = Specific Humidity at 2 Meters (gkg).
- T2M_MAX = Temperature at 2 Meters Maximum (C).
- T2M_MIN = Temperature at 2 Meters Minimum (C).
- WS2M_MAX = Wind Speed at 2 Meters Maximum (ms).
- WS2M_MIN = Wind Speed at 2 Meters Minimum (ms).
- PREC = Precipitation Corrected (mmday).
- UVA = All Sky Surface UVA Irradiance (Wm^2).
- UVB = All Sky Surface UVB Irradiance (Wm^2).
- EVAP = Evaporation and evapotranspiration after 24 hours.
- Moisture = Means' soil humidity rate between 0 cm and 10 cm after 24 hours.
- INFD = Speed of depth infiltration (cm/s).
- INFL = Speed of lateral infiltration (cm/s).

Temperatures in Senegal, range from very warm to hot, with an annual average temperature of 36 Celsius. At least 4 months of the year are tropical and frequently sultry with temperatures above 36 Celsius. The distribution of crop types grown in Senegal correlates with the timing of seasonal rainfall (figure 6 and figure 7). Moreover, some of the practices

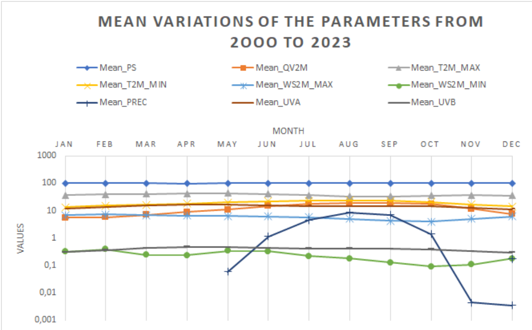

Figure 6: Our study of the mean variations of the parameters from 2000 to 2023.

Table 1: Soil parameters without soils' amendment. These values are our reference before tests.

Soil Type	EVAP	Moisture	INFD	INFL
Ferruginous tropical soil	30	46	20	15
Sandy soil	31	34	40	45
Loamy soil	40	30	13	13
Clay soil	37	46	16	16
Humus-bearing soil	10	75	65	64
Clay and loamy soil	23	50	20	17

of the Green Revolution, especially the use of modern crop varieties and the addition of synthetic fertilizers and pesticides/herbicides are not sustainable practices, especially under climate change conditions. NPK (nitrogen, phosphorus and potassium) inputs are the most important parameters in maximizing yields and economic returns to farmers. However, in the peanut basin it is required to take into account to the soil type, the water quality and water quantity, the pH and the salinity (EC) for agriculture calendar.

The figure 6 illustrates that a considerable number of climatic parameters exhibit minimal variation from one month to another. However, it is primarily the availability of water that is of paramount importance, and this is the factor that gives rise to the seasonal variation in certain activities between the months of June and October. From table I to table V, we select a set of farms' soil types of the peanut basin and show the evolution of evaporation, infiltration and moisture in an average temperature of 36 Celsius. We used DHT11 and soil moisture sensors to measure evaporation rates, infiltration rates and moisture levels for the speculations listed in table 6. This was done to understand and provide decisions based on soil and amendment types.

After that, we use a set of endogenous knowledge to improve soil parameters by using natural soils' amendment like:

- Peanut shells
- Livestock manure
- Poultry manure
- plant mixture

Table 2: Soil parameters after amendment with peanut shells.

Soil Type	EVAP	Moisture	INFD	INFL
Ferruginous tropical soil	10	70	70	60
Sandy soil	21	60	60	55
Loamy soil	10	80	83	80
Clay soil	7	90	86	86
Humus-bearing soil	6	95	85	84
Clay and loamy soil	7	90	80	80

Table 3: Soil parameters after amendment with livestock manure.

Soil Type	EVAP	Moisture	INFD	INFL
Ferruginous tropical soil	12	70	70	65
Sandy soil	23	50	50	55
Loamy soil	14	70	73	70
Clay soil	15	80	76	76
Humus-bearing soil	9	90	80	80
Clay and loamy soil	14	80	70	70

Table 4: Soil parameters after amendment with poultry manure.

Soil Type	EVAP	Moisture	INFD	INFL
Ferruginous tropical soil	12	70	70	65
Sandy soil	23	50	50	55
Loamy soil	14	70	73	70
Clay soil	15	80	76	76
Humus-bearing soil	9	90	80	80
Clay and loamy soil	14	80	70	70

The results show that the amendments improve water retention, infiltration and decrease evaporation. In addition, depending on the amendments these improvements can double the water retention capacity of soil types in consideration of our fundamental metrics (cf. table 1). This makes it possible to rationalize water and improve the frequency of watering according

Table 5: Soil parameters after amendment with plant mixture.

Soil Type	EVAP	Moisture	INFD	INFL
Ferruginous tropical soil	12	64	65	65
Sandy soil	25	40	40	50
Loamy soil	10	75	75	75
Clay soil	15	80	76	76
Humus-bearing soil	10	83	70	70
Clay and loamy soil	13	76	67	67

Table 6: Our list of practical case' speculations.

Carrot, Sweet potato, Eggplant, Lettuce, Cabbage, Okra, Tomato, Turnip, Melon, Zucchini, Cucumber, Bell pepper, Chilli, Onion, Cassava, Potato, Hibiscus sabdariffa, Parsley.

to the types of soil and crops. Based on the data from our sensors, it is possible to deduce that farmers can improve the composition of their soils to optimise water use according to the soil types and crops on their plots. The types of soil studied in this study are naturally available in the peanut basin and improve water retention and infiltration. In order to assess agricultural calendar to help farm's activities over time and find the relationship between crop production and soil amendment, we use the following speculations list to test our soils understanding highlighted in this work.

For each speculation, we consider such needs:

- NPK_hec(Kg): nitrogen, phosphorus, potassium for each hectare.
- Water_Day(L): stream-day water requirements (litre).
- Temperature(C): Temperature (Celsius).
- Light(UV): Means of Ultraviolet (UVA and UVB).
- Soil_type: Soil type (tropical ferruginous soils, Sandy soils, loamy soils, clay soils, Humus-bearing soils and Clay and loamy soil).
- Ripening_time(day): Number of days before harvest.
- Salinity tolerance: Electro conductivity (EC).

For the comparison of needs, we used Elbow method (Umargono et al., 2020) and the KMeans algorithm (Onoda et al., 2010) which is an artificial intelligence algorithm in order to find the crops' similarities. The table 7 below, shows the similarity between a set of speculations regarding their needs, the soil' parameters and the climate' parameters that are determining the crop adaptation.

Table 7: Cluster assignment by similarity.

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Carrot, Eggplant, Zucchini, Cucumber, Onion, Potato	Sweet potato, Okra	Lettuce	Cabbage, Tomato, Turnip, Melon, Bell pepper, Chilli, Cassava, Hibiscus sabdariffa, Parsley

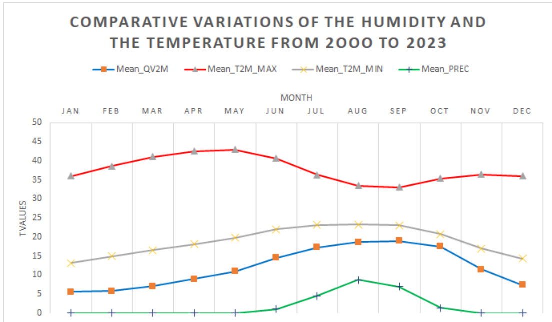

Figure 7: Comparative variations of the humidity and the temperature from 2000 to 2023.

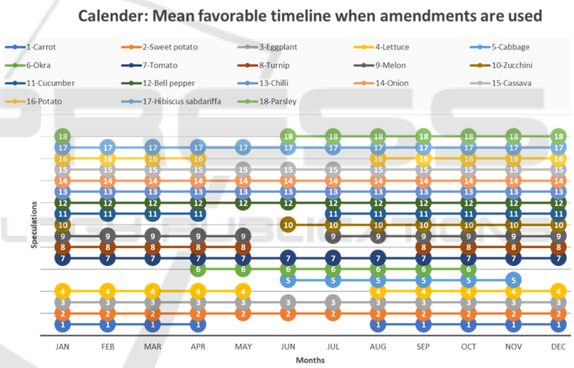

Figure 8: Agricultural calendar for a good distribution of farm activities to avoid the seasonality of agriculture.

Depending to the analyse of the figure 6 and the figure 7, we propose the following agricultural calender (figure 8) by taking into account the possibility of an out-of-season cultivations. This in order to overcome the abandonment of agricultural perimeters or an agriculture depending on the raining season.

This figure 8 in combination with the tables 1, 2, 3, 4 and 5 permit to find a set of other speculations adaptable in the peanut basin when the salinity (Electro Conductivity) is between 0.1 and 1.2 and Ph (Potential of Hydrogen) between 5 and 8. The comparison with the results in (Faye et al., 2024b) shows how important is to take into account the types of soil and types of amendments that can improve the cultural calendar. This work further proves that understanding climate parameters alone will not help farmers and feed the future generations.

7 CONCLUSION

In Senegal, agriculture dependent highly to soil types, climate, soil salinity and water. This work provides a set of results in order to know, how to optimize water in different soil type and it proposes an agricultural calendar for a good distribution of agriculture activities over time and find the relationship between crops. Our results show the effectiveness of our solution to avoid the dependences on raining season. This makes possible to understand crops' dependencies and anticipate the agroecological phenomena, the planning of production facilities and variations in agricultural yields. In the future we aim to disseminate this technique in the other agroecological area of the Senegal. Incorporate an analysis of the socio-economic impact of our agricultural calendar on local communities by selecting performances metrics and comparison with traditional methods.

REFERENCES

ANSD (https://www.ansd.sn/regions, 2024). Agence nationale de la statistique et de la demongraphie/accueil/regions.

Cheng, W., andXiaoting Wang, T. M., and Wang, G. (2022). Anomaly detection for internet of things time series data using generative adversarial networks with attention mechanism in smart agriculture. *Frontiers in Plant Science*, page https://doi.org/10.3389/fpls.2022.890563.

Faye, P. F., Faye, J. A., and Senghor, M. (2024a). Decentralized intelligence for smart agriculture. *In Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART 2024)*, 1:240–247, ISBN 978–989–758–680–4, ISSN 2184–433X. DOI: 10.5220/0012342100003636.

Faye, P. F., Faye, J. A., and Senghor, M. (2024b). Machine learning for a better agriculture calendar. *In Proceedings of the 19th International Conference on Software Technologies(ICSOFT 2024)*, pages 307–314, ISBN 978–989–758–706–1, ISSN 2184–2833, pages 307–314. DOI: 10.5220/0012691800003753.

Faye, P. F., Sall, M. M., Dembele, B., and Faye, J. A. A. (2023). Plateforme numérique de guides culturaux dans un contexte de changement climatique et de baisse des rendements agricoles. *RAMReS Sciences des Structures et de la Matiére*, pages vol. 7, no. 1, pp. 85–115, ISSN : 2630–1180.

Faye, P. F., Senghor, M., and Ndione, G. A. (2022). Stable trade coordinations in smart agriculture. *International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, pages 215–222.

Feng, Q., Wang, S., Wang, H., Qin, Z., and Wang, H. (2022). Circle fitting based image segmentation and multi-scale block local binary pattern based distinction of ring rot and anthracnose on apple fruits. *Frontiers in Plant Science*, 13:doi: 10.3389/fpls.2022.884891.

Fu, L., Li, S., Rao, Y., Liang, J., Teng, J., and He, Q. (2022). A novel heuristic target-dependent neural architecture search method with small samples. *Frontiers in Plant Science*, page 10.3389/fpls.2022.897883.

Maia, R. F., Lurbe, C. B., and Hornbuckle, J. (2022). Machine learning approach to estimate soil matric potential in the plant root zone based on remote sensing data. *Frontiers in Plant Science*, page https://doi.org/10.3389/fpls.2022.931491.

Onoda, T., Sakai, M., and Yamada, S. (2010). Careful seeding based on independent component analysis for k-means clustering. *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, 3:112–115.

Paswan, R. P. and Begum, S. A. (2013). Regression and neural networks models for prediction of crop production. *International Journal of Scientific and Engineering Research*, pages Volume 4, Issue 9,ISSN 2229–5518.

Sellam, V. and Poovammal, E. (2010). Prediction of crop yield using regression analysis. *IEEE Trans. Knowl. Data Eng.*, pages vol.23, no. 10, pp. 1498–1512.

Sun, M., Xu1, L., Luo, R., Lu, Y., and Jia, W. (2022). Fast location and recognition of green apple based on rgb-d image. *Frontiers in Plant Science*, 13:doi: 10.3389/fpls.2022.864458.

Umargono, E., Suseno, J. E., and K., V. G. S. (2020). K-means clustering optimization using the elbow method and early centroid determination based-on mean and median. *International Conferences on Information System and Technology (CONRIST 2019*, DOI: 10.5220/0009908402340240:pages 234–240.

Uyeh, D. D., Iyiola, O., Mallipeddi, R., Asem-Hiablie, S., Amaizu, M., Ha, Y., and Park, T. (2022). Grid search for lowest root mean squared error in predicting optimal sensor location in protected cultivation systems. *Frontiers in Plant Science*, page https://doi.org/10.3389/fpls.2022.920284.

Zhang, L., Lei, L., and Yan, D. (2010). Comparison of two regression models for predicting crop yield. *IEEE International Symposium on Geoscience and Remote Sensing (IGARSS)*.

Zingade, P. D., Buchade, O., Mehta, N., Ghodekar, S., and Mehta, C. (2018). Machine learning-based crop prediction system using multi-linear regression. *International Journal of Emerging Technology and Computer Science(IJETCS)*, pages Vol 3, Issue 2.