ISSN: 2754-477X

Journal of Food Technology & Nutrition Sciences

SCIENTIFIC Research and Community

Research Article

Open Access

Innovative Data-Driven Analysis of Water Management for Effective Agricultural Practices

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ABSTRACT

Objective: To measure, investigate, analyse variables and factors that influences water resources management as used in the agricultural sector, and how water management techniques, systems, decision making processes can be optimized for a more efficient and effective water-agriculture-food nexus.

Methods: Using current and historical real world data from validated open source data stores; analysis was carried out on agricultural, socio-economic, demographic, geo-climatic, gender, wireless technological factors and variables; that influence available and needed water capacity for farming (Wc) in selected African Countries and Globally. The methodical and data-driven analyses were carried out using Analytics, Machine Learning and Wireless Cooperative Communications algorithms.

Results: The available and needed water capacity for farming (Wc) was calculated and predicted using factors and independent variables of real world data that were shown to influence Wc, and that were statistically measured and analysed. Time based, qualitative, quantitative, predictive, simulative, clustering, statistical data analyses confirmed that available water resources, socio-economy, demography, agricultural factors, Gender diversity & inclusion, Climate Change and Wireless Communication technologies; can influence water availability and water management for agriculture.

Conclusion: Modern data-driven, cost effective analytical processes can be used to productively analyse and develop strategies, processes, systems and technologies for innovative, efficient and effective water management for improved agricultural practices and a sustainable environment.

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Received: February 17, 2023; **Accepted:** February 24, 2023; **Published:** March 03, 2023

Keywords: Water Management, Agriculture, Food Production, Data, Analysis, Machine Learning, Wireless Cooperative Communication, Innovative, Women, Climate Change

Introduction

All over the world, the issue of food security has been in the fore front of the campaign for sustainable development. Experience and news received from all over the world reveals that food security is dependent on effective agricultural practices. This also implies that areas with food shortages in the world would be required to step up agricultural production in the face of ravaging desertification caused by excessive draught and in the daunting face of global insecurity.

The challenge of food security necessarily suggests that global water management strategies need to be looked into in the light of improving agricultural development in sustainable manner. This is important to ensure year-round food production in areas with excessive dry season which includes Sub-Sahara African nations. Cameira and Pereira (2019) identified land and water as primary determinants of agricultural output calling for an innovative approach to land and water governance. Similar challenges have been identified by A. Inocencio, Sally and Merrey while providing an overview into the use of innovative approaches to agricultural water use for improving food security in Sub-Saharan Africa [1-3]. The World Bank, Food and Agricultural Organisation have at different times made similar calls for improvements in water management techniques, policies, strategies, systems, technologies globally to aid effective agricultural practices and ensure food security in the midst of challenges such as the reality of climate change.

Hence, the Innovative Analysis and Management of Water Resources for Effective Agricultural Practices has become a global concept. The concept seeks to foster effectiveness of global water resources management practices to enhance food production. It also seeks to design and promote a coordinated strategy for the development and management of water, land and related resources, to maximise agricultural yield. Therefore, the increasing challenge of modern agriculture meeting up with the production of food for the continued increase in global population, in the context of the ever-growing competition for water and land, climate change, drought, anthropic water scarcity and less participatory water governance; requires urgent and a thorough approach for the good of humanity. For a data-driven world of ours, innovative measures to analyse and recommend effective and efficient water management techniques and approaches becomes relevant and would help overcome challenges associated with field study; by providing cost effective, efficient, intelligent and safer measures to ensure better decision making for more effective water management policies to increase agricultural output efficiency and environmental sustainability.

Therefore, innovative issues and measures must be applied in agricultural water management and practices for both field and system, to mitigate water scarcity, increase environmental friendliness and the welfare of society, and thereby increase food production. The aim of this research work is to investigate and analyse factors and techniques that influences and aids water resources management, as used in the agricultural sector; and how water management techniques, systems, technologies, processes, policy decision making can be optimized for a more efficient water, agriculture and food nexus; with the use of data analysis, algorithms, machine learning methodologies and simulation tools.

Literature Review

Agriculture and Water

Agriculture is critical for food security and economic growth in developing countries, and it is the primary source of income for three out of every four impoverished people on the planet [4]. Food production, on the other hand, demands a lot of water. Agriculture takes 70% of all water from rivers and aquifers around the world. North Africa, South Asia, and the drier portions of Sub-Saharan Africa are among the regions where physical water scarcity is already serious (SSA). One of the most important concerns that humanity faces today is water scarcity. Over 1.4 billion people live in water-stressed river basins, with 3.5 billion predicted by 2025. Furthermore, more than 20% of the world's rivers dry up before they reach the sea (World Research institute, 2003).

Existing literatures divide water management elements and impediments into three categories: institutional, technical, and socioeconomic [5]. Barriers include: a lack of regulation and widespread noncompliance with existing laws; the current land ownership structure and concentration of water use rights; and a lack of technical expertise about the suggested changes; a lack of environmental awareness among farmers; a shortage of rainfall. Moreover, the main facilitators are (i) the existence of institutional incentives for the adoption of sustainable practices; (ii) the sector's continuous process of technological innovation; (iii) farmers' positive attitude toward technological change; (iv) collaborative relationships between the various actors; and (v) the sector's financing capacity.

Feizabadi and Gorji used a factor analytic technique to investigate and critically examine the various factors that affects Iranian agricultural water management as described by irrigation professionals [6]. In addition, Jha, Kaechele, and Sieber, performed research-employing a sample survey data procedure to investigate, understand and verify elements that have significant influence on the use or adoption of water conservation measures in Tanzania [7]. They stated that incorporating individual, household, socioeconomic, and farmer attitudes related variables significantly helped to explain and clarify how practices of water conservation are adopted in Tanzania by smallholder farmers. Furthermore, the study discovered that a study approach that involved an integration of methods of water conservation technique adoption better explains the adoption decisions, opportunities, and restrictions that farmers experience at the household level, allowing for targeted agricultural management at the household level. According to the review, 120 farmers (17.12 percent) embraced water conservation practices, and farmer views of rainfall insecurity, household wealth, and food security are all important.

Irrigated agriculture is the primary source of freshwater withdrawals, accounting for over 70% of global withdrawals. Irrigated agriculture has increased agricultural production and helped to stabilize prices, allowing the world to feed its rising population. Non-agricultural water demands are rapidly increasing, as are shifting dietary tastes, global climate change, and new biofuel production demands. The rising costs of producing new water supplies, soil deterioration, groundwater depletion, and inefficient use of previously produced water supplies, etc; all exacerbate the challenges of growing water scarcity for agriculture [8]. Another study by Samian, Mahedia, Saadi, Movahedi was done to investigate, analyse and rsearch agricultural optimal water management's influencing factors in the Hamadan's area [9]. Authors used questionnaire and interview techniques to collect data from 148 farmers and they tested the reliability of their methods they used for data analysis, to obtain findings that indicate legal, technical, knowledge, economic, institutional and social factors all affect agricultural water management.

Wireless Sensor Networks

Wireless sensor networks (WSN) are typically composed of nodes, which are distributed thickly and are able to sensor, pick up and transmit signals and information [10, 11]. The enablement of information to be captured is the core function of WSN's, using a set of sensors able to communicate with each other and process data inside the network itself (processing in-network) in order to do a specific set of tasks which cannot be done by humans due to their inherent limitations and physical survival conditions [12]. Additionally, the WSN can also be applied where there is ongoing need for environment monitoring(for example agriculture) and control and in tasks that would demand too much time and resources if manually done This way, many applications like agriculture, electronic commerce, animal tracking and industrial activities, need their data to be available at real time [13, 14]. This real time concept is characteristic of applications which transactions must satisfy their deadline, so as to allow that data may be handled without losing its temporal validity. This enables the system to react in a efficient way, due to the obtained data correctness and consistency [15].

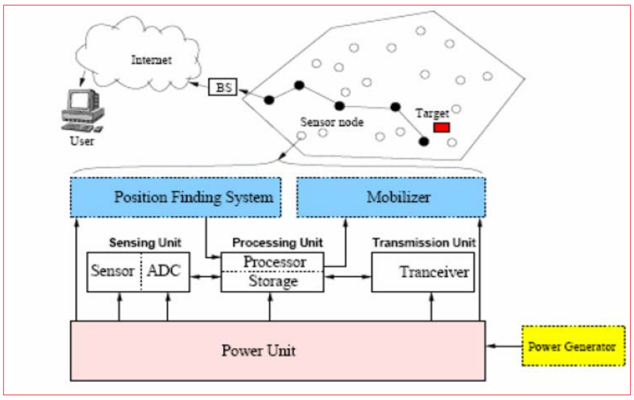

Figure 1: WSN Sensor Node General Structure [16].

Wireless Cooperative Communications

The method of cooperative communications, involves the creation of spatial diversity through an array of single antenna users combining to produce a 'virtual MIMO' system. The principle basically involves a user/node and its 'partner' node/mobile sending independent copies of the user's information to the destination (base station) at a given time, to create a diversity called 'cooperative diversity', with the aims of improved overall performance and reduction in overall energy consumption; this therefore means that the baseline transmit power of the users/nodes will reduce as each user/node would need to transmit with a lesser power to achieve a target performance criterion [17, 18]. Therefore, users/nodes share their antennas and other resources to create a 'virtual MIMO' or spatial diversity system through distributed transmission and signal processing, thereby each users/nodes acts both as a source and a relay of information, unlike earliest works which was modelled according to the basic 'relay channel', where each user or node just forwarded or re- transmitted the signal it received , but not having its own signal to send; thereby assuming a 'memory-less' relay channel of which cooperation may not be possible when relay channel is poor [19-21].

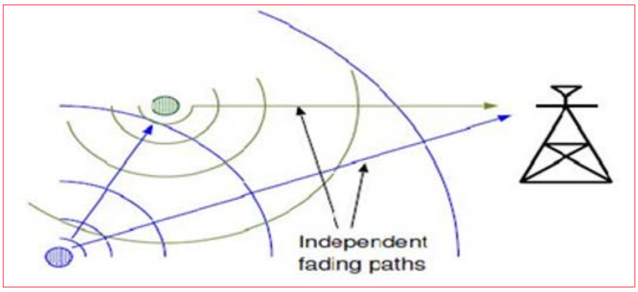

Figure 2: Cooperative Communication [20].

Work thus far generally considers that the users/nodes transmit equal power, but it could be possible to improve performance by varying user/node power based on the nature of the inter-user/node channel; therefore, this makes power control schemes an important factor in developing effective cooperative communications [20]. On Energy efficiency, it has been shown that both users/nodes in a two- user system obtain improved energy efficiency, saving a significant amount of energy through cooperation, though 'weaker' (lesser power) users/nodes benefit more than the 'stronger' (more power) users/nodes during cooperation [20-23]. Also, much work has been done at the physical layer, at which cooperative methodologies are quite different from other higher protocol layers [20-25].

Furthermore, for reduced complexities and ease of analysis, most works have assumed mutually independent inter-user and uplink channels, a perfect channel state information (CSI) at all receivers (users/nodes and base station) though this may not always be the case practically, as the wireless channel could vary unpredictably; this of course has been considered by some works, where a feedback mechanism is used in the uplink transmission to address an imperfect CSI situation [20-32]. Additionally, works also analysed the MIMO techniques for cooperative communications based on a two user/node system, that is to say each user just having one partner, this was also aimed at simplicity to avoid more complex algorithms for accurate partner assignment which is important in a much more practical multi –partner system; and also a Rayleigh flat fading wireless channel type was assumed which is typical for a 'non – line of sight' (NLOS) system as in wireless cellular networks [17-31].

Methodology

Existing literatures divide water management elements and impediments into three categories: institutional, technical, and socioeconomic. Barriers, which includes a lack of regulation and widespread noncompliance with existing laws; the current land ownership structure and concentration of water use rights; and a lack of technical expertise about the suggested changes; a lack of environmental awareness among farmers; and a shortage of rainfall. Hence, in our study we will conceptualize factors identified by existing literatures and that have varying impacts on water management with respect to effective agricultural practices. This research study is very much data driven, as it involves the synthesis of extensive agricultural, geo-climatic and demographic data relevant to the literature from diverse databases and portals. The analysis was carried out in two broad sections of Factors and Techniques respectively that influence water security and water management in agricultural practices. The research activities revolved around the various data analysis, data analytics involving statistical social science terminologies, data science and Machine Learning processes to carry out the necessary studies and obtain results. In addition to the theoretical and practical concepts and parameters already known; new metrics are derived to capture and measure and confirm key tests and analysis.

Furthermore, for such various methodical analyses; data acquisition, data cleaning, data wrangling are among key preliminary steps to ensure that the required data is importantly used for such analysis, following the key important steps:

- **Step 1 :** Acquire data from validated open access data stores and live data web portals
- **Step 2 :** Clean the data, label it appropritely, wrangle it and make it fit for purpose
- **Step 3:** Store the data and partition them accordingly for use
- **Step 4 :** Feed the data into the particular analysis tool, model and process as required.
- **Step 5 :** Prepare and specify how results will be reported

Research Process Flow

The research activity carried out in addition to data acquisition and associated process, is summarized by the flowchart in Figure 3.1.

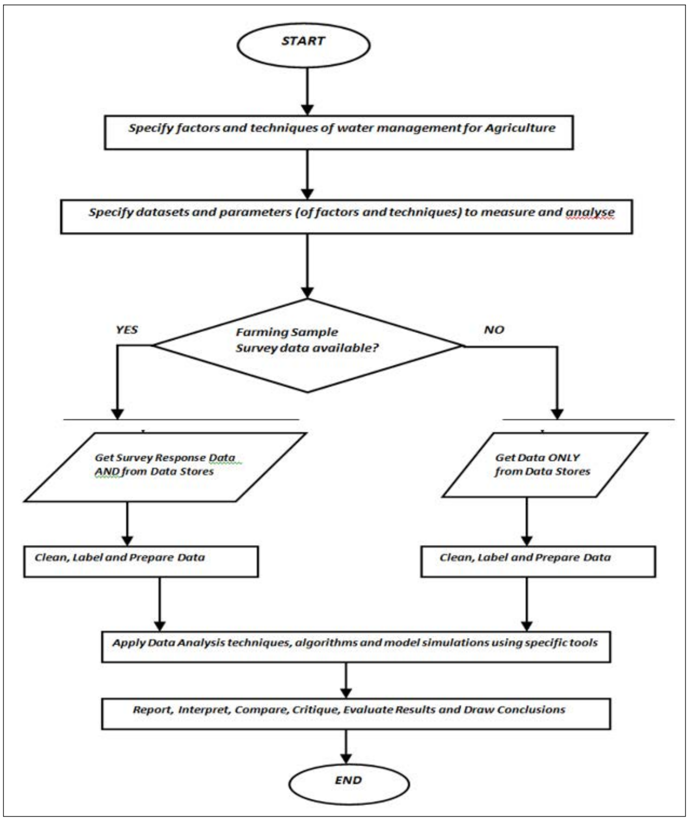

Figure 3: Summarized Research Process Flowchart

Factors influencing Water management for agriculture

Evidences have shown that for effective modern agricultural practices, adequate analyses should take into account influencing factors categorized as physical, agricultural and socioeconomic factors that act as drivers in the management of water resources as used in agriculture [34]. These factors are highlighted in the literature and must be properly investigated and analysed to ensure an efficient management of water resources for effective agriculture, since water is a limited resource and modern agriculture has to face the increasing scarcity of water for irrigation, as a result of the reduced availability and the increasing competition of civil and industrial sectors [35].

Physical Factors These include climate conditions, geological situations, soil types, hydrological conditions, and all other physical geographic conditions unique to an environment (for example aquifer conditions and underground water levels) that influences how water is used and management for effective agriculture.

Agricultural Factors As also explained in the literature, these includes irrigations systems and methods, crop section techniques, groundwater levels, use of effective technologies (for example wireless systems) and automotive systems and water body availability.

Socioeconomic Factors These are factors that influence water management/security for agriculture from a social, economic and political aspect, which is also very critical to develop effective and efficient water management strategies. Such drivers include water policies and laws, population and farmer population distributions, farmer profit, agricultural revenue, market prices (including cost of production using various systems).

Conditional Factors These are factors that are not directly measured but act as catalysts to water management results and processes for effective farming; and so must also be understood for more robust effective strategies. Such factors could be farming expertise and processes, fertilizers/chemicals, diversity/inclusion, management strategies and political will.

Conceptual Model of Influencing Factors

Considering the drivers or factors that influence water management for effective agriculture, certain measurement metrics for our analysis are derived and defined to specifically define how water is used for agriculture and how it can be managed and decision making processes can be optimized for more efficient water, agriculture, food nexus.

From the literature and earlier described principles, we build a conceptual framework to describe and analyse the link between the (dependent variable): Available and Needed Water Capacity for Farming per Region/Country (***Wc***) (i.e. a regions/area/country available amount of water (both ground and surface) per population) and the key factors (independent variables) affecting water management for effective and efficient agriculture. These independent variables are : Amount of Rainfall per Region/Country(mm)(***VAR1***), Population(***VAR2***), GDP per capita(USD) (***VAR3***), Arable land area (m^2) (***VAR4***), Agricultural annual revenue (***VAR 5***), Agricultural Irrigation, water technology and fertilizers costs (***VAR 6***) , Amount of Ground and Surface Water per Region/Country (***VAR 7***) and Amount of Water Demand/Use for Agriculture (***VAR 8***). By incorporating these independent variables, a more robust predictive model for ***Wc*** can be obtained which can aid effective and efficient policy decision making and resource forecasting.

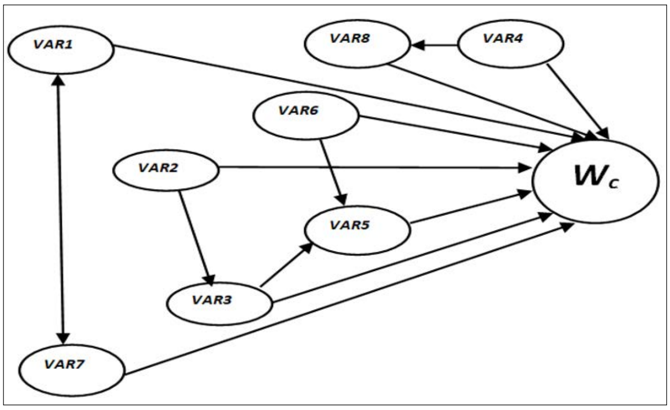

Figure 4: Conceptual Model for Needed Water Capacity (***Wc***) for Farming

Research Questions and Hypothesis

Having established a good theoretical background and link between the factors that influences water management for effective agriculture and the amount of water available for farming in a given region; we then built a model on how all these connect and carry out analyses. We then want to test how these factors influence the Available and Needed Water Capacity for Farming per Region/Country (***Wc***) or amount of water available for farming in a given region as a key metric for effective and efficient agriculture via optimal water management. Our research questions and accompanying hypotheses are thus:

Q1: Can the amount of water available and needed for farming in a given region be determined or measured and/or predicted?

Hypothesis 1(H1): Available and Needed Water Capacity for Farming can be measured and also predicted.

Q2: Is Available and Needed Water Capacity for Farming for Region/Country affected by other factors aside amount of Ground and surface water available?

Hypothesis 2(H2): Internal factors or independent variables within a Region/Country can positively or negatively affect how much water capacity for farming is available.

Q3: Which of the factors most influences how much water is available and needed for Farming?

Hypothesis 3(H3): Some factors have greater influence than others on the Available and Needed Water Capacity for Farming in a region/Country.

Statistical Analysis
For a robust and thorough analysis which forms the objectives of this research work, additional statistical analysis that affects the social scientific aspects of this research is carried out to further investigate how these socio-economic and conditional factors directly and indirectly influences the Available/Needed Water Capacity for Farming per Region/Country (***Wc***).

The important Statistical Analysis and associated parameters for this research work are briefly described in relation to their specific derived typical hypothesis tests for such Analysis:

Descriptive Statistics This is to confirm the validity of our data and how the values obtained for each factor considered is relevant and adequately describes the data. From *Mean, Median, Skewness, Kurtosis* and *Deviation* values; these are to effectively analyse and describe our datasets.

Reliability Statistics This statistical test is used to mainly determine how reliable set of data is and how available or measurable such datasets are. From the **KMO** and ***Bartlett's*** tests, to the ***Cronbach Alpha*** Tests; these reliability statistics parameters are important in social science to determine how reliable obtained datasets are for a valid scientific experimentation. ***Cronbach Alpha*** is a coefficient of internal consistency is commonly used as an estimate of the reliability of a psychometric test for a sample of examinees. Reliability is met when Cronbach's alpha of a latent construct is 0.70 or greater [36]. A Typical Reliability research question is:

Q1a: Are all the variables or influencing factors measurable?

Hypothesis 1a (H1a): All variables can be accurately/acceptably measured
Hypothesis 1b (H1b): None of the variables can be accurately/acceptably measured
Hypothesis 1c (H1c): Some variables can be accurately/acceptably estimated.

Correlations, Variable Normality, Multicollinearity Are statistical assumptions that will first be examined to investigate statistical relationships between variables and how these variables influence and affect other variables.

Pearson Correlation a Pearson product-moment r correlation is conducted to assess the relationship between variable 1 and variable 2.

Pearson r correlation is a bivariate measure of association (strength) of the relationship between two variables. Pearson correlation analysis assumes that the variables have a linear relationship with each other [37]. A Typical Pearson Correlation research question is:
Q2a: Is there a statistically significant relationship between each or some of the variables?

Hypothesis 2a (H2a): There is a statistically significant relationship between all of the variables
Hypothesis 2b (H2b): There is a statistically significant relationship between some of the variables.
Hypothesis 2c (H2c): There is no statistically significant relationship between all the variables

Exploratory Factor Analysis (EFA) An exploratory factor analysis will be conducted to determine the factor structure of variables. Exploratory factor analysis identifies any underlying relationships among a set of scale variables. This iterative procedure is repeated until all requirements are met. A Typical EFA research question is:

Q2b: What are the underlying dimensions of the variables?

Hypothesis 2(H2d): The EFA model adequately depicts the variables.
Hypothesis 2e (H2e): The EFA model does not adequately depict the variables.

Techniques for Effective Water Management in Agriculture
Though while also recognizing that the utilization of technologies and techniques to aid water management and water security for agriculture is only part of the solution; it's very much pertinent to understand these technologies/techniques and the methodical analysis of their impact and how they can be optimized are important for the development of efficient water management activities for effective and productive agricultural practices. From ***irrigation technologies, to water saving technologies, crop specific water saving techniques/technologies***, ICT based and Wireless technologies; these are the more common types of important water management technologies that contributes to effective agriculture and aids associated analysis, needed to continually improve or develop even newer technologies that apply new processes and techniques for an even more efficient water management methods for effective agriculture in the context of the ever-growing competition for water, climate change, drought and other forms of demographic, societal and climatic challenges.

For this data-centric research work, emphasis is on using some data analysis, Machine Learning and Wireless technology algorithms and techniques to analyse water management/security processes for effective agriculture and to meet the challenge of how to incorporate innovative technologies and management approaches in decision making and long term water management policy making to increase and optimize agricultural output and processes with lesser resources and maintain environmental sustainability [38].

Mathematical Analysis for Optimal Water Management in Agriculture
For this mathematical approach to water management/water security analysis; the focus is to be able to water resources can be efficiently used for agriculture and how farmers' optimal economic gains can be measured and monitored with respect to water used for effective agriculture. The analytical background for this is described:

By Applying the Integral Theory of Calculus:

$$V = \int_a^b A(x)\,dx \qquad (3.1)$$

Where ***V*** is the Volume or Capacity of water that can cover a cross-sectional farm area of land for a unit Crop ($c = 1$) (where other factors affecting water source remains constant). Let the crop farming cross-sectional area of land that lies between $x=a$ and $x=b$. Let the continuous function $A(x)$ represent the cross-sectional area of the farm section of land in the plane through the point x and perpendicular to the x-axis.

Therefore,
The Total water capacity or volume of water (***Vc***) needed by a crop (***c***) :

$$V_C = c.V \qquad (3.2)$$

Then for a Multi Crop Farm, having crops ($c_1, c_2, c_3, \ldots c_N$) occupying farm areas ($A_1, A_2, A_3, \ldots A_N$) respectively; the total volume of water for ***N*** number of crops (V_T) is defined as:

$$V_T = W_C = (V_{c1} + V_{c2} + V_{c3} + \ldots + V_{cN}) + R_{VcN} \qquad (3.3)$$

Where R_V is the adequate volume of rain (where other factors affecting water source remains constant) needed by N crop(s) and W_C is the water capacity or needed water volume in a farm or region.

Furthermore,
The total volume of water or water capacity available in a farm area (W_V) is defined as:

$$W_V = W_C + W_W \qquad (3.4)$$

Where W_W is the volume of wasted water (that can be stored) not needed by N crop(s)
For water efficiency W_{EFF}, which is a measure of the efficient use of water in a farm by ***N*** crops, while other factors remain constant is defined as:

$$W_{EFF} = W_C / W_V \qquad (3.5)$$

Then: Farmers-Water-Agric-Profit (P_{WA}) = $R_A - X(W_C)$ (3.6)

Where $X(W_C)$ is the total cost(including cost of irrigation, associated technologies, etc) of producing the water volume or needed water capacity by the farm and R_A is the total revenue from Agriculture for a farm or region or country.

Where $X(W_C)$ is the total cost(including cost of irrigation, associated technologies, etc) of producing the water volume or needed water capacity by the farm and R_A is the total revenue from Agriculture for a farm or region or country.

Simple Moving Average (SMA) Time Series Forecast
Time series is a collection or sequence of observations recorded at regular time intervals, which may have hourly, daily, weekly, monthly or even annual frequency of observations. Time series analysis is about understanding aspects of the nature of the series, so as to create meaningful and accurate forecasts with the information from the series.

Assuming an additive decomposition, then we can write

$$y_t = S_t + T_t + R_t \qquad (3.7)$$

Where: y□ is the data, S□ is the seasonal component, T□ is the trend-cycle component, and R□ is the remainder component, all at period t

Multivariate linear Regression Model
The multivariate machine learning (ML) model using Python programming language was incorporated for the dependent variable to be determined using the independent variables. The Regression model is chosen, as it is evident that the factors or variables changes linearly with time change. A multivariate ML regression model is defined by the equation:

$$Y = m_1X_1 + m_2X_2 + m_3X_3 + \ldots + m_NX_N \qquad (3.8)$$

Where: Y is the dependent variable values matrix; $m_1 \ldots m_N$ are the coefficients (weightings) of the independent variables values (X matrices).

K-Nearest Neighbour (KNN) Algorithm
K-Nearest Neighbors (KNN) is a supervised machine learning algorithm that can be used for either regression or classification tasks. Since the KNN algorithm does not make assumptions about the underlying distributions if the data, it is thereby know to be non-parametric in nature.

To perform the algorithmic procedure, we choose k, which is the number of nearest neighbours, and p is the number of classes or number of data columns.

Where: $k = \sqrt{Nt/2}$; Nt = Number of training data.

Also, ***k*** should be an odd numbered value and must not be a multiple of the number of classes.

The distance between the sample data points is described as the *Minkowski* distance (***Dm***) is calculated using the formula:

$$\left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{1/p} \qquad (3.9)$$

Where: where ***X*** and ***Y*** are specific data points or data nodes, ***n*** is the number of dimensions, and ***p*** is the Minkowski power parameter.

Grey System Analysis
A grey system is typically a system in which part of information is known and part of information is unknown. For real life scenarios where the meanings of the criteria are different and there exists much difference among the values of variables/or factors observed; the fixed weight clustering method is applied in such a situation.

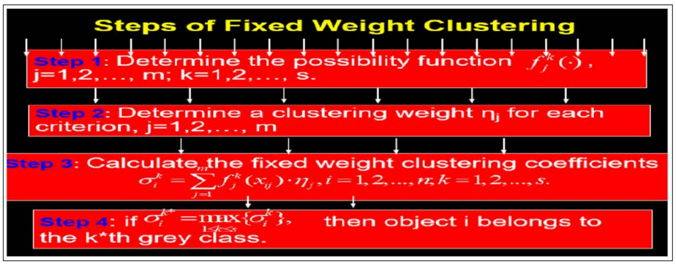

Figure 5: Fixed Weight Clustering Algorithm of Grey System Analysis

Hybrid Relay-Cooperative Wireless Sensor Network System

For the hybrid relay - Cooperative system as shown in Figure 3.4, it is a combination of a Multi – hop relay system and a two sensor nodes (i.e. source N and cooperating node N C) cooperative wireless system.

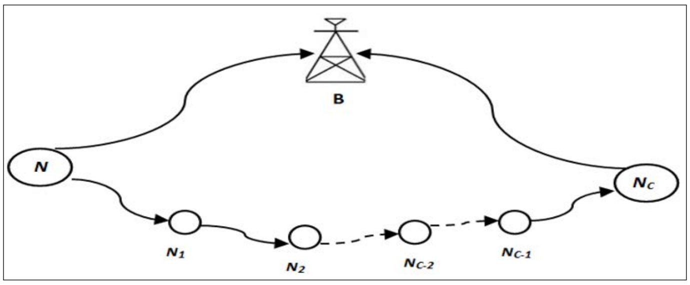

Figure 6: Hybrid Relay-Cooperative Wireless System

In this case as shown in Figure 3.2, there are relays: N_1, N_2,..., N_{C-1} between the source transmitting sensor N and the 'last relay' which is the cooperative node N_C. This system is suitable for a case where the sensor nodes can access geographical data, and so the cooperating sensor node is selected based on its location, needed to provide effective cooperation to the source sensor node. The sensor nodes between the source node and the cooperating node act as relays (limited intelligence and communication resources) of the signal by forwarding hop by hop the signal from the source to the cooperating sensor node, which then sends the signal to the Base Station (Sink Node) ***B***, where it is combined with the direct signal from the source to the destination, and then the resultant signal is effectively detected by ***B***, thereby benefiting from cooperative communication. The base station then transmits the signal via internet or cellular network to the farmer's mobile devices and intelligent information is received and acted on. The main ***advantages*** of this system are that it reduces the need for extra hardware and communication resources all around the farm or field, due to the use of less complex relays used to hop signals and a limited number of processing nodes (source and cooperative). This thereby makes the system more cost effective, energy efficient and environment friendly.

The cooperative communications MIMO(Multiple Input-Multiple Output) technique of ***Amplify and Forward (AF)***, which involves each relay and/or cooperative node amplifying the received signal and then forwarding it to the Base Station; while the ***Decode and Forward (DF)*** algorithm involves the relay and/or cooperating nodes in turn tend to detect each node's transmitted data (bits/symbols) and then re-transmitting it to the base station (destination) thereby providing spatial diversity to combat the effect of fading on each individual node's signal.

For the ***Coded Cooperative*** algorithm, which involves more complexity and better performance, it is described in more details as follows:

In the first period: The source node N which is also the node closest to the intended or target area of measurement, sends its data vector X to the first relay node N_1 and the base station B, with the received signals given as $Y_{N,N1}$, $Y_{N,B}$ respectively; and $H_{N,N1}$ and $H_{N,B}$ being the channel co-efficient matrices with their associated Gaussian noise ($n_{N,N1}$ and $n_{N,B}$) ; as given in equations (3.9)and (3.10) respectively :

$$Y_{N,N1} = X.H_{N,N1}.\sqrt{P_N} + n_{N,N1} \quad (3.10)$$

$$Y_{N,B} = X.H_{N,B}.\sqrt{P_N} + n_{N,B} \quad (3.11)$$

Also, where P_N is the Average signal power of the source node, which is normalized to 1.

At the second period: Since the relay network is actually a multi-hop system, the first relay node detects the received signal Y_{N,N_1} from the source and forwards it to the next relay node N_2 as ($Y_{N1,N2}$) :

$$Y_{N1,N2} = Y_{N,N1} .H_{N1,N2} + n_{N1,N2} \quad (3.12)$$

So from one period to another, the relay nodes keep hoping the signal received from a previous relay node to the next relay node, until the data arrives at the last relay node (i.e. the cooperating node N_C) as:

$$Y_{NC-1,NC} = Y_{NC-2,NC-1} .H_{NC-1,NC} + n_{NC-1,NC} \quad (3.13)$$

Then at the final period, the cooperating node N_C detects and forwards the signal $Y_{NC-1,NC}$ to the Base Station B, as shown in equation (3.19):

$$Y_{NC,B} = Y_{NC-1,NC} .H_{NC,B} + n_{NC,B} \quad (3.14)$$

Then the signal $Y_{NC,B}$ from the cooperating node N_C is then optimally combined with that from the source node $Y_{N,B}$, and then effectively detected.

At each relay node, and also at the cooperating terminal/node N_C, the appropriate cooperative communication technique(e.g. Coded)/protocol is applied to combat the effects of fading, shadowing, thus processing the signal to ensure that the signal can be detected efficiently.

For the **Coded hybrid relay-cooperative system**, at the first period as similarly described;
the source/ transmitting node punctures its coded signal N_T (codeword) and sends its first part ***NT1*** to the first relay node N_1, and the base station ***B***. At the second period, the punctured codeword is de-punctured and decoded by the first relay N_1, and then re-encoded, punctured and sent again to the next relay node, N_2. So the source node's codeword ***NT1*** is de-punctured, decoded and then re-encoded, by each relay node and then punctured and hopped from one relay node to another until the last relay node (the cooperating node N_C); which is assumed to have successfully decoded the $NT1_{NC-1,NC}$ parity bits from the previous relay node N_{C-1} using the Viterbi decoder. Then N_C sends the punctured (second) part $NT2_{NC,B}$ of the source node's codeword to the base station, where the codeword of the source node is de-punctured and then effectively combined.

For a **Coded hybrid relay-cooperative system** with more than one cooperative node (multi-cooperation); MRC is employed first by the base station, to combine all the several versions of the transmitted codeword ***NT2*** from the cooperating nodes, to form one optimal second parity codeword of the source node's signal. Then the base station then carries out the de-puncturing and efficient detection using the hard decision viterbi decoder, in this case also, it must be pointed out that decoding was assumed to be successful at every cooperating user and the base station, thereby the CRC would need not to be implemented.

Table 1: Cooperative Wireless System Parameters

Modulation Scheme	QPSK	FFT Size for OFDM	64
Multiple Access Scheme	OFDMA	Cyclic Prefix Size	12
Fading Channel Model & Number of Taps	Rayleigh Frequency selective fading & 13Taps	Data Frame Size	128
Simulation Technique	Monte Carlo	Target Bit Error Rate (BER)	10^{-3}

Wireless System Figures of Merit

• ***Bit Error Rate (BER)*** - The *BER* was used as a measure of the performance of the systems analysed, therefore it is the figure of merit used to achieve one of the targets the Hybrid Cooperative Communication system. The *BER* indicates the probability of bit error P_b, or how many bits are in error for a given transmission, range of available energy, and channel conditions; thereby providing a measure of the quality of data transfer.

Therefore;

$$R = Ne/Nb \qquad (3.15)$$

Where: *Ne* is the number of bit errors, and *Nb* is the number of bits transmitted

• ***Signal to Noise Power Ratio (SNR)*** - In harmony with the second key 'target' of this project work, which is ***Energy Efficiency*** described in Chapter1 of this thesis; the SNR is used as a measure of the energy (processing and transmission) consumed to achieve good quality communication at a target *BER*.

$$SNR\ (dB) = E_b / N_0 \qquad (3.16)$$

Where: E_b is the energy per transmitted bit, and N_0 is the noise spectral density, denoting the noise power.
So in the simulations, the ratio of energy consumed in the transmission of a bit to the noise, provides the particular *SNR* or rather energy consumed. Therefore, the ***BER vs*** E_b/N_0 curve is a standard in this work for analysing the performance and overall energy consumption of each system model simulated.

Also, another figure of merit relating to energy efficiency is the ***Energy Saved***, which is a measure of the overall amount of energy saved (SNR) to meet a target BER as more processing is done in the system:

$$Overall\ Energy\ Saved\ (dB) = E_P\ (dB) - (dB) \qquad (3.17)$$

Where: E_P is the energy spent in processing, and E_{PER} is the reduced energy spent to achieve the new improved performance.

Results and Discussion

Descriptive Statistics of the Described Independent Variables Affecting *Wc*

Independent Variables (VAR) Sample (N= 266) *mio = 1million	**Mean**	**Median**	**Variance**	**SD (Standard Deviation)**	**Max.**	**Min.**
Rainfall/Precipitation *mio m3_Year 2011 ***(VAR 1)***	400751.5	36489.1	1.78E+12	1334755	15333391	0
Population_Year 2018 ***(VAR 2)***	29305386	3510076	1.62E+16	127433900	1439323776	0
GDP Per Capita (USD)_Year 2018 ***(VAR 3)***	16639.66	6363.313	6.61E+08	25708.42	185978.6093	0
Arable Land (hectares)_Year 2016 ***(VAR 4)***	5328663	297500	3.43E+14	18527500	156463000	0
Agriculture GDP (per millions USD)_Year 2017 ***(VAR 5)***	12965.5	919.5	4.52E+09	67245.61	991020	0
Investment Cost (USD)_Year 1995-1999 ***(VAR 6)***	30252767	5085816	6.46E+15	80352260	1000525651	0
Ground & Surface water amount *mio m3_Year 2011 ***(VAR 7)***	240763	14890	7.54E+11	868494.9	11194572.5	0
Agric Water Use(10^9 m3 per year)_Year 2012 ***(VAR 8)***	6.868502	0.025078	897.3064	29.95507	388	0

Table 2: (Data Sources: UN Statistics Division; March, 2011: https://unstats.un.org/unsd/environment/waterresources.htm ; FAO Aquasat DataStore: https://www.fao.org/aquastat/statistics/query/index.html July, 2022 & Live Web Portals: June, 2022)

As shown by the obtained figures, the average value or mean value for Rainfall/Precipitation amount was about twice the amount (100%) from Ground & Surface Water volume in 2011, indicating that there was more than sufficient water source from Rainfall to the earth. Furthermore, the standard deviation values are quite high, indicating that our dataset is more spread out (globally across countries in the world) around the mean values, and this confirmed the non-necessary step of calculating the skewness or kurtosis for such a widely dispersed real life dataset taken from different years, for countries (where available) across the world.

From the obtained data; the Rainfall/Precipitation amount which is twice that from Ground & Surface Water volume indicates that there was more than enough rainwater to replenish the water bodies in 2011. This of course implies that there was enough water for agricultural practices, which should reduce costs of water production and irrigation activities and farming in general, thereby also increasing cost food production.

Furthermore, the well dispersed nature of the datasets obtained for the years across countries globally, brings to light the variations in factors that affect water availability with respect to effective agricultural practices across different regions. This therefore, implies that extensive analysis, strategy and policy developments; as well as adequate technologies on water management in relation to effective agricultural practices; will need to also incorporate various factors and unique conditions of different regions, locations, countries and environments for a robust solution to the water availability challenges affecting agriculture.

Reliability Tests

The analysis performed was done using datasets from reliable and approved data sources, stores and portals, approved as global statistical benchmarks; so therefore, the datasets are assumed to be reliable. The ***Statistical Reliability Parameters*** are thereby not tested as they can be assumed to be valid and satisfactory. The obtained real life datasets from approved datastores, repositories and databanks; thereby supports **Hypothesis 1a (H1a)**; that indeed, all the independent variables defined can be accurately/ acceptably measured; thereby indicating that Hypothesis 1a can be accepted. However, Hypotheses 1b and 1c which states that none and some the independent variables defined can be accurately/ acceptably measured respectively; can be both rejected, as they are not supported by the obtained datasets.

Correlation and Multicollinearity Tests

Pearson Correlation Tests –

Bivariate Test	Pearson Coefficient	Bivariate Test	Pearson Coefficient
VAR1 and VAR2	0.0187956	VAR3 and VAR5	-0.01489614
VAR1 and VAR3	0.1754243	VAR3 and VAR6	-0.01069805
VAR1 and VAR4	0.03361142	VAR3 and VAR7	0.1701069
VAR1 and VAR5	0.01036505	VAR3 and VAR8	0.08331179
VAR1 and VAR6	-0.02394537	VAR4 and VAR5	0.6457757
VAR1 and VAR7	0.9450426	VAR4 and VAR6	-0.00593164
VAR1 and VAR8	0.02152677	VAR4 and VAR7	0.02246642
VAR2 and VAR3	-0.001868821	VAR4 and VAR8	0.009673465
VAR2 and VAR4	0.8853843	VAR5 and VAR6	-0.007484429
VAR2 and VAR5	0.7668154	VAR5 and VAR7	0.02180795
VAR2 and VAR6	0.003701965	VAR5 and VAR8	-0.001304712
VAR2 and VAR7	0.01561029	VAR6 and VAR7	-0.01936273
VAR2 and VAR8	0.01855559	VAR6 and VAR8	0.1009622
VAR3 and VAR4	-0.02299219	VAR7 and VAR8	0.03406123

Table 3: Correlation Statistics of Independent Variables (Pearson Correlation)

As shown by the obtained and analysed figures using the R statistical software; the Pearson coefficient is of the range -1.0 to +1.0; and so the obtained values shows that there is a moderate to strong associations in the positive and negative directions between the independent variables. The highest coefficient value in the positive direction is between VAR1 and VAR, indicating a strong positive correlation between VAR1 and VA7. Also, the minimum coefficient value in the negative direction is between VAR5 and VAR8, indicating a very strong negative correlation between the variables VAR5 and VAR8. These correlations values also confirm the quantitative nature of the datasets in addition to their qualitative properties; and also indicate that there is a linear relationship between the independent variables as obtained and analysed.

From the obtained data and analysed results in Table 2; the high positive association value between VAR1 and VAR 7 indicates the strongest positive association/relationship between Rainfall/ Precipitation amount and the amount of Ground & Surface Water in 2011, which of course is expected. This then implies for effective agricultural practices sustained by enough water availability, the balance between amount of precipitation and ground/surface water amount must be sustained and would inevitably ensure that there is cost effective water production for an effective water-agric-food nexus. On the flipside also, and as proven by climate science, any reduction in the amount of either VAR1 or VAR7 would negatively affect the other and also the volume of agricultural production. Furthermore, the most minimal negative Pearson's correlation coefficient value of the association between VAR 5 and VAR 8, indicates the strongest negative correlation between the Agricultural GDP amount and the amount of water used for Agriculture. This suggests that as the GDP accrued for Agriculture increases, the amount of water use decreases and vice versa; thereby implying that better and efficient water management (ie. using less water to achieve greater food production) would also lead to an increase in Agricultural revenue, because costs relating to water related agricultural practices will be reduced.

Additionally, the coefficient values between independent variables obtained as an indication of the relationships between the variables are classified as either statistically significant or not statistically significant, as indicated by the coefficient values within the range of -1 to + 1; with the values closer to either +1 or -1 as being more strongly correlated or statistically significant (positively or negatively). Therefore, the results obtained supports **Hypothesis 2b (H2b)**, that indeed, there is a significant statistical relationship between some of the independent variables; thereby indication that Hypothesis 2b can be accepted. This further suggests that certain independent variables affecting the available and needed water capacity (***Wc***) needed for agricultural purposes, are correlated and influence each other, and further implies that analyses, strategies, management processes and systems for effective water management or water capacity management for agriculture, must take into account influences between variables as it affects amount of water needed for effective agriculture. However, Hypotheses 2a and 2c which states that there is significant statistical relationship between all the independent variables and there is no significant statistical relationship between the independent variables respectively; can be both rejected, as they are not supported by the obtained results and tests.

Multicollinearity Test Analysis using OLS Regression by Machine Learning

Independent Variables	Coefficients	T	p>|t|	[0.025	0.975]
VAR1	0.289	7.317	0.000	0.209	0.365
VAR2	2.7156	0.876	0.283	-3.423	8.854
VAR3	1.3620	2.091	0.039	0.071	2.652
VAR4	-2.2539	-1.260	0.210	-5.798	1.291
VAR5	-0.2112	-0.584	0.560	-0.927	0.505
VAR6	-0.8552	-0.442	0.659	-4.688	2.978
VAR7	0.1534	2.570	0.011	0.035	0.272
VAR8	445.6320	0.792	0.439	-669.531	1560.795
	97.5% Confidence Interval of parameters/coefficients (0.975) Durbin-Watson: 2.022 Skew : -0.579 Kurtosis : 19.755 p : Exact probability of t [t : T value for null hypothesis]				

Table 4: Results of Multivariate Regression Analysis Model using OLS by Machine Learning

As shown by the obtained and analysed figures using the Python for Machine Learning Linear Regression; the Durbin-Watson value of 2.022, which is almost at the ideal value of 2; means there is no multicollinearity and further indicates that there is no autocorrelation between the independent variables. From the obtained data and analysed results briefly described; absence of multicollinearity between the independent variables, means our datasets and independent variables are statistically significant; thereby indicating that all or most of the independent variables do influence the dependent variable (***Wc***) whether in small, medium or large amounts. This then implies that the analysed independent variables or factors all influence and affect the available water capacity for Farming in a region, location or Country. Therefore, the results obtained supports **Hypothesis 2 (H2)**, that indeed, internal factors or independent variables within a Region/Country can positively or negatively affect how much water capacity for farming is available; thereby indicating that Hypothesis 2 can be accepted.

Exploratory Tests Using a 4 Factor Hypothesis Test Analysis

Independent Variables (VAR)	Uniqueness	Loadings/Weightings			
		Factor 1	Factor 2	Factor 3	Factor 4
VAR 1	0.005		0.971	0.205	
VAR 2	0.005	0.989			
VAR 3	0.966		0.181		
VAR 4	0.005	0.924		0.367	
VAR 5	0.401	0.751		-0.142	0.122
VAR 6	0.999				
VAR 7	0.005		0.890	0.208	0.399
VAR 8	0.997				

Chi Square Stats.	Degree of Freedom	p-value	Number of Factors
4.83	3	0.0892	4

Table 5: Exploratory Data Analysis of Independent Variables

As shown the table 4; the latent/underlying factor Loadings coefficient close to -1.0 or +1.0; indicate that the underlying factors strongly influence the independent variable; while that close to 0, influences the independent variables weakly. So from the obtained values, two underlying factors (i.e. Factors 1 and 2) more strongly affect most of the independent variables (i.e. VAR1, VAR2, VAR4, VAR5, VAR7). Also, the 5 or less value of the chi-square(i.e. 4.83) or as some scholars would prefer, the ratio of the chi –square value divided by the degrees of freedom; indicates that the sample data is a good fit whereby the values of 5 or less is a common benchmark. The chi-square value further indicate that there is a high correlation between the expected and observed values, as there is very little difference between the expected and observed values, which confirms the dataset as a good fit.

From the obtained data and results; the values of Factors 1 and Factors 2 indicate presence of underlying/latent factors affecting almost all the independent variables; meaning that among such independent variables there exists some form of underlying strong relationships. This suggests that most of the variables actually can be adequately part of the model, and there are underlying factors affecting the independent variables that influences the available and needed water capacity for effective farming, and therefore must be taking into consideration in such practical cases. Such internal factors could include soil type, and how they also influence water management and usage with respect to agricultural practices.

Additionally, the chi-square and its related degrees of freedom values, further confirms the validity of the EFA (Exploratory Factor Analysis) model as being a good fit and adequately depicts the independent variables modeled, which supports **Hypothesis 2d (H2d)**, thereby indicating that Hypothesis 2b can be accepted. The correlation of the variables as indicated by the chi-square values, suggests that the model is a good fit and that a good number of the various independent variables influence each other, and their underlying internal factors must be accounted for and analysed to be able to develop effective strategies, systems, policies and processes for the effective management of water needed for farming. However, Hypothesis 2e (H2e) which states that the EFA model does not adequately depict the variables; can be rejected, as H2e is not supported by the obtained and analysed results and tests.

Agricultural Water Resources Profile Analysis

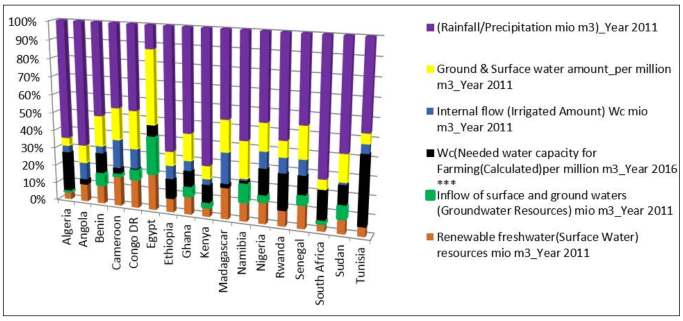

Figure 7: Agricultural Water Resources Profile of Selected African Countries (mio = 1 million) (Sources: UN Statistics Division; March, 2011: https://unstats.un.org/unsd/environment/waterresources.htm & Live Web portals: June, 2022). *** Calculated values for ***Wc***: for 1 unit of farm crop occupying 1 unit cross sectional area.

As shown in the profile plot in Figure 7, some Countries have close to 50% of Rainfall/precipitation in 2011 and less than 20% of Ground & surface Water for the same year; and with ***Wc*** being also about the 15-20% available. As further indicated, ***Wc*** is noticeably not related to the amount of rainfall, and other water sources for each of the Countries; implying that the Needed/Available Water Capacity (***Wc***) for Farming is not proportional to the amount of water source available to a region or country.

For ***Wc***, which is a mathematical function of the amount of Arable land available; such Countries having far greater proportion of Rainfall than surface/ground water will need to innovatively harvest or store its excessive/waste rainfall to make up for such a shortfall in surface water, which may reduce in size due to so many socio geographic, economic and political factors; with such approach a cost effective and efficient water-agric food system will be optimized to perform excellently even with distortions in natural weather patterns brought about by factors including the reality Climate Change. According to the scenarios described in the IPCC Special Report on Emissions Scenarios, changes in precipitation and temperature may lead to changes in runoff and water availability, which, in turn, could affect crop productivity [39-41]. Furthermore, the non-proportional relationship between ***Wc*** and the water sources for farming in a country, is one of strong interest, as it does suggest that a good number of factors including arable land measure, does influence the amount of water available for farming, which is not just about how much water sources are in a region. This further suggests, that for adequate provision of water for farming, necessary strategies, systems, processes and tools will be needed to ensure that the right amount of ***Wc*** is available for farming, because the analysis indicates to us that a region may have enough natural water sources, but may lack adequate water for effective farming due to poor water management strategies, systems, policies or even negative climatic conditions/changes; this of course further makes the effective and innovative management of water resources an important activity for effective and sustainable agriculture and food production. Additionally, increases in physical water productivity by agriculture, through better management and uptake of more efficient technologies, such as drip irrigation and adoption of other water saving farm practices, has contributed to higher farm production. Overall the OECD average water application rate per hectare irrigated decreased by 7% between 1990-92 and 2002-04, while in most cases the volume of agricultural production increased [42, 43].

Global Agro economic Profile Analysis for Female Gender Inclusion in Agriculture

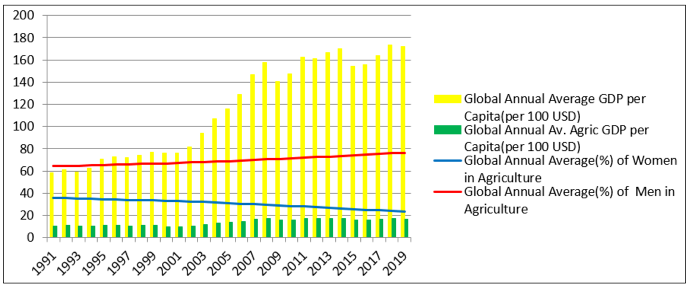

Figure 8: Global Agricultural Value and Gender Distribution (Source: World Bank Data: https://data.worldbank.org) July, 2022.

The plots in Figure 8 shows a continuous decline in average Women participation in Agriculture globally, while there is an increase in average Men's participation; with noticeably close to a ratio of 3: 1 Men to Women average amount in Global Agricultural employment. This decline in Women Agricultural amount has interestingly also reflected in the average annual GDP accrued globally from Agriculture, which has also not improved for over 10 years. Furthermore, the plots in Figure 2 also indicates that for each bi-annual percentage amount of Women in agriculture, there was some slight changes in the average GDP globally from Agriculture, though the changes were minimal for some years.

From the plots and analysed results; the noticeable decline in Women participation in Agriculture and the low average annual GDP from Agriculture globally can also adversely affect effective agriculture and food production in many countries globally. From such observation, it is clear that an increased Women participation or rather increased Gender equality in this sector will likely boost Agricultural revenue, thereby making countries richer and creating a more efficient and effective Food production system which will also influence the better management and processes of water resources optimization needed for effective Agriculture. Additionally, focusing on the unique challenges women face and their lack of access to resources is an important key to increasing overall agricultural productivity [44]. Women are often excluded from decision-making and have little choice over the services they receive. They have limited access to water and this is often coupled with their limited access to land. Securing access to land among poor farmers, particularly women, can lead to secure access to water rights [45, 46].

Furthermore, the changes in average global GDP in agriculture over the years shown, further indicates the effect of female population in agriculture over the years and suggests that an investment to support and increase the amount of women in agriculture will create further positive changes and growth in agricultural GDP, as well as overall GDP of regions or countries globally. Furthermore, these GDP changes also suggest that additional factors like accompanying workforce of men in agriculture, availability of modern tools, equipments, systems, processes, policies and strategies; will also further positively affect and contribute to empower Women to be even more productive agriculturally and contribute to effective water management for a greater GDP in Agriculture and food productions for regions and Countries globally.

Time Series Forecasts of Global Average Annual Precipitation and Internal Freshwater, and as also affected by Climate Change.

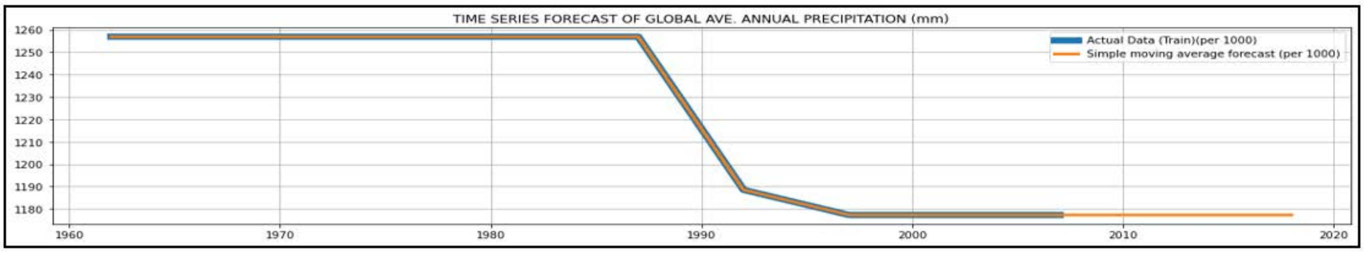

Figure 9: Time Series Forecast of Global Average Annual Precipitation (mm) (from 1962 – 2018) (Source: World Bank Data: https://data.worldbank.org) July, 2022.

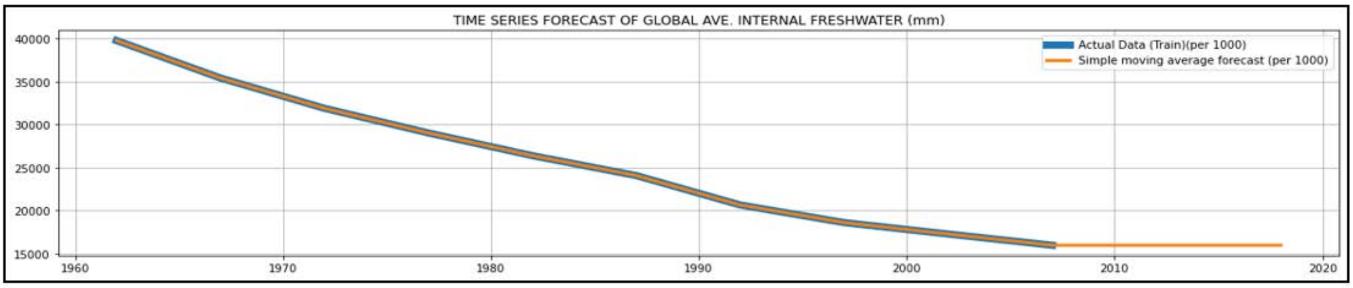

Figure 10: Time Series Forecast of Global Average Annual Internal Freshwater (i.e. Surface water and Ground water) (from 1962 – 2018) (Source: World Bank Data: https://data.worldbank.org) July, 2022.

The plots in Figure 9 and Figure 10 show a steady and significant decline in the average amount of Precipitation and Internal Freshwater globally, which should be a cause for concern. Furthermore, the forecast does not indicate an increase in amount for both water sources in the near future, and the declines appears to be more pronounced and almost linear for internal Freshwater for over 10-20 years, which curiously are the major sources for irrigation Farming globally; another indication of the effect of Climate Change and the need to tackle it. Additionally, the accurately fitting time series forecasts plots of Figures 9 & 10 also indicates a good corresponding curves fit and matching of the historical and future datasets per time, as a continuous measurement of the average amount of precipitation and internal freshwater globally.

As analysed from the plots in Figures 9 & 10; the significant continuous declines in the average global amount of precipitation and internal freshwater, calls for urgent innovative water management and monitoring systems, processes and management strategies such as intelligently and technologically monitoring and harvesting water resources, saving and recycling waste water, etc; to ensure that agricultural practices are not negatively affected and the growing need of food production globally is adequately met. Furthermore, global collaborations will need to be intensified to fight Climate Change and pother water reduction factors, to ensure that the adequate amount of water needed for agriculture is maintained, available and efficiently utilized to create an effective and efficient water agriculture food production nexus need by an increasing world population. Also, the well-fitting time series plots, indicates that the average amount of precipitation and internal freshwater can also be predicted and continuously monitored for data-driven climate change related analysis as it relates to water management for effective agriculture, and when combined with even more geographic, climatic and crop information data; more agroclimatic indices can be obtained and analysed.

Prediction of Global *Wc* Using Multivariate Linear Regression Analysis from Independent Variables/Factors

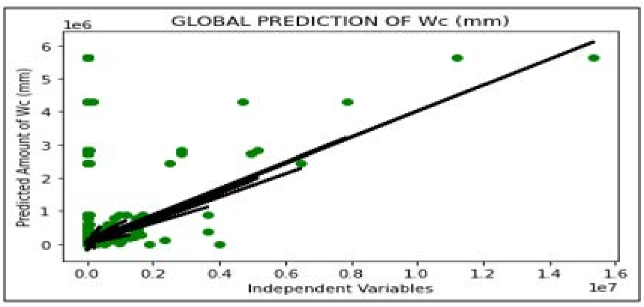

Figure 11: Predicted Global amount of Needed/Available Water Capacity (WC) for Farming using a Multivariate Linear Machine Learning Regression Model (Data Sources: UN Statistics Division; March, 2011: https://unstats.un.org/unsd/environment/waterresources.htm & Live Web portals: June, 2022).

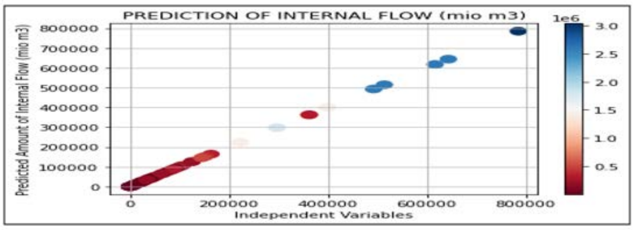

Figure 12: Predicted Global amount of Internal Flow of Water for Farming using a KNN Analysis Machine Learning Model (Data Sources: UN Statistics Division; March, 2011: https://unstats.un.org/unsd/environment/waterresources.htm & Live Web portals: June, 2022)

The result plot in Figures 11 is to study, analyse and predict the average Needed/Available Water Capacity (***Wc***) for Farming Globally for a specific time period form independent variables (***VAR1, VAR2, VAR3, VAR4, VAR5, VAR6, VAR7,* and *VAR8***) as described by the conceptual model in the methodology section using the Ordinary Least Square Regression (OLS) model . Furthermore, with the aim to thoroughly analyse water sources for Agriculture; a study, analysis and prediction is also made in Figure 12 for the average Global ***Internal Flow of water*** using the KNN Machine Learning probabilistic Model from independent variables: ***Rainfall/Precipitation, Inflow of surface and ground waters (Groundwater Resources), Renewable freshwater (Surface Water) resources, Waste water*** (where mio m3 is million m3) for the year 2011. These analyses are key to the development of effective intelligent processes, systems and management strategies for water management to aid effective agricultural practices.

As shown, the linear profile of both plots shows a significant accuracy of the prediction models, with an average prediction model Accuracy of 82%. Furthermore, the plots indicates the influence the two sets of independent variables have on the sets of predicted dependent variables (i.e. ***Wc*** and Internal Flow); in addition to the linear increase of these predicted values which also indicates an increased demand for ***Wc*** and Internal Flow for water as due to the expected increase in food demand globally and the need for a more effective agriculture for cost effective increased food production.

As shown in the table of values of the prediction plot of ***Wc*** in Table 4; the coefficients of the respective independent variables are shown and can be either positive or negative values, which means an increase in every unit of that independent variable will have a positive or negative impact on the dependent variable. As also shown by the p values from Table 4 for the prediction plot of ***Wc***, some of the independent variables (i.e. VAR1, VAR 3, and VAR7) are more statistically significant than other independent variables of lesser statistical significance; with the most statistically significant being VAR1 (i.e. having the minimum p-value); which also indicates that any changes in the value of VAR1 will most greatly affect the value of the dependent variable (***Wc***).

For the KNN Internal Flow prediction analysis, the model was built, as defined in the methodology with the following parameters: (K Nearest-Neighbours = 5, Number of Classes or Columns = 4, Total Data Sample Number (N) = 181, Training Data Sample size = 144); shows a **f1-score** of over 0.9(90%) which is very good and excellently optimal and indicates the model has done an excellent job of predicting the global average amount of Internal Flow of water giving other independent global average water sources variables (i.e. ***Rainfall/Precipitation, Inflow of surface and ground waters (Groundwater Resources), Renewable freshwater (Surface Water) resources, Waste water)*** for the year 2011. For a real life situation as this case, the f1-score is of most importance and a better metric due to the presence of imbalance class distributions which usually associated with real life datasets. Furthermore, the almost perfect alignment of the linear prediction KNN plot in Figure 12 is an indication of its **precision**, which has a score of 0.94(94%) which is very close to the highest or best score of 1(100%); which indicates that intuitive ability of the model not to label as positive a data sample that is negative and vice versa. Additionally, the close to perfect prediction plot is further confirmed by the **recall** score of 1.00(100%); which is the best and highest recall value and indicates the intuitive ability of the model to find all positive samples, which also means the ability of the model to predict positive outcomes out of actual positives. Also, a very important classification metric of the KNN predictive model if the confusion metrics shown as:

Confusion Matrix: [[0 2]
[0 34]]

The values of the matrix, indicates that there are only two sample negative values incorrectly predicted as positives (i.e. False Positives (FP)); and also 34 sample positive values correctly predicted as actual positives (i.e. True Positive(TP)); and no sample positive values incorrectly or correctly predicted as negatives (i.e. TN= 0 and FN = 0). This therefore, indicates that the KNN model experienced very minimal or negligible confusion during prediction and so its prediction accuracy is very good as also indicated by the f1_score.

From the interpreted results briefly described; For the predictions and models; estimating and/or forecasting the amount of water resources available for Farming and Internal Water flow are an important steps in the process of developing effective systems, strategies, processes and resources for effective water management to aid optimized agricultural practices with the uncertainty that financial, geo-climatic, and demographic limitations provide. This will ensure that resources are well managed and distributed for an effective water agriculture and food nexus needed especially in Countries experiencing acute water shortages or flooding that also negatively affects farmlands, and also globally.

The multivariate linear regression method is the most commonly used regression method for a continuous datasets of independent and dependent variables, which are also common in real life; though this regression method is sensitive to noise/errors and requires a large set of complete data. The accurately acceptable prediction plot and values of ***Wc*** supports **Hypothesis 1(H1)**, that indeed the Needed Water Capacity for Farming can be measured and also predicted; which will aid better management, strategy development, design of systems, more efficient personnel and resource management needed for an optimized water management needed for effective agricultural practices. Furthermore, the predictive plot of ***Wc*** and the values obtained in Table 3; further confirm that the set of independent variables (i.e. VAR 1 to VAR8) do affect the Available/Needed Water Capacity for Farming in a Region/Country positively or negatively in accordance with **Hypothesis2 (H2)**. This therefore, further implies that by considering factors affecting each of the independent variables and managing such factors appropriately, the Wc would be affected and thereby properly managed for better agricultural practices while also maintaining a needed sustainable environment.

For the more statistically significant variables and in particular the most statistically significant variable VAR1, and how greatly it affects the dependent variable ***Wc***; this indicates that a variable, in this case (VAR1), can have or has greater influence on the dependent variable or rather the Available/Needed Water Capacity for Farming in a Region/Country, in harmony with **Hypothesis 3(H3)**. Furthermore, for a further analysis, such independent variables which have a greater influence on the dependent variable can be separated from other variable and another model can be created to analyses how much such variables affect the dependent variable. All these aid adequate and effective management of water resources as some variables can be effectively tuned or adjusted while keeping other variables while keeping other variable(s) constant and thereby greatly influencing the amount of Needed Water Capacity for Farming in a Region/Country greatly in a cost effective manner without spending so much on adjusting all variables per time.

The excellent prediction plot and values of the KNN Analysis for Internal Flow also supports **Hypothesis 1(H1)**, that the Global average internal flow of water can be measured and also predicted; which will also add to better management, deeper strategy development, design of a variety of systems, more efficient personnel and resource management needed for an optimized water management needed for effective agricultural practices. The results also indicates that the independent variables of ***Rainfall/ Precipitation, Inflow of surface and ground waters (Groundwater Resources), Renewable freshwater (Surface Water) resources,*** and ***Waste water;*** do also influence the amount of internal Flow in line with **Hypothesis2 (H2)**. This can also mean that any of the independent variables can be modeled as a dependent variable and other water sources can be analysed as independent variables, to determine the effect of variables on a particular dependent water source variable. Such flexible analysis would further enhance insights to how well water sources can be better managed, measured, predicted, and optimized to aid effective agriculture that also importantly makes use of waste water and creates an efficient water, agriculture and food nexus, that contributes to environmental sustainability as a green initiative.

The KNN analysis has the advantages of being very easy to implement, faster and accepts new data seamlessly than other algorithms, because it requires no training before predictions; but it also has some cons, which are that it does not work well for categorical features due to distance calculations and larger datasets which will require a higher cost of more calculations during predictions. The KNN classification analysis method further aligns with our theory that such analytic data-driven approach can be carried out on a variety of water sources and water related agricultural data, which will very much aid the efficient and effective policy , strategy, systems and management developments needed to innovatively management water for effective agriculture for the cost effective and efficient production of food for the ever growing world population, limited and decreasing water resources which is under the increasing pressure of demand.

The predictive analyses are vital for the effective and efficient management of water resources for agriculture, because for climates that are humid, surface water forms the main source for irrigation; but for sub-humid and arid climates, the major source for agriculture and food production is underground water. Though generally, water for agriculture is classified broadly as either surface or underground (ground) water [47]. There is no doubt that water availability and withdrawals vary widely around the world, and with the present global water use for agriculture and food production being at about 70% of total water usage; there will sure be water availability problems as demand also rises and there will be extreme variations in water resource availability across various regions and countries to meet the projected requirement of year 2025 [47]. Also, According with the Food and Agriculture Organization of the United Nations, FAO demands for water for growing more food will increase causing shortages in regions that up to know are self-sufficient in water resources all these indicate the need for more analytically driven water management analysis, to be able to efficiently forecast and management water resources needed for agriculture and ensure that availability problems and challenges are well taken care of.

Grey Analysis of Agriculture and Water Related Factors for Selected African Countries Per Sub Region

Country	f_1^k	f_2^k	f_3^k	f_4^k	f_5^k	σ_i^1	σ_i^2	σ_i^3	max(σ_i^k)
Algeria	0.1046512	0.081078	0.198922	0.558246	0.050072	0.310643	0.493319	0.174572	0.493318595
Angola	0.6540698	0.00232	0.123494	0.42673	0.342107	0.493319	0.174572	0.398135	0.493318595
Benin	0.5465116	0.000894	0.057229	0.110764	0.023734	0.174572	0.398135	0.769186	0.769185949
Cameroon	0.8197674	0.011919	0.162651	0.163751	0.203707	0.398135	0.769186	0.660663	0.769185949
Congo DR	0.4593023	0	0.189759	0.005687	1	0.769186	0.660663	0.586088	0.769185949
Egypt	0.2790698	1	0.059842	0.310621	0.005429	0.660663	0.586088	0.265878	0.660663285
Ethiopia	0.9098837	0.141569	0.431295	0.0382	0.252099	0.586088	0.265878	0.280797	0.586088286
Ghana	0.5101744	0.015635	0.11747	0.267995	0.070064	0.265878	0.280797	0.481455	0.481455128
Kenya	0.4709302	0.030953	0.150602	0.195975	0.103166	0.280797	0.481455	0.273414	0.481455128
Madagascar	1	0.211331	0.081325	0	0.238766	0.481455	0.273414	0.765287	0.765286751
Namibia	0.2122093	0.003203	0	0.781412	0.056695	0.273414	0.765287	0.192086	0.765286751
Nigeria	0.4505814	0.089534	1	0.232032	0.287326	0.765287	0.192086	0.237911	0.765286751
Rwanda	0.8851744	0.001594	0.010593	0.040069	0	0.192086	0.237911	0.550985	0.550985001
Senegal	0.6947674	0.033514	0.072289	0.144129	0.028754	0.237911	0.550985	0.756124	0.756124291
South Africa	0	0.155187	0.35241	1	0.137379	0.550985	0.756124	0.193312	0.756124291
Sudan	0.693314	0.421263	0.572987	0.033451	0.282121	0.756124	0.193312	0	0.756124291
Tunisia	0.1177326	0.044019	0.063253	0.487097	0.001134	0.193312	0		0.19331191

Table 6: Grey Analysis results of categories of selected African Countries based on incomplete information available (Data Sources: UN Statistics Division; March, 2011: https://unstats.un.org/unsd/environment/waterresources.htm ; FAO Aquasat DataStore: https://www.fao.org/aquastat/statistics/query/index.html July, 2022 & Live Web portals: June, 2022).

As earlier described in the methodology, the grey system of analysis shown in Table 5 is to analyse and categorise selected African Countries from each of the Sub regions in relation to their respective Water and Agricultural data: **[1. Total Employment in Agric. (%)_Year 2017 (%), 2. Agric Water Use (10^9 m3 per year)_Year 2012), 3. Arable Land (hectares)_Year 2016, 4. GDP Per Capita (USD)_Year 2018** and **5. Rainfall/Precipitation (mio m3)_ Year 2011]**; as a key step to effectively and efficiently analyse and manage water resources for effective agriculture strategies and processes; it can also be applied to other Agricultural and economic processes. Here, the following Grey Analysis parameters were used to carry out the required analysis:

$\eta_1 = 0.20$; $\eta_2 = 0.50$; $\eta_3 = 0.40$; $\eta_4 = 0.25$; $\eta_5 = 0.60$ and Where: i = Selected Countries in each Continent :

j = list of criteria/categories (1, 2, 3, 4, 5); $K = k^{th}$ grey scale (1, 2, 3).

From the results obtained in Table 5, the maximum values **(max($\sigma(_i^k)$))** based on all the factors considered indicates that that Nigeria, Egypt, Ethiopia can be classified as being in Group 1; Algeria, Benin and South Africa are in Group 2; While Ghana, Senegal, Rwanda are in Group 3 and so on. These classification or groupings represents three clusters or groupings based on the three data classifications used for our analysis and how we can treat each Countries under a specific group/class as similar entities affected by similar factors and having similar Agro water related conditions, even with limited partial data or information available; which of course is the key advantage and use of the Grey analysis system. From the interpreted Grey analysis results briefly described; therefore, in this situation, in reference to the three criteria selected; by considering all the factors analysed, Water related Agricultural issues for each of the Countries in the same Group can be analysed similarly as common entities within the same class/cluster affected by similar factors. This intelligent analytical process, has the advantage of helping Agricultural systems, Water management systems and personnel to proactively categorize, understand, analyse, forecast and manage unique country or regional methods to effectively monitor and manage water resources for efficient Agricultural practices, processes, systems, and strategies; in line with unique factors and metrics which are of influence in each country and across countries in specific regions. Though the method can be analytically cumbersome and when the number of factors are much more; bit it is very ideal for a situation where not many or a few variables or factors are being considered and can be adequately categorized using incomplete datasets available as is typical in a real world scenario, which is a key advantage of this Grey analysis method.

When data from a variety of influencing factors for a Country/Region are categorized; adequate measurements can be made, forecasts and planning can be improved, predictions can also be even streamlined into sections and more revelations with respect to specific datasets and factors affecting a variable can be determined to further produce better water management and effective agricultural practices specific to a region or Country efficiently. Being aware that a specific environment, Country or Regional factors do uniquely affect agricultural processes and practices in a region per time; such sectionalized analytical process and groupings, ensure that strategies are efficiently developed and can be implemented for specific locations with respect to each Country(s) or Region(s) unique agricultural and water peculiarities. As can be deduced from the groupings, we see for example that when the size of arable land is considered, agricultural employments, Rainfall amount , GDP per capita and amount of water use for agriculture; Nigeria, or Egypt or Ethiopia or Angola…, can be used as a case study for the Countries under Group 1; thereby creating accost effective study and water management strategy developments creation that would positively affect the effective and efficient practice of agriculture in these Countries making up such Group.

Such a procedure can also be replicated for other Category Groups to ensure an elegant and intelligent cost effective analytical approach to the analysis and management for water management processes for effective agricultural practices that can be well applied to a specific farm, region, Country or even on a Global scale. Such analytical classification can also influence water pricing and cost which has also been highlighted in this work as an independent variable, which also affects Wc and varies across Countries and Regions and clustering countries with similar conditions analytically is a key efficient step in innovatively analyzing water management and improving water pricing and costs for effective agriculture. Additionally, according to a comprehensive analysis by the World Bank in various countries and regions around the world, the ratio of water charge to net income and to output per hm2 can be used to determine the range of affordable water prices for peasants so such grouping analysis by the grey system is vital for effective and efficient water management for agriculture.

Furthermore, the grey cluster analysis for selected African countries presents an innovative collaborative policy approach for which countries with similar influencing factors can support each other by strengthening the cumulative water management resources in the region, which will also have a positive cumulative effect on farmers in the region, continent and even a global scale. From collaborative systems, policies, strategies, development, and financial steps, such community based analytical clustering can improve the overall efficiency and effectiveness of water management for an optimized agricultural sector; because reliable access to water remains a major constraint for millions of poor farmers, mostly those in rain fed areas, but also those involved in irrigated agriculture. Climate change and the resulting changing rainfall patterns pose a threat to many more farmers, who risk losing water security and slipping back into the poverty trap. The need, therefore, to strengthen the communities' capacity to adopt and disseminate agricultural water management technologies, processes and strategies cannot be overemphasized [49].

Such analytical clustering mechanisms is vital in supporting efficient monitoring and evaluation exercises, which assist effective scaling up of systems and policies. Such policies cut across key areas like policy engagements, project financing and knowledge management as also areas where such analytical approach for water management is critical. In scaling up agricultural water management impacts, it is important to conduct an assessment of the local context to identify the best possible pathway to use as an entry point and as a building block to groupings and analyzing similarities across regions and communities. Furthermore, this data based groupings using grey analysis, can be used to impact, analyse and scale up effectively water management policies greatly in such areas as : Integrated natural resources (land and water) management policy framework, Water user groups should be responsible for O&M of irrigation infrastructure, Targeting poor and vulnerable members of the community, Participatory watershed management and planning, Project financing, Private-sector involvement, Climate change and many others as related to farmers and clusters of community(ies) at large.

Performance (BER) Comparison of Cooperative MIMO techniques for the Hybrid Cooperative System

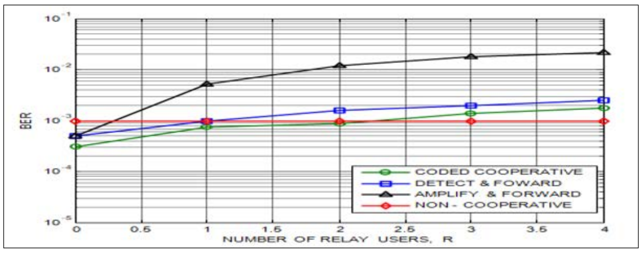

Figure 13: Performance (BER) Comparison of Cooperative MIMO Techniques for the Hybrid Relay / Cooperative System Having R Relay Nodes, Between the Source Nodes and Cooperating Node.

Energy Consumption Comparison of Cooperative MIMO techniques for the Hybrid Cooperative System

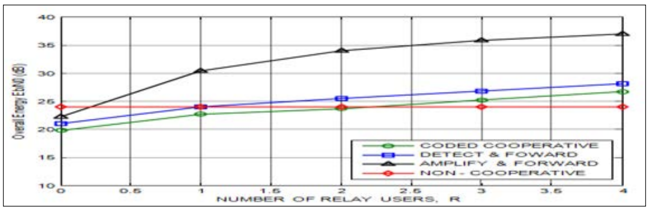

Figure 14: Overall Energy Consumption Comparison of Cooperative MIMO techniques for the Hybrid Relay / Cooperative System having *R* Relay nodes between the source(N) and cooperating node (Nc), where the inter – node and uplink channels have the same mean SNR (E_b/N_0).

As earlier described in the methodology, this Hybrid Cooperative Communication System is designed and analysed to investigate the performance and Energy Consumption of such a system and the output of each of the cooperative MIMO techniques in such a system. Here in Figures 13 and 14, more cooperative communications techniques **(Amplify and Forward (AF), Decode and Forward (DF)** and the **Coded Cooperative System)** and are compared with respect to their Performance and Energy Consumption as against a non-cooperative wireless system. Where the relays nodes (***N1…Nc-1***) and indicated as ***R***, the cooperative node(s) (***Nc***) as ***C***; and the Base/Control sink node or station as ***B***. For this analysis, he nodes (i.e. Source, Relay and Cooperative) are also 'unpaired', and just one cooperating node (***Nc***) provides cooperation to the transmitting/source node (***N***); while the inter – node and uplink channels have the same mean SNR (Eb/N_0).

As shown in figure 13; the comparison in performance (*BER*) was made at a fixed SNR (Eb/N_0) of 24dB for the non – cooperative case that gives the target BER of 10^{-3}. As shown the cooperative systems show significant decline in performance as the number of relay nodes, increases; this because the multi – hop protocol has the draw – back of loss of data integrity as the links gets longer (reduced end-end reliability), because the data received and then forwarded by a relay would be also contain more noise, thereby reducing performance. For the **Amplify& Forward** and **Detect & Forward** techniques; this is more evident because of their repetitive protocol, for the ***AF***, this is because each relay amplifies the signal received, thereby also amplifying more noise, while for the ***DF***; since each relay forwards the data it receives, so it forwards also erroneous bits, therefore reducing the performance of the system. The ***Coded*** cooperation on the other hand shows a better performance than the other two techniques because of the inherent error correcting ability of the channel code, but as the number of hops gets longer, performance degrades, as the number of erroneous bits can no longer be handled by the code. This again confirms that increased processing, and channel coding gives a boost to cooperation, as coded cooperation benefits from its error correcting ability of its code.

As shown in Figure 14; the comparison in overall (total) energy consumed by cooperation was made with the non – cooperative case at a fixed target BER of 10^{-3}. As shown the energy efficiency also reduces as the number of hops increases. This is due to the limitation of the multi – hop system, whereby data integrity reduces as the link gets longer, therefore, making the relay nodes need more energy to maintain link quality, henceforth leading to an overall increase in energy consumption. As shown, the for the **Amplify & Forward** and **Detect & Forward**, show very low energy savings, due to the repetitive nature of their protocols as explained in the performance section above, so as loss of data integrity increases, they would need more energy to maintain a good performance. Furthermore, as shown in Figures 13 and 14; the ***AF*** and ***DF*** algorithms show acceptably good performances and energy savings when the number or relay users are at minimal values. Though small, but on a practically larger scale of many nodes, this incremental savings of energy and performance advantages can also be of very good use; as it has the advantage of lesser coding that accompany the ***coded*** system. As indicated, the Coded Hybrid cooperative system will give a better performance in terrains where there tends to be signal distortions, which will enable a more intelligent monitoring and management of water resources for effective agricultural processes. As shown, the **coded cooperative** having the advantage of the error correcting ability of the code, is the most energy efficient of the three techniques, though also nor being very energy efficient as the number of relay hops increases, thus the diversity gain and also the coding gain is reduced, as typical of sensor nodes as also confirmed by other research work that simulated output results for the two wireless sensors differed as the number of nodes increased; when there were more nodes, the packet loss ratio increased, and the throughput decreased [50] . So also, this system's performance and energy efficiency reduces as the number of relay hops increases, though the cooperating node tries to improve the performance and energy efficiency.

For the integrated algorithm approach, this extra simplification provided by the ***AF*** and ***DF*** for minimal number of relays and also shorter hops, can be put to use by developing an integrated system that incorporates ***AF*** and ***DF*** schemes for specific hops and then the ***coded*** algorithm for specific longer hops, to ensure that a tradeoff between simplicity and cost is achieved by ensuring the whole network of nodes operates optimally and at minimal energy consumed with the use of different MIMO schemes/techniques at different hops and linkages. Therefore, it can be deduced that the hybrid relay / cooperative system can also be profitable, meeting performance targets and also being energy efficient and environmentally friendly; by ensuring a coded cooperation technique or a technique with channel coding is used, using short relay hops between source(s) and cooperating nodes(s), lesser hardware and power consumption. Channel variations are a major issue in practical wireless systems, and so this makes efficient power control schemes for cooperative communications a key factor of practical importance [32-51].

Also, the possession of geographical data (as needed in an agricultural setting) would serve well in this case, thereby using the short and even possibly longer relay hops to route the data from the source to the cooperating node via energy efficient routing algorithms, since the position of the best cooperating node as well, as other nodes would be known. As also in previous researches a typical WSN agricultural system as demonstrated can be the implementation of an Irrigation Management System based on WSN, which incorporates a remote monitoring mechanism via a GPRS modem to report soil temperature, soil moisture, WSN link performance and PV power levels. Furthermore, previous research also proposed a complete agricultural solution for the farmer based on Wireless Sensor Networks and GSM technology; and as also described by previous research works, the sensor/node data uploaded to the internet using the data logging unit can be accessed from both personal computers (PCs) and mobile phones [16-53].

Analysis of the Hybrid Cooperative Wireless System and Number of Cooperating Nodes

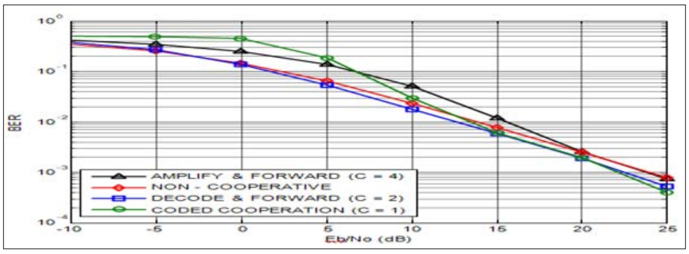

Figure 15: Cooperative MIMO techniques for the Hybrid Relay / Cooperative System and having one Relay, ($N_1 \ldots N_{c-1} = R = 1$) and number of Cooperating nodes (***Nc*** = C); where the inter – node and uplink channels have the same mean SNR (E_b / N_0).

The Hybrid Cooperative system is analysed as shown in Figure 15, with respect to number of cooperating users, with the intent to investigate how the system Performance and Energy Efficiency varies with respect to each of the cooperative MIMO techniques. As shown in figure 15, the nodes are also 'unpaired'; and each cooperative MIMO technique is shown with the amount of cooperating nodes (***Nc*** =***C***), each technique needs to achieve at least the performance of the non – cooperative case. Also shown by the BER values, the ***performance*** of this system improves as the number of cooperating nodes to the source, and the relay increases; this is so, because as diversity, better signal integrity increases; there would be fewer errors at the receiver(s). Furthermore, the minimum number of cooperating users (***Nc*** =***C***), in relation to the amount of relay nodes differs with respect to the cooperative MIMO technique, due to each technique's protocol as earlier explained.

Also, as shown in figure 15 at a target *BER* of 10^{-3}; ***energy efficiency*** improves for each cooperative technique as the number of cooperating nodes' increases; this as earlier pointed out is due to more processing by more nodes, reduced errors, and more diversity, thereby reducing the overall energy consumption of the system. Furthermore, as management of resources is also a key potential of this system; each technique is shown to require a minimum amount of cooperating users to be added to a minimum amount of relay nodes (one in this case), to provide at least a performance as good as the non – cooperative system, and saving a sizeable amount of energy.

Therefore, from this basic analysis, based on the target BER; the cooperative techniques would require the following least amount of cooperating nodes to meet the set target Performance and Energy threshold:

- Coded cooperation - $Nc = C \geq R$
- Detect & Forward - $Nc = C \geq R + 1$
- Amplify & Forward - $Nc = C \geq R + 3$

Where, R =1; is the minimum number of relay nodes [($N_1 \ldots N_{c-1}$) = ***R***], and (***Nc*** =***C***) is the minimum number of cooperating nodes.

Also, as shown is that as the number of cooperating users are increased or made larger than the number of relays, the performance and energy efficiency improves for each technique, though each technique would require a unique criterion for the minimum number of cooperating users needed. This hybrid system can also have the potential of providing effective management of resources, because any relay while acting as a multi – hop link between a source and a cooperating user, can simultaneously be a cooperating user to another source, thereby maximizing system resources. Additionally, as a typical WSN wireless network, based on the network connectivity, the power consumed in the network can also be computed or also estimated and then can be predicted. As shown by other research works WSN nodes have three energy consumptions states: sleep, transmit and receive; but for this research work, the focus here is transmitting/transmission wireless power [54].

The hybrid relay / cooperative system mitigates loss of data integrity associated with a repetitive multi – hop system (which has also been shown to be less energy efficient as the number of relays became larger than the number of cooperating users for all cooperative MIMO techniques). Additionally, the coded cooperative technique of the Hybrid/Relay cooperative system was shown to be the best in terms of performance and energy efficiency, and for even further improvement of the coded cooperative technique, the use of more robust coding schemes like turbo codes, overlay block – fading codes could be implemented to improve performance over the RCPC codes as used in this research work [20-28].

Furthermore, from the comparative analysis results of the three Hybrid/Relay cooperative MIMO techniques; further increased performance and energy efficient cooperative communications could be achieved by using cooperative technique(s) that involve channel coding (maintaining quality signal strength and performance is regardless of the conditions of the wireless channel); pairing between users, appropriate relay assignment scheme (s), and possibly more cooperating users for greater cooperative diversity gain.

Limitations and Recommendations of Study

This research study was focused on the analyses of water resources as it relates to effective agricultural potential and usage. Though a thorough analysis of the various factors affecting water capacity for effective agriculture was carried out, there were also a few limitations within the scope of this study. In terms of data acquisition, the datasets used were from approved and dedicated data stores, repositories and databanks, which in some cases were not fully complete with respect to certain regions or countries; thereby limiting further extensive regional or country based analyses; for example, in specific environments, up to date gender related data of women in agriculture not being readily available provides a challenge in carrying out adequate and additional specific comparative and informative analyses for regions and locations. Also, for an item like soil, specific functions and subsequent values provided by ecosystems are variable and rely on numerous soil physical, chemical, and biological properties and processes, which can differ across spatial and temporal scales [55-58]. As such, selection of a standard set of specific properties as indicators of soil quality can be complex and varies among agricultural systems and management purposes [59]. Additionally, the data analysis did not involve sample surveys from respondents, which could further add more perspectives to the study, by employing mixed or data triangulation methods.

Furthermore, with respect to the available water capacity for effective agriculture, a non-exhaustive list of key variables were considered and analysed in relation to physical, agricultural, socio economic and conditional factors influencing water management for effective agriculture [60]. However, some other variables were not part of this analysis, variables such as that relates to political and policy frameworks; specific types of irrigation systems and specific types of crops; which would provide even more analysis that can provide additional insights on how such factors also influence water management for effective and efficient agricultural practices [2]. For the effect of climate change on agriculture; the biggest limitation or problem occurs with the uncertainty surrounding the effects of climate change and the unknown time frames. It is still uncertain who will be most impacted by the changes and this fosters a lack of initiative for taking action now to mitigate the effects of climate change. Thus, continuous education, monitoring and knowledge acquisition will be necessary factors in the study and preparation for climate changes as it affects specific regions or locations under unique conditions [61].

Also, for the cooperative hybrid/relay wireless system; the code rate of the RCPC codes can be made more flexible by dividing the frames into more sub frames, and thereby adjusting the sizes of the frames for much improves performance and energy efficiency, especially in a multi –user system [26]. Furthermore, pairing and the issue of partner assignment was not implemented in this work; it is an issue in multi – user systems, and can be effectively implemented by using effective algorithms or schemes that give optimal or near optimal performance by efficient choice of partners in a multi – user environment making the base station able to treat all nodes fairly, based on the knowledge it has of all the channels between nodes.

Also, this work was done on the basis of equal transmit power of wireless sensor nodes; but it can be taken further by implementing an adaptive power control mechanism, that varies as nodes' transmit power based on the instantaneous channel (inter – user and uplink) conditions; in this way much more energy efficiency and improved performance would be achieved. Additionally, as it's also known that the range of battery-operated wireless sensor devices is limited; so, multi-hop communication is also very useful in sending data to control or base station [62].

Tests on the cooperative MIMO techniques can also be done on a variety of environments, which do possess unique channel characteristics; in this way much more developments in the cooperative MIMO techniques as well as improving each techniques' performance with reference to unique wireless environments shall be obtained. This hybrid relay / cooperative system can be further investigated, with energy and performance efficient routing protocols developed, so as to 'unlock' the potentials of this system. This system promises efficient resource management, effective geographically based communications, improved performance and energy efficiency, and other potentials which may not be fully known at this stage.

Conclusions

Agriculture is the primary source of income for three out of every four people on the planet who are living in poverty, and it is crucial for food security and economic development in developing countries. Therefore, innovative concerns and measures must be used in agricultural water management and practices for both field and system in order to decrease water scarcity, increase environmental friendliness and societal welfare, and thereby increase food production. This study's main objective was to examine the methods and variables that influence how water resources, water security, and water management are used in the agricultural sector, as well as how water management and policy decisions can be made to improve the efficiency of the relationship between water, agriculture, and food production. Datasets from trustworthy and recognized data stores, portals, and sources were used for this study's research work, analyses, demonstrations and investigations; as a result, it may be assumed that the datasets are reliable and credible.

This analytical research work, investigated, analysed and demonstrated that the needed and available water for farming (***Wc***) in a location, region and/or Country and the internal variables affecting and influencing ***Wc***, can be measured and also accurately predicted. Furthermore, this study suggests that these independent variables (which are also influenced by underlying factors) holistically affects ***Wc*** and can be accurately accounted for, as needed information for effective and efficient strategy, systems, policies, technologies development, to aid effective water management for agriculture.

With respect to water resources and its relationship to available water for Farming; this work by using a case study comparison of some selected African Countries, demonstrated that ***Wc*** can be innovatively and mathematically determined, and should be adequately sustained by the robust, improved, innovative management of natural and artificial water resources within a country or region, to overcome the challenges of water scarcity, droughts and flooding; brought about by higher demand for water, climate changes, socio-geographical, economic, and political factors; to culminate in more effective agriculture and food production.

On the high importance of more diversity and inclusion in global economies and with respect to the need for increased Women participation in Agriculture; this research paper analysed and examined the socio-economic importance and impact of gender equality also in Agriculture; shown by the need for more Women to participate actively in Agriculture, which will potentially contribute positively and greatly to effective agriculture, including more efficient water management and also increased food production, as well as the average GDP of countries globally.

Furthermore, the reality and importance of combating climate change cannot be overemphasized, as this work further contributes to the body of research by depicting using a time series analysis the linear continuous reduction in water resources(Precipitation and Internal Freshwater) as a negative effect of climate change and on why as an urgent need, more research, analysis, processes, investments, systems, policies, and actions needs to be continually investigated, analysed, created and implemented; to combat climate change and mitigate its effects on water resources, agriculture and humanity in general.

Cooperative communications has been shown in this work to improve performance in terms of BER and also energy efficiency by saving a good amount of total energy (for similar channel conditions), thereby reducing the overall (total) energy consumption of the system, compared to a non – cooperative system. Therefore, the trade – offs in performance and transmit power is confirmed; because, having more wireless nodes cooperating would mean more processing at each node leading to better performance, though this would arguably mean more node power for processing; but each node would transmit with a reduced energy to maintain network quality, thereby reducing the net energy consumption of a cooperative system. Analysis of the Hybrid/Relay cooperative communications system, showed useful potentials and benefits in terms of performance and energy efficiency and thus is a key technology needed to further improve wireless communications, which will be very useful in the intelligent and technologically driven management of water resources for effective agriculture; by ensuring that useful information on weather, soil, environment, crop, demographics, water sources and water related and irrigation information and data can be accessed, transmitted in real time and used to analyse, monitor, manage and implement timely actions and policies that would further optimize the water agriculture and food nexus for the great good of society.

Data-driven analytical (including Machine Learning and Grey Analysis) and simulation tools, methodologies, techniques and theories were employed to measure, analyse, investigate, deduce, predict and draw meaningful conclusion in this research work; to ensure that the objective and the aims of this research were effectively met and important results, observations, inferences and conclusions were actualized. This work thereby investigated and methodologically presented a cost effective analytically robust approach to water management for effective agriculture, which would lead to even further research works and also contribute to efficient and effective food production and the sustainable wellbeing of humanity and the environment globally.

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