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The Role of Virtual Nature Environment and Self-Agency in Improving Psychological Wellbeing in Student Populations in Nigeria: A Randomized Group Design

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Abstract:
This study examined the connections of virtual environment and self-agency and how they may increase the level of psychological wellbeing of university students. Participants were university students in Abuja and Ondo State. Participant's responses selected for the study were seventy-two (n=72). Participants were randomized into 1st control group n=24, 2nd control group n=24, and experimental groups n= 24. Pictorial image and self-report questionnaires were used to administer well-established psychometric surveys and Likert type scaled Watson, et al. (1988); Positive and Negative Affect Schedule (PANAS) and Rotter's (1966) Locus of Control Scale (LCS). This was a two-in-one study conducted in two phases: Pre-intervention assessment phase, and intervention and post-intervention phases. The pre-intervention assessment phase focused on how the predictor variable (self-agency) relate with student' level of psychological wellbeing. Phase 2 of the study (intervention and post-intervention phases) was designed to evaluate the extent to which virtual environment enhanced psychological wellbeing among participants who scored low on the measure of psychological wellbeing. The results indicated that the difference between pre-test and post-test scores of participants in the experimental group was significant [t (24) = 13.23, p <. .01]. The outcome of these comparison implied that virtual environment affected those in the experimental group. Based on the findings of the study is recommended that technologically-based psychological applications should be developed in better improve psychological therapies that impact psychological wellbeing.

Keywords: Virtual nature environment, self-agency, psychological wellbeing, students, Nigeria.

INTRODUCTION

Background to the Study

The changing environmental conditions and the depletion of natural environments such as natural reserves and parks, lakes, streams, hills, mountains, wildlife being clearly adversely affected. It behooves of researchers and experts within the field of psychology seek supplementary options that offer alternative possibilities in carrying out studies that concern the pragmatic use and adoption of virtual environments to solving human challenges. With the growth and development witnessed in artificial intelligence, the future looks promising for studies that adopt virtual reality in healthcare practice. The term virtual natural environment is a networked computer software application that provides interaction and instant feedback between a user and the simulated natural environment (Mattila, *et al.*, 2020; Mostajeran, Krzikawski, Steinicke & Kühn, 2021). Virtual natural environment elicits psychosomatic experience in which the exposed individual perceives experiences comparable to that which is experienced in natural settings (Blascovich, 2002; Mattila *et al*., 2020). In other words, virtual natural environment implicates process of identifying simulated environment through an absorbing preoccupation into virtual reality experience (Adams, 2004; Mostajeran *et al*., 2021).

Researchers within the field of psychology (Mattila *et al*., 2020; Nukatinen *et al*., 2021; Calogiuri, *et al.* 2018; Kim, & Lee, 2018; Kjellgren & Buhrkall, 2010) have established that virtual environment is not substitute for natural settings, rather the use of virtual environment seems a feasible vista as researchers to leverage on as an alternative that complement existing situation that enhance environmental awareness and green behaviours (Mnich, Weyland, Jekauc, & Schipperijn, 2019; Melo, Gonçalves, Monteiro, Coelho, Vasconcelos-Raposo, & Bessa, 2020; Nukarinen, *et al.*, 2021; Litleskare, MacIntyre, & Calogiuri, 2020; Yu, Lee, Lu, Huang, & Browning, 2020). The growing impact of technology, coupled with the potential benefits of virtual natural environments, it is expected that studies which address the importance of virtual natural environment could become a lifeblood in scientific research (Palanica, Lyons, Cooper, Lee, & Fossat, 2019). Studies on natural and virtual environment have revealed reliable positive results with improved psychological wellbeing (Fredrickson & Levenson, 1998; Fredrickson & Anderson, 1999; Pretty, Armstrong, 2000; Hagerty, *et al.*, 2001; Griffin, Sellens & Pretty, 2003; Pretty, Peacock, Sellens & Griffin, 2005).

According to Gallagher (2000) self-agency refers to the sense of oneself as the agent of one's actions, this notion allows oneself to feel distinct from others or external cues, and significantly contributes to psychological phenomenon of self-consciousness. Self-agency is sometimes referred to as internal locus of control. Self-agency is considered a significant factor in how individuals cope with various life issues, it is hinged on the belief that individual with self-agency have a higher level of life satisfaction and psychological wellbeing (Renes & Aarts, 2018; Kesavayuth, Tran, Zikos, & Georgantis, 2022). Several studies have demonstrated that self-agency plays an important role in psychological health of individuals (Kesavayuth, Poyago-Theotoky, Trans & Zikos, 2020). Researchers have considered self-agency as significant factor in understanding how people control their behaviors in relation to their health and wellbeing. Self-agency has been associated with motivation to behave in certain ways and also an effective measure that helps individuals to regulate behavior as a result, enhancing self-agency has been argued to improve people's motivation to act, and to control their behavior more successfully in line with their set goals.

Psychological wellbeing has been extensively researched across several academic disciplines, it has been linked to improved psychological state and health in people (Diener, Suh, Lucas & Smith, 1999). Quite a few definitions of psychological wellbeing have been put forward and there seems to be no consensus on the definition of the subject (Das, *et al.*, 2020). However, Diener (1984) who is considered as one of the earliest advocates in the study of psychological wellbeing refers to psychological wellbeing as the psychological state of feeling and thinking in which an individual perceives his or her life as being desirable with little regard for the other people view. Several authors have reported a significant association between virtual natural environments and wellbeing of students are connected (Berto, 2014; 2015; Payne, Loi & Thorsteinsson 2020; Wilkie & Davinson, 2021; Marselle *et al.*, 2021). Thus, it can be said that natural environments produce some adaptive resources that help individuals and students equally to become habituated to the environment that serve as perceptive and affective resources which consequently promotes psychological wellbeing (Ohly, White, Wheeler, Bethel & Garside, 2016; Ain *et al.* 2021; Marselle *et al.*, 2021).

From a hypothetical standpoint, theories have been developed to explain the psychological benefits of contact with nature, The Stress Reduction Theory (SRT) (Ulrich, 1983; Ulrich *et al.*, 1991) and the Attention Restoration Theory (ART) (Kaplan, 1995; Kaplan & Kaplan, 1989) have provided some clarifications. The SRT suggests that human evolvement from natural environments continues to be positively adaptive for modern humans and nature tends to produce less intensity than urban environments and therefore has comparatively positive in fostering wellbeing in people. Similarly, ART developed by Kaplan and Kaplan (1989) theorized that automatic effortless attention has the capability to restore focused concentration using the human brain as the main catalyst a such, exposure to natural environment have positive effects on stress, mood and mental fatigue (Kaplan, 1992). In addition, stimulation of natural environment through videos, virtual reality and photographs have been proven to be effective for the improvement of psychological health (Knopf, 1987; Stone *et al.*, 2014; Vujicica *et al.*, 2017; White *et al.*, 2018; Roche, Liu, & Siegel, 2019; Trangsrud, Borg, Bratland-Sanda, & Klevan, 2020; Browning, Saeidi-Rizi, McAnirlin, Yoon, & Pei, 2020; Naylor, Ridout, & Campbell, 2020; Wilkie & Davinson, 2021; Chan, *et al.*, 2021; Mostajeran *et al.*, 2021; Owens & Bunce, 2022).

Statement of Problem

The challenge faced by research conducted in natural environments, is the limited access and rapid degradation of nature, brought about by human activities such as rapid urbanization and the conversion of public natural environment for capitalistic purposes (Nukarinen, *et al.*, 2021). This challenge has led to researchers and scholars to seek alternative options in conducting research as such, researchers and scientists have adopted the use of virtual nature simulations in behavioural research (Browning, *et al.*, 2020). The recent mounting evidence that exposure to virtual natural environment is associated with wellbeing outcomes and can significantly lower the cost of healthcare makes it a good prospect for scholars and researchers. Researchers in Europe and Asia have adopted diverse methodologies through simulated environment in improving psychological wellbeing and these studies have shown conflicting results (Thompson *et al.*, 2012; Vujcica *et al.*, 2017). This evidence needs further exploration because the significance of virtual natural environment is relatively new field of research endeavour (Roe *et al.*, 2013; Chan, *et al.*, 2021). The investigation into the importance of virtual natural environment in Nigeria would be a timely approach that promises cost effective incentives to government at the primary healthcare level and the entire public, especially in black Africa.

Research on virtual natural environment may have not benefitted from the same level of empirical and theoretical engagement from scholars as other conventional research methods, and this may have practical implications on the view of psychological wellbeing. Thus, finding new ways of theorizing this experience is the only way research can change the status quo, which clearly holds the key to the future for scientists (Mnich, *et al.* 2019; Melo *et al.*, 2020; Marselle *et al.*, 2021). Understanding the roles of virtual environments and self-agency in improving psychological wellbeing in student populations is an area of research that is not received extensive research. Owing to this, research focused on this subject-matter are relatively scarce and the few studies conducted in this direction have been carried out in Europe, Asia and America, studies of this capacity has not been conducted within African clime (White *et al.*, 2018; Browning *et al.*, 2020). The implication of simulated virtual natural environment on psychological wellbeing among students has been a source of growing concern within scientific research.

Objectives of Study

This research study seeks to examine the connections of self-agency and exposure to virtual natural environment may increase the level of psychological wellbeing. The specific objectives are to:

1. Examine whether students perceived level of self-agency will increase the level of psychological wellbeing.
2. Determine whether groups exposed to virtual natural environment will report significant improvement on psychological wellbeing (positive affect) more than their counterparts who were not exposed to virtual nature environment.

Hypotheses

Based on the research questions, the following hypotheses are formulated:

1. Students perceived level of self-agency will significantly predict the increased level of psychological wellbeing.
2. Groups exposed to virtual natural environment will report significant improvement on psychological wellbeing (positive affect) more than their counterparts who were not exposed to virtual nature environment.

METHOD

This study was a multivariate correlational survey design. This study was a 2-in-1 study conducted in two phases: Pre-intervention assessment phase, and intervention and post-intervention phases. The pre-intervention assessment phase focused on how the predictor variable (self-agency) relate with students (participants') level of psychological wellbeing. Phase two of the study (intervention phase) was designed to evaluate the extent to which exposure to virtual natural environment psychological wellbeing among students. A detailed description of each of the phases is presented below.

Phase 1: Pre-Intervention (Assessment Phase)

Research Design:

Correlational survey was adopted for this phase of the study, as it attempted to analyse data collected from a representative sub-set (students) at a specific point in time. The dependent variable was student's level of psychological wellbeing. The predictor variable was self-agency.

Participants:

A total of 72 students in both the pre-intervention and intervention phases of the study, and they were selected using simple random sampling. These students were undergraduates at the time of the conduct of this study. The students consisted of 45 males (62.5%), and 27 females (37.5%). The age of participants ranged between 18-26 years. The mean age was 21.64 and *SD* of 4.11. 34 participants were Christians (54.7%), and 38 were Muslims (45.3%). Participants were university students who were recruited using SONA Systems. SONA Systems is an automated embedded study sign-up link. The initial pool of students was eighty-five (85). However, upon analyzing it was found the 13 responses had incorrect responses. As result the response collected was seventy-two (72) and this yielded a response rate of 84.7%. Participants were randomized into experiment and control group. The participants were divided into 1st control group n= 24, 2nd control group n=24, and experimental group n= 24. (M = 24.43, S = 4.24).

Measurement:

Psychological wellbeing was measured using the Positive and Negative Affect Schedule (PANAS) which is a self-report questionnaire developed by Watson, Clark, and Tellegen, (1988). The PANAS was developed in 1988 by Watson and his colleagues from the University of Minnesota and Southern Methodist University. Watson *et al.* (1988) developed the PANAS to provide a consistent and reliable measure that has validity in the dimensions of positive and negative affect by extracting sixty (60) terms from the factor analyses carried out by Zevon and Tellegen (1982). The PANAS consists of two 10-item scales that statistically measure both positive and negative affect. Each item is rated on a 5-point scale of 1 (not at all) to 5 (very much). The PANAS score is separated into the Positive Affect (PA) and Negative Affect (NA) scores, with a higher score indicating more positive or negative affect respectively. Sample item include "Thinking about yourself and how you normally feel, to what extent do you generally feel": Interested, Distressed, Excited, Upset, Strong and so on. The PANAS measure has been used widely and mainly as a research tool in studies that involve groups, and it has also been utilized in within clinical and non-clinical populations as well (Kercher, 1992; Watson & Lee, 1999; Crawford & Henry, 2004; Thompson, 2007). The PANAS reports a Cronbach's alpha coefficient of 0.86 to 0.90, for the positive affect and for negative affect the reliability was, 0.84 to 0.87 over 8-week time period, the test-retest correlations were 0.47-0.68 for the positive affect and 0.39- 0.71 for the negative affect (Watson *et al*., 1988).

Self-Agency was measured using 2 dimensional: Sense of Positive Agency (SoPA) and Sense of Negative Agency (SoNA). The SoAC is a 13-item Sense of Agency Scale (SoAS) developed by Tapal, Oren, Dar, and Eitam, (2017). The Sense of Agency Scale (SoAS) was developed as a tool for measuring individuals' beliefs about being agents in the sense of generally experiencing control over one's body, thought and immediate environment. Sample of items include; "I am in full control of what I do", "I am the author of my actions", "I can't predict how my actions will affect my environment". Responses on the SoAS was recorded on a scale from 1 (strongly disagree) to 7 (strongly agree). The reliability of the SoAS two subscales was = 0.80 and 0.79.

Phase 2: Intervention and Post Intervention Phase

Research Design:

A 3-group pre-test post-test design was considered for this phase. The participants were divided into three groups: Experimental group, first control group and the second control group comprised of students who were not tested at the pre-intervention phase.

Table 1: Summary of the Research Design for the Pre-Intervention Phase and Intervention and Post-Intervention Phase

Clusters	Pre-Invention Phase	Intervention and Post-Intervention Phase	
Groups	Pre-test	Exposure (Virtual nature environment)	Post-test
Group1 (Experimental Group) *n* = 24	Yes *n* = 24	Yes *n* = 24	Yes *n* = 24
Group 2 (First Control Group) *n* = 24	Yes *n* = 24	No	Yes *n* = 24
Group 3 (Second Control Group) *n* = 24	No	No	Yes *n* = 24

As shown in Table 1 the experimental and the first control groups were exposed to pretest. The second control group was not exposed to any form of pre-test. Only the experimental group went through the exposure condition (virtual nature environment). All the three groups were exposed to the post-test. Virtual Nature Environment was measured using computer generated 10 coloured, 3-dimensional pictorial images that were measured 1024x1024 which depicted virtual natural scenic environments such as lakes, hills, natural forests, waterfalls, mountainous ranges, gardens and moonlightings and sunsets. Students were exposed to the virtual natural environments for approximately 25 minutes while being seated in an ergonomic chair.

Procedure:
The intervention and post-intervention phase began after the pre-intervention assessment phase. The participants who participated in this phase of the study were drawn from the initial pool of participated in phase I of the study. Two certified Information Technology (IT) experts operated virtual images via desktop computers. The participants were informed on why they were chosen, what the research study entails and the possible solutions and benefits the study will provide in line with the BPS Ethics Guidelines for Internet Mediated Research, (2017). The participants were divided into three groups. The experimental comprised 24 participants (those who scored low on the measure of psychological wellbeing and were exposed to virtual nature environments). The first control group comprised 24 participants (those participants who scored low on the measure of psychological wellbeing but were not exposed to virtual nature environments) and the second control group comprised 24 participants (who were not part of the initial pre-test exercise and they were also not exposed to virtual nature environments), these group of participants served as the control group. The researchers explained the purpose of the intervention and how the participants were chosen into these groups. The researchers informed the participants that there are no implicit physical or psychological harm that will ensue as a result of participating in the study. The duration of the DAT session lasted for twenty-five minutes and each participant had access to a desktop computer.

DATA ANALYSIS

Virtual Nature images lasted for twenty-five minutes, while the control group were exposed to ten (10) natural setting pictures for twenty-five minutes. Independent variable is the stimulus conditions (nature and control) and self-agency. The dependent variable was psychological wellbeing (positive and negative mood). In order to test hypothesis 2, a combination of two sets of t-test for dependent samples was used to compare the pre-test and post-test scores of the experimental and control groups and a Bonferroni's post-hoc test was used to determine the extent to which the three groups of participants were different.

RESULTS

Test of Hypotheses 1

In order to test hypotheses 1, hierarchical multiple regression analysis was conducted. The socio-demographic variables (gender and religious affiliation) were entered into the regression model in step one. In step two of the analysis, the predictor variable (self-agency) was added to the regression model. The results are shown in Table 2.

Table 2: Summary of Hierarchical Multiple Regression on the Influence of Gender, Religion, and Self-Agency on Psychological Wellbeing

Model	Variables	B	*T*	*P*	R	R^2	ΔR^2	*df*	F	*P*
	Step 1				.10	.01	.01	4,271	0.70	>.05
	Gender	.00	-.00	>.05						
	Religion affiliation	.02	.39	>.05						
	Step 2				.14	.02	.01	6,270	0.89	>.05
	Gender	-.01	-.08	>.05						
	Religion affiliation	.01	.03	>.05						
	Self-Agency	.24	.26	>.05						

Note: Gender was coded, Male =1, Female = 0, religion was coded Christianity 1, Islam 0.

Table 2 demonstrated that in step one, none of the socio-demographic variables had independent significant influence on psychological wellbeing. This implies whether students are male of female or which either religious affiliations they identified with did not determine whether students' psychological wellbeing would increase or not. As shown in Table 2, all the socio-demographic variables only contributed 1% to the observed changes in psychological wellbeing [R = 0.10, R^2 = 0.01, F (2, 72) = 0.70, p >.05]. In step two of the analysis, self-agency was added to the model. The variables in the second step contributed 2% to the total variance in psychological wellbeing. This explains just 1% variance contributed by the added variable (self-agency) in step two [R^2 = 0.02, ΔR^2 = 0.01, F (3, 72) = 0.89, p > 0.05]. Extrapyramidal side-effects did not significantly predict psychological wellbeing among students [β = .24; t = .26; p >.05]. Therefore, the results in Table 2 provided evidence in support of hypothesis 1, which stated that self-agency would be significantly related with increased psychological wellbeing. Therefore, the hypothesis was accepted.

Test of Hypothesis 2

Two-sets of t-test for dependent samples were conducted on the data to determine the extent to which the mean scores of the pre-test and the post-test of the experimental group and the first control group were different. The results are presented in Table 3.

Table 3: Summary of t-Dependent Test on Pre-Test Scores of the Experimental and the First Control Groups on Students Psychological Wellbeing

Groups	Test Condition	N	M	SD	Df	t	P
Experimental Group	Pre-test	24	1.84	0.66	23	10.44	<.01
	Post-test	24	3.46	0.51			
	Pre-test	24	1.05	0.34	23	2.45	>. 05
Control Group 1	Post-test	24	1.74	0.58			

The results in Table 3 showed that the difference between pre-test and post-test scores of participants in the experimental group was significant [t (66) = 10.44, p <. .01]. This was such that participants performed better in psychological wellbeing (M = 3.46; SD = 0.51) compared to their performance in the pre-test (M = 1.74; SD = 0.58). Analysis of the pre-test and post-test scores of participants in the control group 1 indicated no significant difference [t (23) = 2.45, p > .05]. This finding was such that their performance in the pre-test (M = 1.74; SD = 0.58). The outcome of these comparison implied that exposure to virtual nature environment affected those in the experimental group. In order to show how efficacious exposure to virtual nature environment is in enhancing psychological wellbeing among students as indicated in Table 3 above, the post-test mean scores of the three groups were compared. Table 4 shows the result.

Table 4: Summary of the Mean, and SD of the Post-Test Scores of the 3 Groups on Psychological Wellbeing

Groups	***N***	***M***	***SD***
Experimental Group	24	3.49	0.61
First Control Group	24	1.78	1.13
Second Control Group	24	0.99	0.59

Table 4 shows that the experimental group (the group that was exposed to virtual nature environment) had the highest mean score (M = 3.49; SD = 0.61) on the measure of psychological wellbeing compared with the First Control Group (M = 1.72; SD = 1.13) and the second control group had the least mean score (M = 0.77; SD = 0.59).

Post-Hoc Analysis on Hypothesis 2

The result of the post-hoc analysis is shown in Table 6.

Table 5: Summary of Post-Hoc test on Psychological Wellbeing of Students

Groups	*N*	*M*	*SD*	*1*	*2*	*3*
First Control Group	24	1.72	1.13	__		
Second Control Group	24	0.77	0.59	0.94*	__	
Experimental Group	24	3.49	0.61	1.78*	2.72*	__

Note: * $p < 0.05$.

Results of the Post-hoc in Table 6 shows that, the highest and significant mean difference (Bonferroni = 2.72, $p < 0.05$) was observed between the experimental group (participants who were exposure to virtual nature environment) and the control group two (students who were neither pre-tested nor exposed to virtual nature environment). Also, the mean difference between experimental group and control group one (students who were given a post-test without exposure to virtual nature environment) (Bonferroni = 1.78, $p < 0.05$) and mean difference between control group one and control group 2 (Bonferroni = 0.94, $p <. 0.05$) were found to be significant. However, these mean differences were lower as compared to the huge mean difference between experimental group and control group two, validating the effect of the exposure to virtual nature environment in determining psychological wellbeing among students. The results in Table 3, 4, 5, and 6 provided evidence in support of hypothesis 2, which stated that groups exposed to virtual natural environment will report significant improvement on psychological wellbeing (positive affect) more than their counterparts who were not exposed to virtual nature environment. Therefore, the hypothesis 2 was accepted.

DISCUSSION

This study examined the roles of self-agency and virtual environment in improving psychological wellbeing among students using a randomized group design. In hypothesis 1, which stated that students perceived level of self-agency will significantly predict the increased level of psychological wellbeing. This result was confirmed therefore, hypothesis 1 was confirmed. Possible explanation of this outcome can be linked to the intrinsic value obtained from self-agency, as individual who tend to internalize events in their life as possibly as their own making, them to manage difficult and seeming unpleasant situation with some level of resilience. This outcome is line with the study of Renes and Aarts (2018) who found that self-agency is strongly associated with motivation to engage in regulating behaviours making it possible for individuals with this attribute to have increased motivation to act, and to control their behavior more successfully in line with their aspirations. Smith *et al.* (2000); Welzel and Inglehart (2010) revealed that individual's capacity and the intention of an individual to take action based on their knowledge and awareness of their particular situation and condition increases the individual's ability to develop physical and mental wellness, knowing that he or she has the responsibility to determine their happiness and satisfaction. Garber (1980) suggested that signs of increased psychological well-being emanate from individuals who report lower levels of perceived stress and depression, and this has significant implications for self-agency. Similarly, Klonowicz (2001), revealed that self-agency is strong determinant of subjective well-being, concluding that high levels of self-agency is associated with positive emotion.

In hypothesis 2, which stated that students exposed to virtual natural environment will report substantial improvement on psychological wellbeing (positive affect) more than their counterparts who were not exposed to virtual nature environment. This result was confirmed therefore the hypothesis 2 was confirmed. One explanation for this outcome is that, human development is intertwined with nature. Human beings interact with nature as nature provides a comforting effect on humans through proximity and attachment that simulates positive feelings. For instance, the Biophilia theory developed by Wilson (1984) proposed that human beings advanced in close proximity with natural environments. Several authors corroborate this position, and there seems to be unanimity which suggest that positive affect improves with exposure to nature even though, it is simulated (Calogiuri *et al*., 2018; Yeo *et al.*, 2020). Another account for this result is that participants who are exposed to virtual nature pictures are habituated to give high levels of responsiveness to the images and this would repress negative thoughts thereby allowing for complete attentional processes (McMahan & Estes, 2015; Browning *et al.*, 2020). However, studies differ with this position, and they instead submit that positive emotion is only associated with real-life nature settings but not in virtual contexts, they contend that virtual environments places too much cognitive demands on individuals and this produces pseudo-feeling of escape that is often short-lived (Valtchanov, Barton & Ellard, 2010; Anderson *et al*., 2017; Liszio, Graf & Masuch, 2018; Yeo *et al.*, 2020; Payne *et al.*, 2020; Owens *et al.*, 2022). The authors of this article differ for the reason that cognitive and perceptual process involved in real nature setting are similar and mimicked by the brain to produce similar experience as those encountered in simulated environment which produces comparable positive wellbeing such as those substances that mimic dopaminergic neurotransmission.

LIMITATIONS AND SUGGESTIONS FOR FUTURE STUDIES

This article has several research limitations. Firstly, the number of participants used in this study is too meagre to make generalizations as a result, researchers reporting the findings of this study should do so with some level of cautiousness. Secondly, this study made use of self-report questionnaires which is reportedly highly open to survey bias as participants may not reflect their true intents. Thirdly, this study made use of virtual or simulated nature environment and this procedure is not subjected standardization and the outcomes as a result of the use of this method may not be consistent with other findings. Fourthly, the study was a pretest-posttest control group design, in that there is a degree of randomization, use of control groups and, therefore, greater internal validity. However, the disadvantage of this type of approach is that the design assumes that groups are equivalent due to random assignment. The patients in the groups may result in a chance of missing an actual effect, and the treatment may become confounded with the pretest (internal validity); as only one group were exposed to virtual nature environment. Future studies should conduct experimental studies by manipulating variables that may portend significant changes on psychological wellbeing among other groups of people.

RECOMMENDATION

Based on the findings of the study is recommended that cost-effective and user-friendly psychological applications should be developed to offer clinically-based results in the understanding of the impact of virtual nature on psychological wellbeing stress and restorative effects of natural environments. It is also recommended that the Nigerian government through Nigerian Psychological Association should encourage more research in this area by offering grant and sponsorship for studies aimed at psychologically-based artificial intelligence to foster interest from scholars and researchers so as to put Nigeria among advanced countries engaging in virtual research innovations. In line with this it is proposed that;

1. Psychological institutions should be established to monitor, regulate and provide training in the advancement of artificial intelligence and virtual simulation so as to bring teach psychology researchers on this newly evolving field of virtual environmental research.
2. Research should be encouraged towards virtual simulation in psychological research so as to give it the attention it deserves as the future for therapeutic treatment.
3. Conferences, training and workshops should be organized to encourage and expose students to the importance of self-agency in achieving life goals.

CONCLUSION

The findings of this study demonstrates that self-agency and exposure to virtual is a significant predictor of psychological wellbeing among students. This study advocates that due to the growing challenges faced by natural environments, scientists and scholars are admonished to engage in alternative means of conducting research and the use of technological seems to have a huge role to play in the future of scientific research.

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Power Quality Engineering Evaluation and Generalization of Deep Learning

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Abstract:
This paper aims to introduce deep learning to the power quality community by reviewing the latest applications and discussing the open challenges of this technology. Publications covering deep learning to power quality are stratified in terms of application, type of data, and learning technique. This work shows that the majority of the deep learning applications to power quality are based on unrealistic synthetic data and supervised learning without proper labelling. Some applications with deep learning have already been solved by previous machine learning methods or expert systems. The main barriers to implementing deep learning to power quality are related to lack of novelty, low transparency of the deep learning methods, and lack of benchmark databases. This work also discusses that even with automatic feature extraction by deep learning methods, power quality expert knowledge is still needed to implement and analyses the results. The main research gaps identified in this work are related to the applications of semi-supervised learning, explainable deep learning and hybrid approaches combining deep learning with expert systems. Providing a stronger level of collaboration between grid stakeholders and academia to monitor power quality events, properly labeling and enlarging datasets for deep learning methods, outlining the end-to-end decision-making of deep learning methods, and offering open-access databases for comparison purposes are some suggestions for overcoming the current limitations.

Keywords: Power quality, Deep learning, Data analysis

INTRODUCTION

The electric power sector is continuously modernizing to become more environmentally friendly, economical, and reliable. The modernization goals are reached by, for instance, integrating renewable energy, installing new devices in both supply and demand ("smart grid equipment"), the deregulation of the sector, and the advancement in measuring infrastructures. However, the ongoing increase of equipment based on power electronics has an impact on the probability of interference through changes in emission, immunity, and transfer of power quality (PQ) disturbances [1,2]. Many of the power grid stakeholders perform continuous PQ monitoring to obtain information on the supply and equipment performance [3,4]. Long-term PQ measurements result in a large amount of data. For instance, [5] shows that a two-year PQ measurement campaign at five different locations resulted in 250 GB of data. The true value of PQ monitoring depends on its ability to analyses and interpret voluminous raw data obtained from that monitoring. Manual analysis of this data type is possible; however, it is time consuming. Proper analytical tools are needed to accelerate the "PQ big data" interpretation process.

The term "PQ big data" refers to a large amount of data resulting from continuous PQ monitoring. The term "big data" itself is not very clearly defined [6]. For instance, in terms of size, big data for the internet is measured in terms of exabytes 1018 and zettabytes 1021 [7] while PQ data is in MB or GB [6]. However, the consensus definition is that big data is a massive amount of data with specific complexities, the so-called 4V's: Volume, Variety, Velocity, and Veracity [8]. Although PQ big data is smaller than internet big database, both types of data are complex and difficult to process by employing traditional methods.

Artificial intelligence (AI) has been applied in many fields to handle analytics in big data. The first applications of AI were based on expert systems making decisions through rules defined by human expertise [9]. However, since the 1970s, a new subset of AI called machine learning (ML) has made computers capable of learning without explicit programming [10]. By employing ML to analyse and learn large amounts of existing data, computers can find patterns, predictions, and judgments to assist humans in making decisions [11].

Driven by the vast improvements in computer processing, a subset of ML based on artificial neural networks (ANNs) has been developed to tackle increasingly complex problems without human intervention. The initial ANNs still required significant human involvement for selecting and defining suitable features. However, the so-called deep learning (DL) applications can automatically extract optimal features from raw data [8]. DL approaches are usually implemented in pattern recognition systems due to the capability of DL to extract optimal information from high-dimensional data. DL methods have shown very promising results, especially in computer vision and image analysis, and performance is shown to be comparable to or even surpassing the conventional ML methods that use handcrafted features defined by human experts [8,12]. Most of the review papers on this subject only cover signal processing and AI techniques to classify and identify PQ disturbances [13–16]. Moreover, most of the existing review papers were published before DL popularity, as in [15] or, even later, they do not fully address DL methods [16,17]. This paper is the first to consider a comparative overview of the literature applying DL to PQ data. The paper also introduces big data from a PQ perspective and used the information from the literature to propose a DL workflow for PQ. After this introduction, the basic concepts concerning artificial intelligence and big data are introduced in Section 2. Section 3 distinguishes between the informatics-related terms used in this paper: AI, ML, and DL. Both Sections 2 and 3 aim to provide the readers from the PQ community with the terminology used in the AI community. Section 4 provides a workflow for applying DL to PQ. Section 4 also describes briefly the most common DL methods and their applications to PQ data. Section 5 provides a literature overview of AI techniques applied for the processing of PQ data, emphasizing the present applications with DL. Section 6 presents a critical discussion and recommendations regarding applications of DL to PQ. Finally, Section 7 concludes the paper.

POWER QUALITY BIG DATA

Concepts of Big Data

The term big data was first used by John Mashey [18] to refer to handling and analysing massive datasets. The concept of big data gained strength in the early 2000s when Doug Laney [19] defined big data by the "3V's": volume, velocity, and variety. By this definition, "big data" refers to a large amount of data that increases fast and is difficult or even impossible to handle by traditional methods. The most common way of defining big data nowadays is by the "4V's" which adds veracity to the "3V's" [20]. The list below details each of the "4V's" based on [21] and [22]:

a. Volume: refers to the amount, size, and scale of the data. The amount of data reaches such a level that it cannot be managed without dedicated analytic tools. The size can be defined either vertically by the number of samples in a dataset or horizontally by the number of features.

b. Velocity: refers to the speed by which the data is generated and how fast the data should be processed.
c. Variety: refers to the heterogeneity of the data. Big data often comes from different sources, which can be diverse in type, format, semantics, and volume.
d. (d)Veracity: refers to the quality of the collected data. It is related to biases, noise, and abnormality in data. The accuracy of any analytic process applied to the data depends greatly on the veracity of the source data.

Power Quality Big Data
The raw data of PQ monitoring consists of voltage and current samples in the time domain. The PQ monitors pre-process such raw data to detect and extract events such as voltage dips and transients. Besides, the raw data is pre-processed by mathematical transformations to obtain indexes to characterize waveform distortion, deviations from the ideal voltage magnitude, and other variations. Both raw and pre-processed PQ data can be considered big data because it contains the 4V's complexities. The following details each of the 4V's of PQ data.

Volume:
PQ monitoring results in a large amount of data. For instance, waveform measurements contain 256 samples per cycle, considering a sampling frequency of 12.8 kHz in 50 Hz. For each hour of measurement, this results in 1 080 000 samples (3 voltages and 3 currents). This volume complexity also holds for the pre-processed data. For example, harmonic values are obtained by Fourier transform and are aggregated every 10 min to simplify the data analysis. However, even with the aggregated values, one year of monitoring results in about 31 million data points per location considering 39 harmonics and 40 inter- harmonics (3 voltages, 3 currents, 10 min values).

Velocity:
The velocity of data is related to the set sampling frequency in the PQ monitor. Considering the previous example of 256 samples per cycle, a new sample in every voltage and current channel is obtained every 78.125 µs. The velocity complexity is also related to the PQ data analysis. streams: offline and online analysis. Offline analyses are mainly suitable for system performance evaluation, problem characterisation, and systems diagnosis. For online analysis, results are convenient when actions must be taken immediately.

Variety:
Even though the raw data comes from only two signals (voltage and current), it is diverse in terms of measurement sources. PQ monitors are installed in distinct voltage levels and locations of a power system to obtain enough data for understanding and characterizing PQ phenomena. Besides, PQ data is collected from many other monitoring devices on the system (intelligent relays, smart meters, digital fault recorders, phasor measurement units, etc.) [23]. In addition to the multiple data sources, the pre-processed PQ data is heterogeneous. Depending on the monitor settings, the pre-processed data can contain, for example, har- monic values and THD obtained each 10 min, voltage dips and transient waveforms with 256 samples per cycle, and rms voltage over 150 cycles of the power-system frequency. Although there are standardized methods to extract the data, as IEC 61000-4-30 [24], PQ monitors can also be configured with different settings, which results in data with different sampling, formats, and sizes. To reduce this complexity, the IEEE 1159.3 PQDIF Task Force has developed a standard format called Power Quality Data Interchange Format (PQDIF) [25].

Veracity:
According to the standard IEC 61000-4-30 [24], PQ measurement devices must comply with specific accuracy requirements (class A requirements). For harmonics, accuracy requirements are defined in IEC 61000-4-7 [26]. This accuracy is influenced by many factors, which include external sensors (e.g., instrument transformers, Rogowski coils), A/D converters, or measurement algorithms (e.g., aliasing, leakage) [27]. The requirements in [24] for PQ measurements point out the veracity complexity of PQ data.

Big Data Analytics
Big data analytics is the process of extracting information and detecting patterns from datasets with the 4V's complexity [22]. Conventionally, statistical methods, data mining, and visualization techniques were the most used tools for big data analytics. Recently, ML methods (artificial intelligence) have gained attention in analyzing big data. In the context of big data analytics, the exploration of time-varying data remains a key challenge in informatics [28]. Time-varying data is defined as spatiotemporal volumetric data, which means that each variable exhibits different values at particular time intervals. Several methods have been applied to extract patterns of time-varying data, such as visualization tools, clustering, and feature extraction [28].

PQ Monitoring and Analytics of PQ Big Data
PQ monitoring is the process of gathering, analyzing, and interpreting voltage and current measurements into useful information [52,53]. The continuous PQ monitoring allows the network operators to obtain information about the performance of utilities and customer facilities [54]. Moreover, the analysis of continuous measurements from PQ monitoring allows researchers to obtain knowledge of the PQ phenomena. Several tools are available for reducing large data volumes from PQ monitoring; this is mainly done through indices and reporting formats, like the ones defined in IEC 61000-4-30 [24] and the recommendations by CIGRE C4.112 [29]. The IEC document defines 10 min values, for among others, harmonics and inter harmonics. With many monitors and several years of data, this could still result in large amounts of data.

Reports employing classical statistical techniques in 10 min values might hide important information about variations with time. In some cases, shorter time scales should be employed instead of the 10 min values [30]. For instance, 10 min values of the harmonic voltage might not be proper for PV installations because the distortion varies over shorter time scales, depending, among others, on the solar irradiance and dynamic changes caused by fast cloud passages [45–48]. A more recent example is the charging of electric buses, where the charging is rarely longer than 10 min. The resulting data can be even larger if shorter time scales are employed instead of the 10 min values. In some cases, shorter time scales should be considered to proper addressing PQ. Analysis of PQ variations over time is essential to identify, for instance, excessive waveform distortion on power systems as a function of load and system characteristics (e.g., resonance conditions) [23]. Many approaches have been proposed to analyse and visualize time-varying events, such as Kalman filter [31], Parseval's [32], Hilbert–Huang Method [33], S-transform [34], and Wavelets [35]. An overview of such methods can be found in [36, 37]. In addition, graphical methods [38], expert systems [39], ML, and DL [40–43] have been applied to PQ measurements to extract additional information and provide better visualization of the raw data. One of the remaining challenges is detecting the dynamic changes and selecting important time intervals on a large amount of PQ measurements.

ARTIFICIAL INTELLIGENCE: EXPERT SYSTEMS, MACHINE LEARNING, AND DEEP LEARNING

The term AI refers to the entire universe of computing technology that exhibits anything resembling human intelligence [44]. In other words, AI is the enterprise of constructing an intelligent artefact. The most accepted definition of AI is one by Alan Turing, a computer can be said to possess AI if it can mimic human responses under specific conditions [45]. Since 1956 [46], AI has been considered an interdisciplinary subject to meet human intelligence. The period between the 1950s and 1960s is known as the first AI wave when many theoretical developments were made. However, the computers were not mature enough to process large neural networks, and not enough data was available for developing purposes. The following period is known as the first winter of AI. A second wave started in the 1980s with the development of expert systems that were based on rules defined by human experts. AI faced the second winter in the late 1980s and early 1990s mainly because expert systems required specialized hardware, and commercial vendors failed to provide an ample assortment of applications. In the same period, the development of the backpropagation algorithm played an important role in the progress of training multilayer neural networks [47]. A major milestone of AI is related to IBM's Deep Blue in 1997 [48], an AI system designed specifically for playing chess. Deep Blue was the first machine to beat a world champion in chess. The development of Deep Blue inspired researchers to create AI approaches that could tackle other complex problems. Since then, AI has faced a new wave associated with three main factors: availability of large amounts of data, advancements in computer processing, and massive investment from the industry [49]. AI can be grouped into six main categories [11]: game theory, decision-making algorithms, statistical models, search/optimization methods, expert systems, and learning methods (ML and DL). AI also covers or shows overlap with other fields such as robotics, sentimental analysis, and artificial emotion. In this work, we limit ourselves to those AI algorithms that are or can be applied to PQ. To this point, Fig. 1 illustrates these AI techniques for PQ, showing that ML is a subset of AI while DL is a subset of ML. The first applications of AI were based on expert systems which make decisions through rules based on expert knowledge [9]. On the other hand, ML and its subset DL have been made computers capable of learning without explicit programming [10].

Expert Systems

Expert systems are a type of AI that relies on expert knowledge and an inference engine. The basic idea behind expert systems is that the expert knowledge is transferred to a computer program through an inference engine. The inference engine is a set of "if-then" rules: if some condition is true, then a specific inference can be made, or action can be taken [50]. Due to the inference engine, expert systems are also called rule-based systems. The rules can be based on Boolean logic or Fuzzy logic. In Boolean logic, the rules incorporate only two values: "0" or "1". Fuzzy logic presents a gradual transition from "0" to "1" by expressing a set of values between the two logic states [51]. The main benefit of expert systems over ML is the explanation facility. A decision taken from an expert system can be explainable through the rules. The main limitations of expert systems are in creating inference rules; experts do not always agree, they are not always able to explain their reasoning, and some rules may be difficult to implement in terms of computational costs. Section 5.1 lists the applications that have employed expert systems in PQ field.

Machine Learning

ML using a large amount of data is a small subset within AI [10]. Conventional ML methods rely on human expertise to design the best features from the data for various tasks, such as classification, prediction, and regression. The general idea behind most ML applications is that a computer learns to perform a task by studying a training set of examples. Two main strategies can be employed in ML: supervised and unsupervised learning. Two other categories can also be incorporated into ML: semi-supervised learning and reinforcement learning.

Supervised Learning:
In supervised learning, the training set contains data and the correct output of the task with that data [10]. Supervised learning can be employed by logic regression, support vector machines, classification trees, random forests, artificial neural networks (ANNs), among others.

Unsupervised Learning:
The training set in unsupervised learning contains data but not the outputs, which means that the computer must find the solutions independently [10]. Unsupervised learning includes clustering algorithms as k-means, dimensional reduction techniques as principal components analysis, and ANNs.

Semi-Supervised Learning:
Semi-supervised learning is a type of ML that is between supervised and unsupervised. Its training combines a small amount of labelled data with a large amount of unlabeled data. To this point, semi-supervised learning is convenient when the ground-truth labels are available only for part of the data. Furthermore, the combination of labelled and Artificial intelligence groups and examples of some techniques.

Reinforcement Learning
Reinforcement learning is a type of ML that can be trained by interacting with a real-time environment. A solution is found by the computer employing trial and error to a given problem. The learning system is referred to as an agent, which can observe the environment, select and perform actions, and get rewards or penalties in return. The agent's objective is to maximize the total reward, and the best action is called policy [52]. This type of ML has been applied to robotics, game theory, and data science [53].

Deep Learning
Driven by the huge improvements in computer processing, a subset of ML-based on ANNs has been developed to tackle evermore-complex problems without human intervention. These so-called DL applications can perform a specific task by automatically extracting essential features from raw data [8]. A deep learning method is composed of a multilayer stack of simple models that maps non-linearly its output by its input [54]. Each layer further refines the previous layer's outputs that enables to increase both the selectivity and the invariance of the representation [54]. The mapping is learned from the input data by adapting the weights of each neuron by using an algorithm called backpropagation [63]. The weights are adapted based on the gradient of the error at the output. The backpropagation algorithm calculates the gradient of the error and distributed it back in terms of weights to the previous layers. The objective is to minimize the error in the output, and this weight adapting process is repeated over many iterations.

DL approaches are usually implemented in pattern recognition systems due to the power of DL to extract abstract concepts from high- dimensional data. Section 4.4 provides an overview of the main DL architectures used in PQ.

DEEP LEARNING WORKFLOW FOR POWER QUALITY

This session summarizes the steps in applying DL to a PQ problem. The workflow provided in this session should not be considered a strict practice. Instead, this workflow aims to give a guideline for the useful implementation of DL for PQ. The workflow proposed here is inspired by DL guidelines presented for other fields such as computer science [55], space weather [56], and medicine [57].

Problem Formulation

The first step in applying DL is to formulate the problem and map the specific needs that require DL. Then, the use of DL should be justified by indicating the limitations of traditional methods for solving this specific problem. In this stage, the need for data should be addressed; where no or insufficient data is available, there is a need to perform new PQ measurements. Traditional methods of presenting and analyzing PQ measurements can help to provide directions for selecting a DL method. For instance, it can help verify the type of training that suits better for a DL algorithm. Supervised learning is suitable if labels are either available for the data or if manual labelling is possible. On the other hand, unsupervised learning is the best choice when no labels are available. Semi-supervised learning is an option if part of the data set contains labels. Linking the measurements with other data sets can be used for labelling. For instance, labels or sequences can be correlated by the simultaneity among PQ events or variations with their causes and effacts. The algorithm should be selected once a decision is made between supervised, semi-supervised, and unsupervised.

Data Pre-Processing

Once the raw data from the PQ measurements are available, they should be pre-processed to transform them into useful data features for the DL application. Pre-processing consists of three main steps: cleaning, normalization, and splitting.

Cleaning:

Failures in the measurements can result in missing data points. Malfunctions in the measurement systems can also produce outliers, which are erroneous values in the data set. A common practice in pre- processing is to fill in the missing values and remove or minimize the effects of outliers. For DL applications, it is essential to assess beforehand if the method for handling missing data and measurement errors could impact the results. Recommendations for handling both missing data and outliers can be found in [58].

Normalization:

Data normalization is the pre-processing step that transforms the data into a common range, making an equal contribution to each feature. The main objective of normalization is to minimize the effect of features with higher numerical contributions than others. In case the importance of the features is not known, the importance of the features will be assumed equally distributed. Different normalization methods can be implemented, and mathematical details and recommendations are presented in [59].

Splitting and Reshaping:

The data is usually split into three sets for supervised learning: training, validation, and testing. The DL learning model is trained with the training data set. The validation data set is the one to proceed with evaluating the DL method during the DL model training. The testing data set is used to verify the performance of the trained and validated DL model.

In this stage, the imbalance of the dataset should be verified, i.e., if some classes have more data instances than others. A common approach is to correct the imbalance in the training data to reduce the biases to- ward the predictions. The different methods for correcting the imbalance in data sets are summarized in [60]. For unsupervised learning, data reshaping can help provide the most proper input for the DL model. Data reshaping consists of rearranging the data form without changing the content of the dataset. An example is the transformation of yearly time-series into daily time-series [42].

Algorithm Selection:
The algorithm choice should be based on the class of problem addressed, i.e., supervised, unsupervised, or semi-supervised. A comprehensive overview of the most appropriate algorithms for each class of problem is presented in [61]. Methods employed for supervised learning are deep neural network (DNN), convolutional neural network (CNN), deep belief network (DBN), recurrent neural network (RNN), and its variants such as long short-term memory (LSTM). For unsupervised learning, common algorithms are deep autoencoder (DAE), generative adversarial network (GAN), self-organizing map (SOM), restricted Boltzmann machine (RBM), and deep belief network (DBN). For semi-supervised learning, GAN is often applied as a method to estimate unknown labels. The forthcoming sections contain a brief description of the most common DL methods and their applications to PQ data: DNN, CNN, DBN, RNN, LSTM, GAN, and DAE. For more details and other techniques, the reader is referred to [54, 61].

Short Illustration Table: 1

1. Concepts of Big Data
   1.1 Definition of Big Data
      - 3V's: Volume, Velocity, Variety
      - 4V's: Adding Veracity
   1.2 Explanation of Each V
      - Volume: Amount, size, scale of data
      - Velocity: Data generation speed, processing speed
      - Variety: Data heterogeneity from different sources
      - Veracity: Data quality, accuracy, biases

2. Power Quality Big Data
   2.1 Raw Data and Pre-processing
      - Voltage and current samples
      - Event detection and extraction
      - Mathematical transformations for indexes
   2.2 The 4V's of PQ Data
      - Volume: Large amount of data from measurements
      - Velocity: Sampling frequency and data analysis speed
      - Variety: Diverse sources, monitoring devices
      - Veracity: Compliance with accuracy requirements

3. Big Data Analytics
   3.1 Definition and Challenges
      - Extracting information from 4V's data
      - Traditional methods vs. Machine Learning (ML)
      - Challenge of time-varying data analysis
   3.2 Methods for Time-varying Data
      - Visualization, clustering, feature extraction

- Kalman filter, Parseval's, Hilbert-Huang, etc.
- AI methods: ML, Deep Learning (DL)

4. PQ Monitoring and Analytics
  4.1 Purpose of PQ Monitoring
    - Gathering, analyzing, interpreting measurements
    - Utility and customer facility performance
  4.2 Handling Large Data Volumes
    - Indices, reporting formats
    - IEC 61000-4-30, CIGRE C4.112 recommendations
    - Need for shorter time scales in some cases
  4.3 Analyzing Time-varying Events
    - Methods for identifying dynamic changes
    - Kalman filter, Parseval's, ML, DL

Deep Neural Network (DNN):
DNN are essentially neural networks with multiple hidden layers, each of which further refines the previous layer's outputs [62]. The term deep comes from the fact that the network contains more layers (is deeper) than conventional neural networks [63]. Because of this, conventional ANNs are also called shallow ANNs. DNN is applied to power quality in classification of disturbances [64] and microgrids dynamic stability [65].

Convolutional Neural Network (CNN):
CNN is a multichannel input DL structure composed of learnable weight and bias. The term "convolutional" indicates using convolution instead of matrix multiplication in at least one layer. The simplest CNN architecture contains one convolutional and one pooling layer, option- ally followed by a fully connected layer for supervised prediction. Pooling layers are applied to reduce the data dimensions by combining the outputs of a group of neurons at one layer into a single neuron in the next layer. CNN is applied in PQ mostly for classification of PQ events [66–85], voltage dip classification [40,86,87], recognition of voltage dip causes [88,89], prediction of harmonics [41, 90], and control of voltage unbalance in microgrids [91].

Deep Belief Network (DBN):
DBN are composed of multilayers of Restricted Boltzmann Machine (RBM). In turn, RBM is a type of ANN that can learn a probability distribution from its input [92]. DBN are applied in PQ for classification of PQ events [93,94]. According to [93,94], DBN avoids global fine-tuning and improves the accuracy of power quality disturbance classification compared to traditional ML methods.

Long-Short-Term Memory (LSTM):
LSTM is a variant of recurrent neural network (RNN), composed of a cell, an input gate, and a forget gate. RNN is a DL structure similar to a feedforward neural network that allows exhibiting temporal dynamic behavior. However, unlike a feedforward neural network, RNNs can use their memory to process variable-length sequences of inputs. The unit is called a long short-term memory block because the program uses a structure founded on short-term memory processes to create longer- term memory. Each layer of the LSTM categorizes some level of information, refines it, and passes it along to the next layer. It uses long, short- term memory blocks to provide context for how the program receives inputs and creates outputs. The LSTM block is a complex unit with various components such as weighted inputs, activation functions, in- puts from

previous blocks, and eventual outputs. LSTM is applied to classification of PQ events [95,71–74], recognition of voltage dip causes [96], voltage dip classification [97], harmonic prediction [41,98,99], and islanding detection in microgrids [100,101].

Generative Adversarial Network (GAN):

A GAN is a network that consists of a generator and a discriminator. The generator learns certain data distributions and generates synthetic data according to the distributions. The discriminator distinguishes between the true and synthetically generated data. GAN is applied to the classification of PQ events [75,76] and voltage dip labelling [102].

Deep Autoencoder (DAE):

DAE is an unsupervised learning architecture composed of three main parts: encoder, coding and decoder. The encoder takes the input data and transforms it into a smaller dataset in the coding layer. The decoder takes the dimensional reduced dataset and reconstructs a similar representation of the encoder input and its output. DAE is trained to reduce reconstruction errors. The encoder and decoder contain several fully connected layers instead of one; the number of layers and the number of neurons is symmetric between the encoder and decoder. The main application of AE and DAE is to obtain the principal features of a dataset. The applications in PQ are for feature extraction as part of the classification of PQ events [103–105]; and unsupervised feature learning for clustering of daily harmonics variations at a single location [42], multiple locations [106], spectral data [107], and analytics of waveform distortion in railway installations [108].

Tuning the Hyperparameters

Once the method is chosen, the DL architecture (number of layers and the number of neurons per layer) and the hyperparameters should be selected, depending on the chosen method and application. Hyper- parameters are values that control the learning process, such as the number of epochs, learning rate, and batch size. Although there are benchmark methods for some types of data, such as Alex Net for images [109], there is no standard way to determine the DL architecture and hyperparameters. Therefore, a common practice is manually tuning the method by trial and error [110]. Some recommendations for defining this task are found in [111]. In addition, automatic tuning based on optimization methods has started being proposed in the literature [112].

Training, Validating, and Testing

During the training stage, the values of the DL model are adjusted to fit the training data. The adjustable parameters (weights) define the input-output function of the DL model. A typical DL model contains millions of adjustable weights. Optimization methods based on stochastic gradient descent are often employed to update the weights to minimize the error in estimating the outputs. During the training, validation plays a role in providing an unbiased evaluation of the DL model. After training, the performance of the DL model is evaluated through the testing data set. The test aims to generalize the ability of the DL model to produce outputs based on inputs that were not seen in the training stage. A DL model with good performance in the training stage can present worse performance on estimating outputs with unseen instances. This is called overfitting, and it often occurs due to insufficient amount of data. The opposite phenomenon is underfitting when the DL model fits neither the training set nor the testing set. Underfitting is mainly a consequence of the low complexity of the DL model. Both overfitting and underfitting should be avoided. Overfitting can be solved either by reducing the complexity of the DL model by using a lower number of neurons and layers or by using regularization techniques such as dropout. Under- fitting can be avoided by increasing the complexity of the DL method by adding more neurons and layers.

Deployment

This step defines how the model will be deployed as an application tool. Providing transparency to the DL model is important in this step; in other words, ensuring that the results can be interpretable, and the DL method does not appear as a closed box. A possibility is to explain the features extracted by the DL models and their role in estimating the outputs. In this step, it is also important to define how the tool would be delivered to users, in this case, typically PQ engineers, and how they can use it.

REVIEW OF AI APPLICATIONS FOR PQ

Fig. 2 shows that the number of publications related to AI and PQ increased a lot from 1992 to 2021 in the Scopus Database. The legend of Fig. 2 shows the logical structures used for the search. The blue color in Fig. 2 indicates the number of occurrences of references that included the term "power quality" together with any of the AI terms: "deep learning", "machine learning", "artificial intelligence", "expert system". The red color indicates only the number of references that included the terms "power quality" and "deep learning". The search considers the keywords and abstract of the publication.

Although most AI methods have been developed before, the application of AI to PQ started only after 2000.

(b). The text data mining from [113] produces a visualizing tool that groups words from the title, abstract, and keywords of the different publications. If a group of words appears at least five times, it is considered as a cluster. Each cluster is represented by a color and il- lustrates the most correlated word in the analyzed periods. In this perspective, the keywords are related to the diverse AI and signal-processing techniques that have been implemented to detect, extract, and analyses PQ variations and events. Section 5.1 details the techniques and applications before 2017 and Section 5.2 after 2017. Section 5.3 details and compares the applications in the literature of DL to PQ.

Techniques and Applications from 1992 to 2017

The blue cluster in Fig. 3(a) represents the first applications that were based on expert systems that make decisions through rules based on human expertise [114]. Such methods were applied to PQ data to perform the classification and recognition of PQ events until 2010 [9,39, 115–117]. Signal processing methods (magenta and yellow clusters in Fig. 3(a)) play an important role in signal decomposition and feature extraction. The two techniques appearing most were Wavelet and S-transform; these were mentioned in Section 2.4 to analyses and visualize time-varying events. Moreover, signal-processing methods are combined with expert systems or ML tools. To classify PQ disturbances, for example, [118] uses wavelet and fuzzy support vector machines; [119] uses S-transform and ML; and [120] uses S-transform for the feature extraction stage and support vector machines for the pattern recognition problem of non-intrusive load monitoring.
Learning algorithms have been applied for similar applications as the expert system, i.e., for the classification and recognition of different events [121–126]. Most algorithms are based on supervised learning that requires pre-labeled data, e.g., shallow neural networks [93–95, 98], and

support vector machines [96,97]. Few works apply unsupervised learning to find patterns in PQ data without prior.

knowledge: [127] applies principal component analysis and [128] k-means clustering. The work in [128] was the first attempt to find patterns of PQ big data by applying an unsupervised method. However, [128] did not extract the principal features for clustering, and the analysis is limited to the correlation among harmonics. Moreover, [128] did not allow to obtain the typical daily patterns of time-varying distortion and did not result in a user-friendly orientation to further analyses the data Optimization algorithms also appear as a trend for AI applications to PQ. This cluster, represented in red in Fig. 3(a), is related to optimization methods such as genetic algorithms mostly for decision-making on the placement of capacitor banks [129] and active filters [130].

Techniques and Applications from 2018 to 2021

For the period between 2018 and 2021, the techniques explained in Section 5.1 also appear in the clusters of Fig. 3(b). However, those techniques appear primarily in hybrid approaches. For example, the red cluster contains approaches that apply fuzzy logic combined with optimization, mainly for control systems [131–133]. Moreover, methods combining optimization with ML are found in the green cluster. For instance, [134] combines metaheuristics with ANNs and support vector machines to detect, segment, and classify voltage dips. In addition to the green cluster, the group of learning algorithms presents two more sub- groups in Fig. 3(b): ML in magenta, DL in blue and in yellow (the latter with the keyword “convolutional neural network”). In the context of DL (blue), the keywords "classification", "disturbance classification", and "power quality disturbances" are found together with "deep learning".

Applications of Deep Learning for PQ

The analysis by the text mining in Fig. 4 gave a general overview of the DL applications to PQ. To obtain more detailed information, Table 1 stratifies 46 references concerning the type of application, type of data, learning technique, and DL method. The publications were found by searching "power quality" and "deep learning" in the Scopus database and refining the engineering/energy fields search. The references in Table 1 cover the period from January 2018 to September 2022. Table 1 shows that most of the publications are related to the classification and recognition of PQ disturbances. This points out that, even with the possibility of automatic feature extraction, the applications of DL in the literature are still largely the same as the applications of expert systems or the earliest ML tools. Moreover, most of the published studies are based on synthetically generated data and on supervised techniques. Other applications are voltage dip classification, voltage dip estimation, recognition of voltage dip causes, prediction of harmonics, recognition of patterns in daily harmonic variations, identification of spectral patterns, control of voltage unbalance in microgrids, islanding detection in microgrids, and dynamic stability in microgrids.

Table: 2

AI Applications for PQ	
DL Method	
Description and Applications	
DNN	CNN
DBN	LSTM
GAN	DAE

Hyperparameter Tuning
Training, Validation, and Testing Deployment
Review of AI Applications
Techniques and Applications (1992-2017)
Techniques and Applications (2018-2021)
Applications of Deep Learning for PQ

This table provides a structured overview of the discussed topics and their applications in the field of power quality using artificial intelligence and deep learning techniques. You can use this as a reference to create a visual diagram using diagramming software.

DISCUSSIONS AND RECOMMENDATIONS

Lack of Novelty

Many publications have proposed the automatic classification of PQ records by DL. This trend was also identified for PQ applications with signal processing [135]. However, the classification of PQ disturbances does not present any novelty when the classes are individual PQ disturbances such as swell, sag, interruption, harmonics, and transients. Standards such as IEEE 1159, IEC 61000-4-30 and EN 50160 define methods for classifying PQ events based on characteristics such as spectral content, duration, and voltage magnitude. This type of application is already present in PQ monitors and their commercial computing platforms; there is no need for DL applications to replace classification methods defined in standards.

Training Based on Synthetic Data Sets

A substantial part of the approaches within the literature is based on synthetically generated and often non-realistic data. There is a risk of overfitting in case synthetic data is used, and in this case, the test error seems high even for low training error [6].

There are several reasons for using synthetic data in supervised DL by PQ researchers. One is the non-availability and inadequacy of real or realistic power system data, for example, from field devices. With PQ data obtained from measurements, the class labels from PQ data sequences needed to develop a classification system are typically unknown. The use of synthetic data does not suffer from this disadvantage as the labels for the data are known according to the process by which the data sequences are generated. A synthetic set would be better in covering all classes, but it would not be an appropriate statistical representation of the population of disturbances.

The performance of grid measurements in AI methods trained by synthetic data has been evaluated for ML and DL. In the context of ML for PQ, [137] has tested a support vector machine by employing measurements from two different power networks and synthetic data. The classifier presented a good detection rate when trained by data from one power network and tested with measurements from another network. However, the training employed with synthetic data did not produce acceptable results when tested with measured data. Combining measurements and synthetic data improved the performance, but the detection rate was still low compared to the classifier trained with measurements. About DL for PQ, the training of a LSTM for classification of voltage dip types with synthetic data and testing with real data has been done in [138]. It was concluded by [138] that the DL model had a

Table 3: Overview and comparison of recent publications covering the application of DL to power quality big data.

	DAE+CNN [77]	CNN [86,87]	CNN [40]	LSTM [97]
Voltage dip or fault classification	X	X	X	X
Voltage dip estimation	X		X	
Recognition of voltage dip or fault causes	X	X	X	X
Pre-detection/Prediction/Estimation of Harmonics	X	X	X	X
CNN+LSTM [41]	X	X	X	

Unsupervised Semi-supervised low performance when trained with synthetic data and tested with real data.

Enlarging Datasets by Adding Gaussian Noise

An example of non-realistic data generation is the application of noise to the datasets. A large group of publications adds noise to the data to evaluate the robustness of the methods or to enlarge the input datasets.

[67,71,72,75,77–80,85,93,96,103,104,139–141]. However, the noise is Gaussian and does not correspond to real noise in the electrical power grid [142]. Such Gaussian noise might comprise the decision-making of DL algorithms due to the addition of frequency components that do not appear in reality. Studies considering the effect of Gaussian noise instead of real noise are needed in the DL context. Efforts to make available open datasets with real noise can benefit the PQ research community.

Lack of Benchmark Databases

One of the challenges of DL in PQ applications is comparing the performance of the different algorithms. The lack of a standard database that can be used as a benchmark has been reported in [143]. Although some efforts have been made to provide public databases, they are limited in terms of application. Most of the available data are without labels. An example of a raw database is the one provided by the IEEE PES Subcommittee on Big Data & Analytics for Power Systems [144] which contains 1380 files of current, voltage, and active power measurements. In addition, some databases are suitable for studies of only one type of disturbance. For instance, [145] presents a collection of PQ real-life impulsive events, and [22] is a data set that contains waveforms of voltage dips. Also, some databases are for a specific type of application; for example, [146] contains measured voltage and current waveforms of railways, and [147] has harmonic measurements for an installation with electric vehicles. In sum, the public databases do not follow a standard, presenting different disturbances, sampling, and applications.

An attempt to establish a reference dataset for DL classifiers is presented in [143] by proposing an open-source software to enable the generation of synthetic data. However, the tool is appropriate only for the applications that concern events classification in terms of disturbance type. Furthermore, the authors of [143] also emphasize that such a dataset should be explicitly used to compare PQ disturbances classification algorithms. In other words, this tool might be proper for testing, not for training algorithms. The grid stakeholders and academia should make efforts to provide one or more reference databases to compare DL applications to PQ. Suggestions for databases are waveforms of PQ events with labels, long- term measurements of

PQ variations, and sub-10 min values of PQ variations [30] for different power installations and voltage levels.

Learning Strategies and Labelling

Most of the applications of DL to PQ are based on supervised learning, which requires labelled data. This trend is also observed for ML, deep or not, in most applications in different research fields [54]. Controversially, most of the available PQ data is non-labelled. Non-labelled data sets are suitable for unsupervised learning but not for supervised learning. Only a few works have explored unsupervised learning [41, 106, 107, 98], which are also among the few ones that applied measurements instead of synthetic data. The supervised training trend can be again due to the non-availability of field measurements for researchers and scholars. One, yet unsolved, issue is the verification/testing of unsupervised learning of PQ variations. Most DL models for PQ are based on supervised learning with synthetic data. As discussed in Section 6.2, synthetic data is easier to label as the process of synthetic data generation is known. However, the class choices for supervised learning should represent reality in measurements, but that is often not the case. In addition to the classes of individual PQ disturbances, some works propose classes for combined disturbances, such as swell with harmonics, dip with harmonics, dip with transients, and so on. With field measurements, events such as voltage dips always occur in combination with harmonics and transients [148]. Moreover, events can exist of multiple stages: the transient can be the starting, the dip can present many segments, and even it can occur as the initiating event for an interruption [149]. Instead of event classes, the labelling for supervised learning should be based on the origins and consequences of the event. The main limitation against precise PQ classification is the need for ground-truth and notated data [102]. No large ground-truth labelled datasets are available, and it is even more complicated with many measurements [102]. There is an uncertainty in the labelling process, which can be associated with incorrect labelling by power systems operators, or to the automatic method used for labelling, samples close to the borders, samples polluted with noise, and so on [102]. The grid stakeholders should make an effort to keep track of the events and correctly annotate the data.

Annotated data can serve as a basis also for semi-supervised learning. In semi-supervised learning, the algorithms can deal with partially labelled data. In the literature, only [102] has applied DL semi-supervised learning for automatic labelling of voltage dip sequences by using a small set of ground-truth labelled data. The method based on GAN, described in Section 5.4.5, was applied to a large set of measured dips; it presented 83% average accuracy with a 3.2% false alarm rate. Generating synthetic data has not been used yet for unsupervised learning. However, the application of synthetic data might assist in understanding the feature extraction in unsupervised learning.

Low Transparency

Users of ML and DL algorithms, like experts in PQ, might find it hard to trust the results from such an algorithm due to low transparency in the DL process. The core obstacle to the practical use of DL is that most DL algorithms appear like closed boxes. With DL, human experts do not select the features, but those features are obtained by using a learning procedure. It is different from an open box as physical models and expert systems, in which the process of defining an output is explainable in terms of mathematical equations and logic rules, respectively. The explanation of the decision-making process of DL methods can make them transparent. By increasing the explain ability of DL, human experts can benefit through new rules in a decision-making problem.

According to [150], one of the difficulties in interpreting deep neural networks is related to the activation process of neurons. The activation of some neurons can occur for a few data instances, whereas the activation of other neurons can be more globally. In this way, the output is a function of both local and global effects. Therefore, this makes it difficult to map an equivalent function that explains the prediction by DL for the data.

The lack of explanation in the DL decision-making has been pointed out as the main obstacle in sensitive fields such as precision medicine, law, and financial sector [150]. For power systems, this discussion has been considered in the context of ML [151], emphasizing the major barrier of providing trust in ML models such as neural networks and adopting them in practice. A first trial for measuring the explainability and trustworthiness of DL methods for PQ disturbances is presented in [152]; however, the discussion covers only the classification in terms of the type of disturbances. So far, there is no well-defined optimal method for explaining DL [153]. Some suggestions for increasing the explain- ability of DL, in general, are presented in [153]. It includes indexes and methods to evaluate the contribution of features to the predictions. Further efforts are needed to make DL more transparent to be more broadly applied in the PQ field.

Expert Knowledge and Development of Hybrid Approaches

In most applications, even with the possibility of automatic feature extraction and settings, PQ knowledge is still needed to interpret correctly and provide appropriate solutions based on DL results. As discussed in [43], the results provided by DL can be used to decide about further manual analysis of the PQ data. However, there is no standard method available yet for the additional manual analyses. Reference [43] suggests developing a hybrid method that combines the results given by DL with an expert system. The logic rules in the expert system could be defined to take some of the decision-making away from the human expert. However, some level of expert involvement will remain needed, as every case is unique. Approaches that combine DL and expert systems are not yet explored in the literature. Therefore, it is suggested to develop logic-based rules to make the interpretation of DL results at least partly automatic.

CONCLUSIONS

This review has covered the latest applications of DL to PQ big data. DL can be a solution to turn raw PQ measurements into a much more valuable asset. However, a large group of publications has limitations related to innovation and applicability. Even with the possibility of automatic feature extraction, most proposed DL algorithms execute the same task as expert systems or the early ML tools (classification, recognition of events, and underlying causes). By stratifying the publications in terms of application, learning technique, and type of data, this paper has demonstrated that: Most publications apply DL to problems solved by expert systems and early ML tools. Although such works still contribute to the knowledge on DL methods, the practical applicability is limited. A large number of works apply synthetic datasets that do not represent the reality in PQ data, limiting the practical applicability of those works.

Few works have provided new solutions to perform analytics to PQ big data; some examples of new solutions are predicting PQ data, extracting daily patterns, and automatic data labelling. In most applications, even with the possibility of automatic feature extraction and settings, PQ knowledge is still needed to correctly interpret the results and provide appropriate solutions to PQ issues.

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The Engineering Analysis and Composition of Rice Husk Ash, Powdered Glass, and Cement as Stabilizers

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Abstract:
The stabilizing effects of three different compounds rice husk ash, glass powder, and cement on the properties of lateritic soil are contrasted in this study. First, the basic properties of the lateritic soil were ascertained by testing for color, moisture content, specific gravity, particle size distribution, and Atterberg limits. Then, by weight of the soil, varying amounts of each stabilizing agent were added to the lateritic soil: 2.5%, 5%, 7.5%, 10%, 12.5%, and 15%. Compaction tests and California bearing ratio (CBR) tests on the sample mixtures were then used to evaluate the effects of the components on the lateritic soil. To determine the samples' % oxide concentration, chemical tests were also performed on them. The results of the compaction test showed that the three mixed samples with the highest maximum dry densities (MDD) were 2.32 g/cm3 (at a 2.5% cement addition), 2.28 g/cm3, and 2.18 g/cm3 (at a 5% addition of rice husk ash), with corresponding optimum moisture contents (OMC) of 10.06%, 14.3%, and 12.31%, respectively. Cement and glass powder provided the highest values and closely resembled one another in dry conditions, according to the CBR trials, which showed that the CBR values rose in every case when more materials were added. The cement, powdered glass, and rice husk ash, respectively, included sizeable amounts of CaO (53.60%), SiO_2 (68.45%), and SiO_2 (89.84%) oxides, per the chemical analysis.

Keywords: Atterberg limits, optimum, compaction, California bearing ratio

INTRODUCTION

In many tropical nations, lateral soils are the most widely accessible and cost-effective building materials. Due to their wide-spread availability in the tropics and relative simplicity of manipulation on road surfaces, these soils are extremely cost-effective as base material for minor roads with low traffic volumes. However, a few years after construction, the surface of the pavement will begin to crack, stripe, and become uneven, which are the main issues with roads built with laterite [1]. Therefore, it becomes crucial to look into potential sub-base improvement. According to their morphological and chemical characteristics, laterite is a highly worn red subsoil that is abundant in secondary oxides of iron, aluminum, or both.

When subjected to wetting and drying, quartz and kaolinite are either hard or have the potential to get harder [2]. Laterite typically gets its color from the minerals that make up the material, and the different colors can be distinguished by the amount of hydrated iron oxide present.

Stabilization, which entails blending and mixing elements with the soils to either attain a desired gradation or to make them more stable, can be used to improve soils. In this study, the impacts of cement, powdered glass, and rice husk ash (RHA) on lateritic soil will be evaluated in comparison. The finest conventional stabilizer is cement, but it is pricey. As a result, it is necessary to find other stabilizers that are accessible, inexpensive, and made from materials that would otherwise be discarded as industrial waste. These materials are a nuisance to the environment, and, in the case of powdered glass, which is often non-biodegradable, even harmful. In order to assess how efficient, they are as stabilizers, these materials are processed into a usable form, added to the soil, and the resulting properties are compared to those of the soil containing cement.

Worldwide, the use of industrial waste in road construction has recently received consideration. For a nation like Nigeria, which typically offers a favorable climate for the manufacture and importation of glass materials as well as the production/processing of rice, the usage of such materials is based on technical, economic, and ecological reasons. Nigerian cities are currently facing environmental issues due to a subpar solid waste management system since the rate of solid waste generation has outpaced the capability of the relevant authorities. This heralds the beginning of a significant environmental problem that might be avoided or attenuated if these waste materials can be developed and used in the construction of highways in an appropriate manner.

LITERATURE REVIEW

The two main stabilizing techniques are mechanical and chemical techniques [1]. The mechanical techniques of stabilizing soil do not require chemical changes to the soil and either entail compaction or the addition of graded aggregate materials, fibers, and other non-biodegradable reinforcement to the soil [5]. The chemical approaches entail introducing substances to soils that react with them or alter their chemical properties, enhancing the soil's engineering properties. Cement, lime, fly ash, bitumen, calcium chloride, and resinous compounds are examples of such substances.

As a mechanical stabilization technique, compaction entails exerting pressure from above to the soil to artificially increase its unit weight or density. This removes air from the soil mass, lowering the void ratio in the process [7]. The other mechanical stabilization techniques involve incorporating soil reinforcements into the soil, such as geotextiles and engineered plastic mesh, which are intended to hold soil in place while assisting in the regulation of soil permeability, moisture conditions, and erosion. Similarly, bigger aggregates like gravel, stones, and boulders are frequently added where more bulk and stiffness are needed to stop unintended soil migration or to enhance the soil's capacity for bearing loads [9].

According to research, stabilizing soils with modest amounts of insoluble binders including cement, lime, bitumen, and other resinous compounds significantly increased their water resistance and load bearing ability, which helped to slow the rate of cracking [3]. Additionally, for a wider variety of lateritic soils, cement stabilization has been found to be the most effective form of stabilization. Cement, though, is becoming more expensive. As a result, much work is being done to find and create substitute materials for highway construction, with products made from industrial waste like waste glass and rice husk serving as some examples.

Soil Stabilization with Glass Powder and Rice Husk Ash (RHA)

Investigated were the effects of RHA on the compaction properties, California bearing ratio (CBR), and unconfined compressive strength (UCS) tests of cement stabilized laterite soil [4]. The obtained results indicated that as the RHA content was increased from 2% to 8%, there was a general decrease in maximum dry density (MDD) and an increase in optimum moisture content (OMC). With an increase in the RHA content at the designated cement contents to their highest values at values between 4% and 6% RHA, the CBR and UCS likewise saw a significant improvement. With aging, the UCS values likewise increased.

The impacts of rice husk ash (RHA) on a lateritic soil designated as A-2-6 (0) or SW for sub-grade purposes were investigated [5]. These attributes included compaction, consistency limits, and strength. The results showed that an increase in RHA concentration increased the ideal moisture content but lowered the maximum dry density. The RHA levels used were 5%, 7.5%, 10%, and 12.5% by weight of the dry soil. Additionally, it was noted that an increase in RHA concentration, decreased flexibility, enhanced volume stability, and increased soil strength. The 10% RHA content level was the best one found.

On lateritic soil treated with up to 20% glass cullet content, experiments on grain-size distribution, consistency, specific gravity, compaction, California bearing ratio (CBR), unconfined compression, direct shear, and permeability were performed [6]. The results showed an increase in CBR and unconfined compressive strength (UCS), a decrease in cohesion-frictional angle relationship (lower cohesion (c) and higher angle of internal friction (), growth in co-efficient of permeability, k, with increased glass cullet treatment, and changes in moisture-density relationship (lower optimum moisture content (OMC) and higher maximum dry density (MDD). The glass cullet-lateritic soil blend is now possibly a suitable highway material, according to these studies, which also point to the blend's appropriateness for embankments, structural and non-structural fill, and retaining wall backfill.

On clay soil, the stabilizing impact of glass powder in various amounts, including 1%, 2%, 5%, 10%, and 15% (by weight of the soil), was evaluated [7]. The compaction test revealed that adding powdered glass improved maximum dry density values, which gradually increased up to 5% glass powder content before beginning to decline at 10% and 15% powdered glass content. For both the unsoaked and soaked treated samples, the greatest CBR values of 14.90% and 112.91%, respectively, were obtained at 5% glass powder concentration and 5mm penetration. At 10% glass powder content, the maximum cohesiveness and angle of internal friction values of 17.0 and 15.0, respectively, were obtained.

METHOD AND MATERIALS

The waste rice husk, waste glass, cement, lateritic soil, and water were the materials used to conduct this study. Glass is an optically transparent, fragile, non-crystalline, amorphous substance. Drinking glasses and window glass are two examples of the waste glass materials that are typically found in the environment. Most of them are soda-lime glasses, which contain Na_2O, CaO, and various chemicals in addition to roughly 75% silica (SiO_2) [8].

When it comes to its ingredients, silica, alkalis, and trace elements make up the majority of the organic material found in rice husk, which is an organic fiber that contains between 75 and 90 percent organic matter like cellulose and lignin. Additionally, it has a lot of ash in it (between 10% and 20%) [9]. Limestone, clay, and shale are combined to create cement, a substance that functions as both an adhesive and cohesive. The mixture is burned at 1450 degrees Celsius in a kiln, and the resulting clinker is cooled before being sent to the mills, where gypsum is added, and the cement powder is crushed [10]. Finally, water, a universal solvent, can be found in a variety of places (such wells and boreholes), but it must be unrestricted.

The Ogun Engineering Research Institute has a borrow pit where lateritic soil was gathered from depths ranging from 1.0 to 2.0 meters. The glass bottles utilized for this study were obtained from a petty trader's shop in the Ijebu East local government of Ogun state, Nigeria, using leftover brown bottles as a source material. They were crushed and examined via a sieve. The fractions that made it through a 212-mm sieve were utilized. To prevent pre-hydration during storage while left in the open air, it was immediately put in airtight containers.

The local rice milling factory in Ogun North local government of Oyo State, Nigeria, provided the rice husk ash (RHA) used in this investigation. To obtain the ash, it was burned outdoors (open air burning) at normal atmospheric pressure and temperature. The ash was then immediately stored in airtight containers. The fractions passing through the BS sieve 212m were employed for the testing after the rice husk ash was sieved through it. Ordinary Portland Cement (OPC), which was purchased from a trader with a storefront at the Ogun Engineering Research Institute, Ogun State, Nigeria, was the cement that was used. Samples of laterite, rice husk ash, powdered glass, and cement are shown in Figure 1 in that order.

Fig. 1: Laterite, rice husk ash, glass powder, and cement samples

ANALYSIS AND TESTING IN LABORATORIES.

Particle size distribution, specific gravity, and Atterberg limits tests are used to ascertain the characteristics of lateritic soil in its unaltered state. Compaction and California bearing ratio tests are used to ascertain the effects of stabilizing materials on the soil. The materials were also subjected to chemical tests to ascertain their makeup.

The liquid limit (LL), plastic limit (PL), shrinkage limit (SL), and plasticity index (PI) were all determined using the Atterberg limits tests. Based on its water content, which determines whether it exists in one of the four forms of solid, semi-solid, plastic, or liquid, these criteria describe the characteristics of a soil. The compaction test was conducted in a typical proctor mould to ascertain the maximum dry densities (MDD) and optimal moisture contents (OMC) of the soil samples. the ratio of force to weight in the California bearing ratio (CBR) test

Table: 1a

Component	Glass Powdered with Cement	Rice-Husk Ash
SiO2 (%)	28.70	68.45
Al2O3 (%)	13.50	5.21
Fe2O3 (%)	2.27	14.59
CaO (%)	53.60	13.99
MgO (%)	2.21	4.50
Ignition Loss (%)	2.05	9.11

The table presents the chemical composition of three different materials: Glass Powdered with Cement and Rice-Husk Ash. Each material is characterized by the percentage composition of specific components, including SiO_2, Al_2O_3, Fe_2O_3, CaO, MgO, and Ignition Loss.

The percentages indicate the relative presence of these components within each material. For instance, Glass Powdered with Cement has a significant amount of SiO_2 (28.70%), followed by Al_2O_3, Fe_2O_3, CaO, MgO, and a relatively low Ignition Loss. On the other hand, Rice-Husk Ash has a much higher concentration of SiO_2 (68.45%) along with varying percentages of other components. This data is crucial for understanding the elemental composition of these materials, which plays a significant role in their properties and potential applications in various fields such as construction, engineering, and materials science.

RESULTS ANALYSIS AND DISCUSSION

Chemical analysis was used to determine the stabilizing components in the lateritic soil, and the soil's classification was based on tests for natural moisture content, particle size distribution, specific gravity, and Atterberg limits. The compaction and California bearing ratio tests were used to evaluate the impacts of RHA, PG, and cement on lateritic soil.

Table: 1b

Molecular composition	
Sample	**Moisture Content**
Laterite	7.84
Cement	1.12
Powdered Glass	0.00
Rice Husk Ash	8.29

Using a Compact Energy Dispersive X-ray Spectrometer, the materials' chemical characteristics were discovered and are displayed in Table 1.

The table provides information about the moisture content of different samples: Laterite, Cement, Powdered Glass, and Rice Husk Ash.

- Laterite has a moisture content of 7.84%, indicating the presence of water within the sample.
- Cement has a relatively lower moisture content of 1.12%, suggesting minimal water content.
- Powdered Glass shows no detectable moisture content, with a value of 0.00%.
- Rice Husk Ash has a moisture content of 8.29%, implying a significant water presence.

Moisture content is a crucial factor in various applications, affecting material properties and behaviors. This data helps in understanding the water content in each sample, which can influence processes like drying, handling, and utilization in different industries.

Tab: 2

Component \ Sample	Cement	Rice Husk Ash	Powdered Glass
SiO2 (%)	28.70	68.45	89.84
Al2O3 (%)	13.50	5.21	8.43
Fe2O3 (%)	2.27	14.59	16.21
CaO (%)	53.60	13.99	12.17
MgO (%)	2.21	4.50	1.81
Ignition Loss (%)	2.05	9.11	17.78

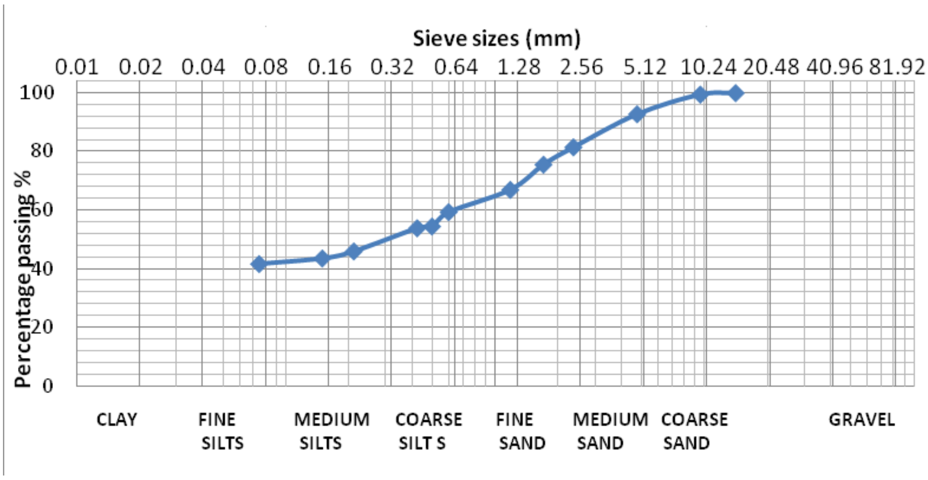

Fig. 2: Lateritic soil particle size distribution chart

SiO_2 (silica) was found to be the main component in both powdered glass and rice husk ash, whereas CaO was found to be the main component in cement because lime was employed in its manufacturing. The fact that the total SiO_2, Al_2O_3, and Fe_2O_3 percent composition of powdered glass and rice husk ash is greater than 70% indicates that they are effective stabilizers [11]. But cement has a notably high percentage of CaO, which is what gives it such strong stabilizing properties.

Moisture Content Naturally

The natural moisture content of the study's materials is displayed in Table 2 for your reference.

Tab. 3: The material specific gravity of the sample.

Sample	Moisture Content
Laterite	7.84
Cement	1.12
Powdered Glass	0.00
Rice Husk Ash	8.29

The study's materials' specific gravities are displayed in Table 3 for your reference.

Tab. 4: The sample materials' percentage of moisture content

Sample	Specific Gravity
Laerite	2.96
Cement	3.11
Glass Slivers	2.24
Rice Husk Ash	2.24

Atterberg Limit Evaluations

Table 4 displays the moisture content values acquired during the Atterberg limits tests. The natural soil sample's liquid limit, plastic limit, and plasticity index were determined to be 43.89, The shrinkage limit was determined to be 11.02% whereas the respective values were 41.0 and 2.89%.

Tab 4: Results for the liquid limit, plastic limit, and shrinkage limit

Maximum Liquid

No	Wet Sample (g)	Dry Sample (g)	Moisture	No. of Blows	M.C.%
1	40	7.3	5.3	2.0	37.74
2	30	13.5	9.5	4.0	42.11
3	21	10.2	7.0	3.2	45.71
4	14	7.8	5.2	2.6	50.00
M.C. on avg (%)		43.89			

Shrinking Range

Test Initial length (Lo), Final length (L1), Shrined length (cm), and Maximum shrinkage (%)
1 14.1 12.7 1.4 11.02

No	Wet Sample (g)	Dry Sample (g)	Moisture	M.C.%
1	1.0	0.70	0.30	45.85
2	1.6	1.15	0.45	39.13
3	1.3	0.93	0.37	38.02
M.C. on avg (%)		41.00		

Distribution of Particle Sizes

With the matching percentages kept on and passing through each of the sieves, Table 5 details the particle size distribution study of the lateritic soil. According to Figure 2, which depicts the particle size distribution curve, the soil is made up of 68% sand and 32% silt. It can be seen that 41.7% of the sample passed through the no. 200 sieve (0.075mm), which is higher than 30%, suggesting that the soil is silt and clay based. The soil is categorized as A-5 (with 'fair to poor' drainage characteristic) using the values of 43.89%, 41%, and 2.89% for the liquid limit, plastic limit, and plasticity index [12]. Therefore, stabilizing the soil is necessary.

Tab. 5: Analysis of the particle size distribution

	Dimensions (mm)	Mass Maintained (g)	Passing Percentage
14	0	0	100
9.5	2.6	0.5	99.5
4.75	33.4	6.7	92.8
2.36	56.7	11.3	81.5
1.7	29.7	5.9	75.6
1.18	43.0	8.6	67.0

0.6	38.1	7.6	59.9
0.5	24.3	4.9	54.5
0.425	2.9	0.6	53.9
0.212	39.3	7.9	46.0
0.150	12.0	2.4	43.6
0.075	9.7	1.9	41.7
Pan	1.6	0.3	0.0

Test for Compactness

On the lateritic soil with and without the additions, compaction tests were performed. Figure 3 illustrates the soil's MDD and OMC in its unstabilized natural state, which were 2.24g/cm3 and 11.65%, respectively. Each addition was incorporated into the soil at various rates of 2.5%, 5%, 7.5%, 10%, 12.5%, and 15% by soil weight. The compaction curves for the lateritic soil with RHA, PG, and cement concentration are shown in Figures 4, 5, and 6, which show

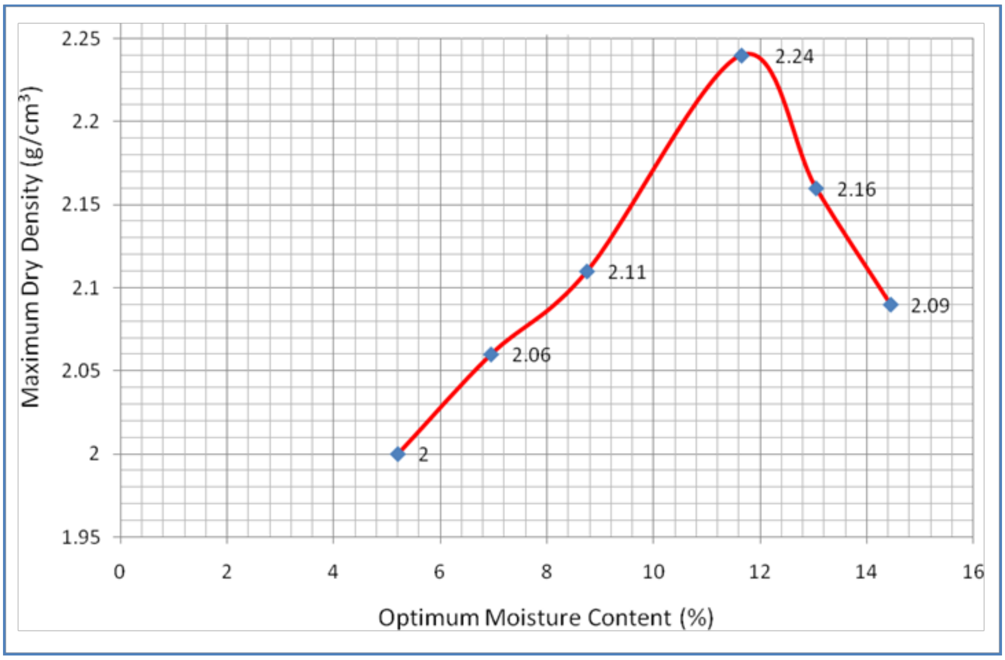

Fig. 3: The lateritic soil's inherent compaction curve

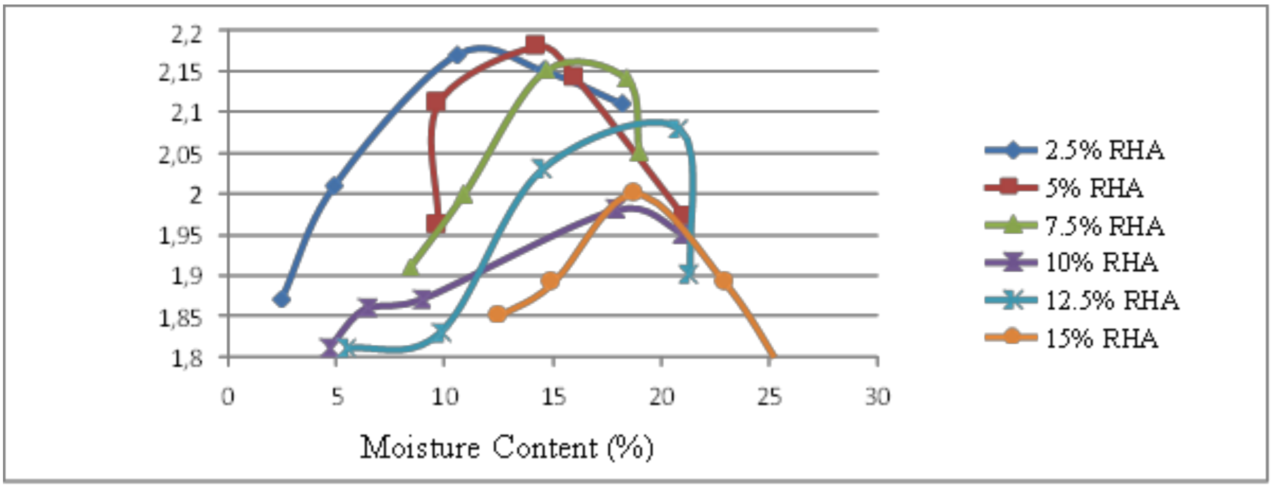

Fig. 4: Compaction curves for soils with various levels of RHA

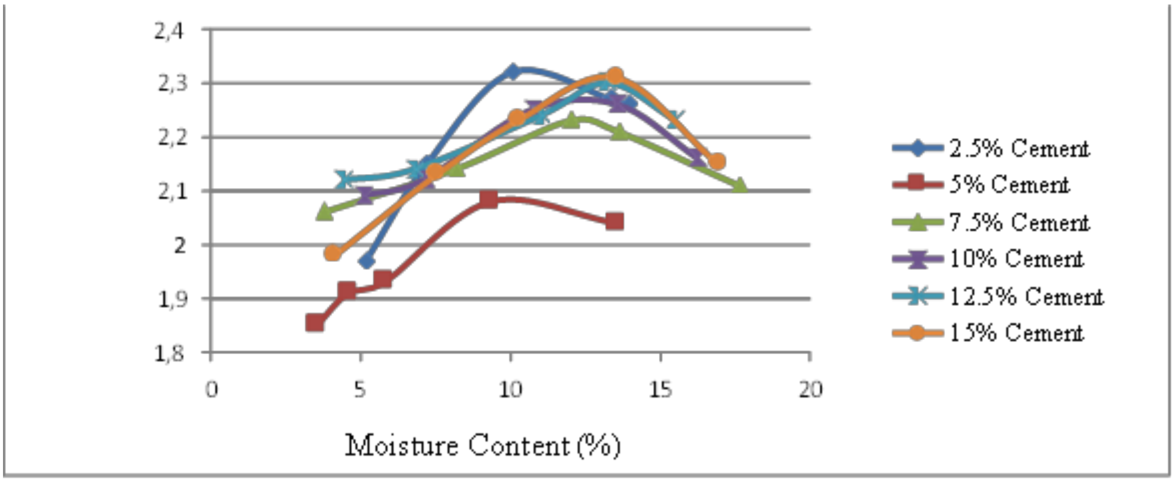

Fig. 5: Compaction curves for soils with increasing amounts of cement.

Th figures revealed the soil's MDD increased from 2.24g/cm3 in its natural state to 2.28g/cm3 (OMC = 12.31%) at 5% glass powder content and to 2.32g/cm3 (OMC = 10.06%) at 2.5% cement concentration. At 5% RHA content, it decreased, reaching a maximum of 2.18 g/cm3 (OMC = 14.3%).

Los Angeles Bearing Ratio

Figures 6 and 7 show the CBR graphs for lateritic soil that contains additives in varying percentages of 2.5%, 5%, 7.5%, 10%, 12.5%, and 15% by weight of the soil when unsoaked and soaked, respectively.

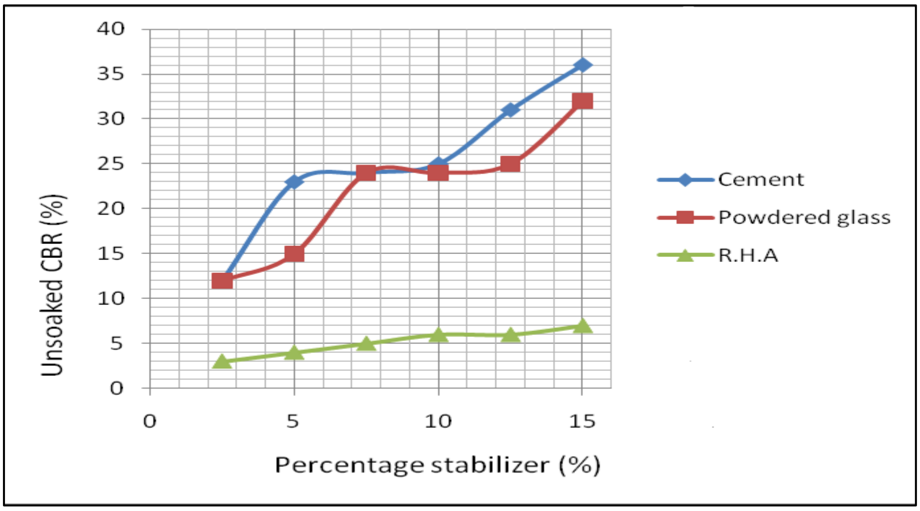

Fig. 6: CBR curves for soil with various additions that haven't been soaked

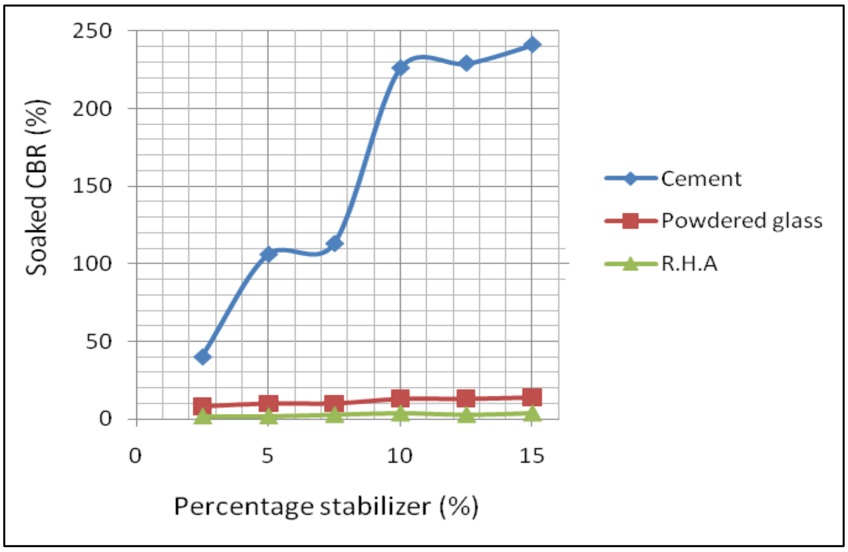

Fig. 7: Curves for the soil's soaked CBR with various additions

The unsoaked CBR curves demonstrate that values increased as the content of cement, powdered glass, and, to a lesser extent, RHA-containing soil increased. This is explained by cement's extremely high flexural strength, which correlates to the mix's high strength of soil and cement. In the soil-powdered glass mixture, the glass functions as a pozzolana (siliceous or aluminous material) that combines with calcium hydroxide in the presence of water at room temperature to form insoluble calcium silicate hydrate and calcium aluminate hydrate compounds that have cementitious properties that make the soil stronger.

Additionally, it can be shown that the unsoaked CBR of cement-rich soil (36%), as opposed to natural soil's (34%), was higher. Additionally, when compared favorably to those of the soil containing cement, the CBR values of the soil containing powdered glass (with the maximum CBR value at 32%) performed well.

The soaked CBR curves reveal that only the cement additive, whose greatest value is 241% and which stands in stark contrast to the native soil's CBR value of 21%, has a very significant positive effect on the CBR of the soil. In this instance, the RHA and powdered glass generate hardly perceptible improvements in the soil's CBR. It appears that when exposed to moisture, powdered glass loses strength.

CONCLUSION

The natural lateritic soil utilized for the study was categorized as A-5 soil utilizing the AASHTO soil classification system based on the Atterberg limits test and the particle size distribution analysis. A-5 soils are a kind of soils that must be stabilized before they can be used as subgrade material for roads.

According to the results of the compaction tests, the lateritic soil treated with cement, powdered glass, and rice husk ash can reach its maximum dry densities at OMCs of 10.06 percent, 14.3 percent, and 12.31 percent, respectively. The soil will be stronger as a result, and it will also be less vulnerable to variations in moisture content that could cause swelling and shrinkage.

The CBR experiments show that, as their percentage contents are increased beyond 15%, the CBR values of soil treated with cement and powdered glass may further rise. The CBR tests also indicate that soil treated with powdered glass will only give outcomes similar to cement. The treated soils in a dry environment. Therefore, in dry conditions, glass powder can be used in place of cement.

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Evaluation of Insecticides for the Management of Field Pea Aphids at Arsi and Westarsi Zones, South Eastern Ethiopia

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Abstract:
Aphid is one of a major yield-limiting constraints in field pea production in Ethiopia. Lack of appropriate selection and use of insecticides in controlling pea aphids is also another obstacle and lacking in the study area. Incase to fulfill the gap of information practical evaluation of available or registered insecticides was done in Arsi and West Arsi zones during the 2021 and 2022 Production seasons. Seed of field pea with a total of six treatments; five registered insecticides, one check/null application arranged in RCBD design with three replications were used during the experiment. The analyzed evaluation result showed highly significant($p<0.01$) for both field pea aphid infestation % and yield and yield traits. Considering other factors, among the evaluated treatments three insecticide; Dimethoate/ Lifothoate 40EC, Profit72EC/profenofos and Hamectin 3.6 EC respectively are recommended for the test/equivalent areas on the behalf of yield and yield component increment. Hence, I recommend that appropriate selection and well-advised use of insecticides can manage field pea aphids including other non-chemical control mechanisms.

Keywords: Evaluation, Insecticides, Field pea, Field pea aphids, management, treatments.

INTRODUCTION

Field pea (Pisum *sativum L.*); is one of the most important pulse crops, which is produced for a long time in high and mid altitude areas of Ethiopia (1800-3000masl) by small holder farmers mainly under rain fed condition (Kindie *et al.*,2019). In Ethiopia, pea weevil, *Bronchus pisum L.*, pea aphid, *Acrythosiphon pisum (Harris)*, *African* boll worm, *Helicoverpa armigera (Huber)* and adzuki bean beetle, Callosobruchus *chinensis L.* are reported to be the major insect pests of field pea (Ali *et al.*,2000).

Pea aphid, *Acrythosiphon pisum* directly weakens the plant by sucking its sap and have piercing sucking mouth parts and may vector viral diseases (Enders and Kandel,2021). Aphids feeding on peas in the early pod stage can result in lower yields due to less seed formation and smaller seed size. The economic threshold for pea aphids on the field pea cultivar is two to three aphids per plant tip when 50-75% of the plants are flowering (Jarso *et al.*,2009).

Lack of appropriate insecticides selection and rate determination against pea aphids is also another constraint and most absent in the study areas. Hence, to fulfill the gap of information using recommended insecticides rate for management of pea aphid practical evaluation on available or registered insecticides were done with the following objective.

Objective
Demonstration and recommending effectiveness of selected insecticide for pea aphid management under field condition.

MATERIALS AND METHODS

Description of the Study Area
The study was conducted at Kulumsa Agricultural research center substations (Kulumsa and Asassa) in 2021 and 2022 during the rainy season. The representative agro ecology of Kulumsa and Asassa characterized as water logged vertisols and terminal drought prone respectively (Birhan,2011) .

Table1: The experimental sites and their agro ecological descriptions

Location	Latitude	Longitude	Altitude/m.a.s.l	RF/Mean	Min temp.	Max.temp.	soil texture	PH
Asassa	07012’N	39020’E	2300	620	5.8	23.6	Clay-loam	6.2
Kulumsa	08005’N	39010’E	2200	820	10.5	22.8	Dark-clay loam	6

Experimental Materials and Testing Procedures
Five Registered insecticides and field pea seed (Bursa / EH05027-2) were used during the experiment. Six (6) treatments with one check/null application and five tested insecticides i.e., Lifothoate/Dimethoate, Abema 3% EC, Profit/ profenofos, Helarat 5 % EC, Hamectin 3.6% and null/check were arranged in RCBD design with three replications. A plot size of 3.2 m width and 4m length with 0.2 m inter row and 5cm between plants spacing was used and the spacing between plots and replications were 1m and 1.5m wide respectively. Recommended seed rate, fertilizer rates (121kg NPS/ $ha1^{-}$) and insecticides rates were applied as per as that of the particular area. Each insecticides were applied when the pest emerges to damaging level using knapsack sprayer with the rates as indicated in the table 2 .

Table 2: Rates of insecticides, water and frequency of application used during the experiment

Insecticides name	Rate of chem.	Rate of water	spray Frequency /days
Dimethoate/Lifothoate 40EC	1li/ha	150 lit/ha	7-10 days
Profit 72EC/profenofos	0.7 -1.4 lit/ha	150 lit/ha	7-10 days
Abema 3% EC	1 lit/ha	150-200Lit	7-10 days
Hamectin 3.6 EC	1 lit/ha	150-200 lit	7-10 days
Helarat 5%EC	325-400 ml	150-400 lit /ha	7-10 days

Data Collection
Stand count both at early growth stage and also during harvesting, number of pods per plant, seeds per pods, insect pest infestation %, Yield kg/ha and Thousand seed weight/TSW were collected.

Grain Yield:
In field pea experiment, yield was measured from the whole plot (gram per plot) and this is later converted into grain yield per ha (kg ha-1) to ease comparisons. First the weight of the plot yield

is adjusted to standard moisture content so that the results from the same trials in different locations and years can be compared. The standard moisture content used for field pea in Ethiopia is 9%.

Number of Pod Per Plant:
It is the number of effective pods on a plant. To determine the average number of pods per plant, five plants are randomly taken from each plot and the total number of pods were counted and divided by the total number of the same plants.

Number of Seed Per Pod:
It is the number of seed in each pod. Total number of seeds of five plants were counted and divided by the total number of pods of same plants to determine number of seeds per pod. In recent released field pea in Ethiopia, this number usually ranges between 5 and 8 on averages.

Thousand Seed Weight (gm):
It was determined from the grain yield of the whole plot as the weight of 1000 seeds adjusted to 9% moisture.

Field Pea Aphid Reaction:
Field pea aphid's infestation % recorded based on the percentage of infected leaves/ stem area damaged (Perring *et.al.,*2015). Foliar diseases are best scored when most susceptible entry in the trial receives about 75% infection by the disease based on foliage coverage. Most of the time, two scoring for breeding materials and several scoring for disease management trials are recommended (Jarso *et al.*,2009).

Data Analysis
Analysis of variance and mean separation were performed following the procedures of Gomez and Gomez (1984) and using SAS version 9.3 (SAS, 2012) and Tukey test for mean separation (SAS, 2002) and Minitab software version 17.

RESULT AND DISCUSSION

Field Performance
The study was conducted for two production seasons (2021 and 2022) at Arsi (Kulumsa) and West Arsi (Asassa), South Eastern Ethiopia. The experimental sites suggested as prone for the field pea aphid infestation. Released five insecticides were bought from market and the recent released Field pea seed (Bursa) was obtained from Kulumsa Agricultural Research Center, Pulse breeding program. During the experiment field preparation, layout, seed sowing, fertilizer applications, weeding, test insecticides applications and physiological and field pea aphid infestation data scoring were undertaken for each plot across the test locations. Each pesticides were sprayed between 7-10 days on each plot using the recommended rates(table 2).

Analysis of Variance/ANOVA
Combined ANOVA of pea aphid and agronomic parameters showed significant variation among evaluated six treatments. The analysis of variance showed highly significance difference at (P<0.01) as illustrated in table (1) below.

Table 3: Summary of ANOVA table for yield and yield trait

SV	Df	Aphid inf%	height /cm	#pod/plant	#seed/pod	TSW/gm	Yield/kgha-1
Rp	2.00	4.33	6.36	1.00	1.00	4.14	29.80
Trt	5.00	108.86**	135.51**	25**	5 **	142.23**	43.34**
Loc	1.00	2.78	69.44*	13**	3*	1.29	41.52
Trt: Loc	5.00	7.58	13.11	3.00	1.00	7.58	14.71***
MSE		8.36	16.54	2.00	0.53	14.00	12.04
CV%		19.06	2.38	13.00	11.00	1.47	11.58
LSD(<0.05)		3.41	4.80	2.00	1.00	6.37	4.09

Key 'SV=Source of variation, Df=Degree freedom, MSE=Mean square of Error, TSW=Thousand seed weight, RP= replication, Trt=treatment, Loc= Location, CV= Coefficient of variations, *= Significant at P < 0.05 and **= significant at P< 0.01, ns(non-significant) at P>0.05.

Yield and Yield Components

Mean of yield obtained in kilogram per hectare ranges from 17.11 to 39.02 among treatments. Similarly pods per plants, seeds per plants, thousand seed weight ranged from 7-12,5-7,170-188.02 respectively (table). Among the six treatments the three mean yield exceeds the average mean and the other left three mean yield result showed below the average mean i.e. ,35.66kg/ha1-(table). On the other hand, the un applied/check treatment yield results below the five tested insecticides. Therefore, application of appropriate insecticides against field pea aphid can increase productivity.

As indicated in the table () below, application of Dimethoate/Lifothoate 40EC, Profit 72EC/ profenofos and Hamectin 3.6 EC for field pea aphid management can increase field pea yield from 19.53kg/acre upto 22.09 kg/acre as compared to the check/un applied, i.e 17.11kg/acre.

Table 4: Mean yield and yield attribute for field pea genotype/ EH05027-2 tested over 2 test locations during (2021-2022) cropping

Treatments	Aphid infn%	height /cm	#pod/plant	#seed/pod	TSW/gm	Yield/kgha-1
Dimethoate/Lifothoate 40EC	10.17d	177a	12.33a	7.33a	188.02a	39.02a
Profit 72EC/profenofos	12.67cd	174.33ab	11.17a	7.16ab	187.31a	37.11a
Abema 3% EC	18.17ab	168.33bc	8.83b	6.00bc	172.21c	21.98c
Hamectin 3.6 EC	12.17cd	173ab	11.50a	6.83ab	185.9a	36.64a
Helarat 5%EC	16.33bc	169.17bc	8.83b	6,00bc	178.14ab	27.86b
Null application/check	21.5a	163.83c	7.00b	4.83c	170.01bc	17.11c
MSE	8.36	16.54	2.00	0.53	14.00	12.04
CV%	19.06	2.38	13.00	11.00	1.47	11.58
LSD(<0.05)	3.41	4.80	2.00	1.00	6.37	4.09

Note that: Treatments with the same letter are not significantly different.

CONCLUSION AND RECOMMENDATION

In the present study; among evaluated insecticides against field pea aphid, I recommend that Dimethoate/Lifothoate 40EC, Profit 72EC/ profenofos and Hamectin 3.6 EC applied field pea yields higher respectively with the recommended application rate(table) for field aphid management across and/or with equivalent test locations. Therefore, the study result signifies selections of insecticides against field pea aphids is an important aspect in addition to time, use of plant protections Equipment/ PPE and recommended rate considerations. Developing Integrated pest management (IPM) strategy, use of resistance/tolerant varieties, other agronomic practices and wise use of pesticides are also crucial points to be taken into account.

ACKNOWLEDGEMENT

I would like to thanks Ethiopian Institute of Agricultural Research (EIAR), Crop protection Directorate and National Entomology programme coordinators and Kulumsa crop protection research department coordinator, researchers, field and technical assistance for their devoted financial and technical supports during the study.

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Approach of Water Balance for Evaluating the Potential Source of Water in Gidabo Dam for Irrigation Purposes

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Abstract:
The implementation of irrigation by constructing dam is the main approach to reducing poverty by increasing productivity. Many dams are multi-purpose dams that are designed to provide water for different purposes. This paper was to study the water balance approach for evaluating the potential source of water in Gidabo dam for Irrigation purposes that is located in the Abaya-Chamo sub-basin of the Rift Valley Lakes Basin. Rainfall and inflow data of 20 years (1997-2017) was used in this study. During the periods of high runoff, the water stored in the dam typically increased and overflow through the spillway occurred. There are rainy and dry seasons in the Gidabo sub-basin. The main rainy season is from April to October with a peak rainy season from April to May and a second peak rainy season from September to October. The mean annual precipitation of the sub-basin varied from 954.98 to 1843.70 mm while mean monthly variation is between 36.82 mm to 187.93 mm. The total inflow into the dam from streams and outflow from the dam were 6387 m3/s and 6170.1096m3/s respectively and the residual volume storage was 216.9904m3/s. The physical characteristics of Gidabo river catchment has similarity characteristics.

Keywords: Water balance approach, Gidabo dam, Hydrological data, Rainfall, stream flow, Ethiopia.

INTRODUCTION

Water is an inorganic, transparent, tasteless, odorless, and nearly colorless chemical substance, which is the main constituent of Earth's hydrosphere and the fluids of all known living organisms (Wikipedia, 2022a).Water is an essential resource for lives and development. The earth's hydrosphere has about 1.36 billion km3 water and 75% of the earth's surface is covered with water containing 97% salty and 3% fresh (Ali, Mushir; Terfa, 2012). Although it needs further detailed investigation, according to the current knowledge, the country has about 124.4 billion cubic meter (BCM) river water, 70 BCM lake water, and 30 BCM groundwater resources. It has a potential to develop 3.8 million ha of irrigation and 45,000 MW hydropower production (Belete Berhanu, 2013). As the human population grows, the demand for water resources will also grow. It is well recognized that water scarcity involves water stress, water deficit, water shortage and water crisis (Fulazzaky et al., 2017). The water balance states that the inflows to any water system or area is equal to its outflows plus change in storage during a time interval. In hydrology, a water balance equation can be used to describe the flow of water in and out of a system (Wikipedia, 2022b). The water regime of a region can be investigated using the water balance approach for the planning and management of available resources at the watershed scale. Water balance is commonly utilized for watershed management practices because it is vital to understand the relationship between physical parameters of the watershed and hydrological components for any watershed development effort (Dananto et al., 2022).

Today Ethiopia is struggling with poverty. The implementation of irrigation by constructing water storage dam is the main approach to reducing poverty by increasing productivity (Dananto et al., 2022). Agriculture is the main stay of Ethiopian economy. The Government of Ethiopia has given the highest and urgent priority to increasing food supply by improving and strengthening agricultural production system in the country (FDRE Ministry of Water, 2019). Ethiopia is called the water tower of Africa due to its combination of mountainous areas with a comparatively large share of water resources in Africa. Only a fraction of this potential has been harnessed so far, 1% at the beginning of the 21st century.

In order to become the powerhouse of Africa, Ethiopia is actively exploiting its water resources by building dams, reservoirs, irrigation and diversion canals and hydropower stations. The benefits of the dams are not only limited to hydropower. Many dams are multi-purpose dams that are also designed to provide water for irrigation, drinking water and flood control. However, hydropower is expected to be the main benefit of the dams (Contributors, 2021). Dams are hydraulic structures used to store, control and divert water, impounding it behind the upstream side of dam in a reservoir for different purposes (https://byjus.com/biology/advantages-of-dams/, 2022).

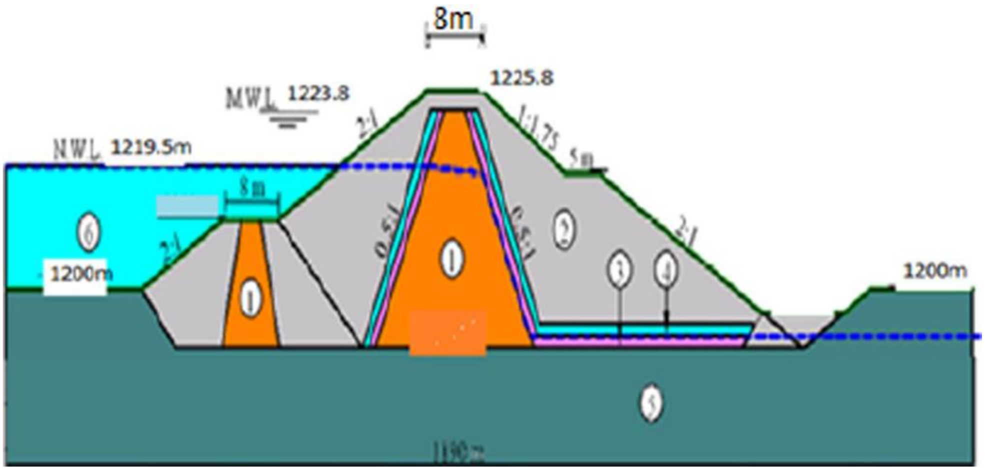
Gidabo dam is rock fill dam, which is constructed by Federal Water Works construction Enterprise of Ethiopia, to irrigate more than 14,000 ha of land (Desta & Belayneh, 2021). There are different economic developments downstream of this dam and one of this is its usage for irrigation purpose for the case of food security. Depending upon the suitability of soils the command area of Gidabo Irrigation Project has been identified on both sides of the river course. From the total study area of about 15000 hectare, leaving the uncultivable area, high lands, rock exposures and streams, the Gross Command Areas on left and right side of Gidabo river are 7113 hectare and 2763 ha respectively, totaling to 9876 ha (FDRE Ministry of Water, 2019). The Gidabo Irrigation Dam, constructed with an estimated cost of 1.1 billion Br and it irrigate 27,043ha of land, 60pc of which lie in the former region, while the rest in the latter.

This study focusses on evaluating approach water balance for the potential source of water in Gidabo Dam for Irrigation purposes. The main dam characteristics and its cross-sectional image is shown in the following table 1 and figure 1.

Table 1: Characteristics of Gidabo Dam

Dam characteristics	Value	Unit
Height of Dam	25.8	m
Catchment area	14,000	ha
Crest length	335.52	m
Storage capacity	102.4	mm^3
Submerged upstream area	1003	ha
Spillway crest level	1219.5	mamsl
Total crest length of spillway	70	m
Discharge capacity	1417	m^3/s
Spillway type	side ogee weir	-

(WWDSE, 2008)



(WWDSE, 2008)
Figure 1: Cross section of Gidabo dam

Objective of Study

The main aim of this paper was to study the water balance approach for evaluating the potential source of water in Gidabo dam for Irrigation purposes. In addition to the above main objective, the following specific objects are also carried out in this study.

1. To estimating the runoff inflow into the dam
2. To identify the sub- catchments and physical characteristics of Gidabo River catchment

Significance of Study Area

Water balance estimation is important to assess the current status and trends in water resource availability in an area over a specific period of time. Furthermore, water balance estimates strengthen water management decision-making, by assessing and improving the validity of visions, scenarios and strategies. Effective water balance approach in dam requires identification of inflow in to the dams. The knowledge of water balance of lakes and reservoirs is an essential component of water management. Today Ethiopia is struggling with poverty. The implementation of irrigation by constructing water storage dam is the main approach to reducing poverty by increasing productivity. Additionally, the significance this study is that it can be used as an important input for the following major aspects: base line for the training, research and community service for nearby Universities, non- governmental Organizations (NGOs) and other interested parties; the output of the study will also be used as information for the future NGOs and governmental offices

METHODOLOGY

Background of the Project

The project area is located in the Abaya-Chamo sub-basin of the Rift Valley Lakes Basin situated in the southern part of Ethiopia, within the administrative Regions of SNNPRS, Sidama and Oromia Regions (Tesfaye et al., 2021). The eastern part is highland having a peak of 3065 m asl and the western part is lowland where the lowest altitude is about 1156 m asl. The river originates from north eastern mountain of Soka-Sonicha, having a length of about 120 km and empties in to Lake Abaya with an annual mean discharge of 550 Mm^3(Belihu et al., 2018). It falls in Abaya district of Borena zone of Oromiya region and Dale district of Sidama zone of SNNPRS near Dilla town to East of Lake Abaya. The project area lies in the low lands, very close to the Dure and Gola marsh. It lies approximately between 6°20' and 6° 25' N Latitude and 38° 05' and 38°10' E Longitude and an average elevation of 1190 m a. s. l (see Figure 2). The study area falls within the traditional Kola agro-climatic zone, which can be classified as semi-arid climate. The climatic data are recorded from the four observation stations Amaro Kelo, Bilate, Dilla and Bule Hora, located nearby the project area. The average minimum temperature varies from 10.2°C in Dec to 12.3°C in July and the maximum temperature ranges from 25.9°C to 30.5°C in February. The average annual rainfall recorded so far in the project command is 1303 mm with minimum of 34.9 mm in January and maximum of 208.3 mm in April (WWDSE, 2008).

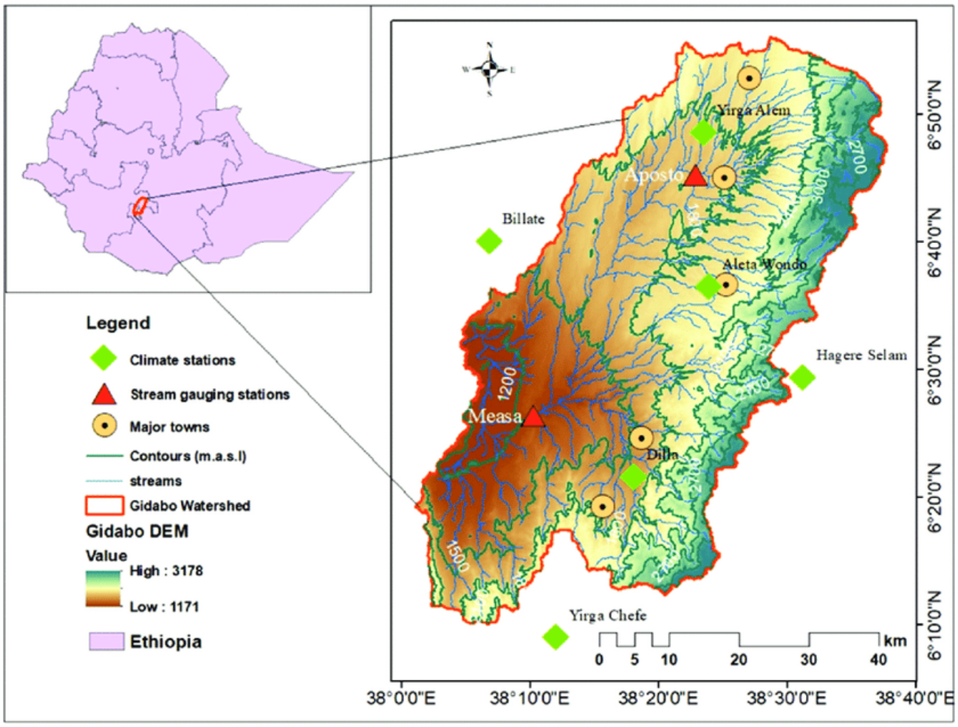


Figure 2: The locational map of Gidabo dam showing stream gauging stations, climate stations and stream

Hydrological Data Compilation

In the Gidabo river basin (total area of 3386 square kilometers), there are four stream gauging stations, namely, Aposto (area of 703 square kilometers), Kola (area of 145 square kilometers), Badessa (area of 76 square kilometers), and Measso (area of 2462 square kilometers) with data periods of 1997–2015 for Aposto, Kolla, and Badessa, whereas Measso has stream flow data from1997–2006. The daily flow data of all stations were collected from the Ministry of Water and Energy of Ethiopia. For all stations (except Measso), daily flow data were available up the year 2015, and a regression model ($r2 = 0.85$) was used to generate the data of Measso from its upper station Aposto. Figure 3 in below shows all the guage stations of the Gidabo River basin monitoring.

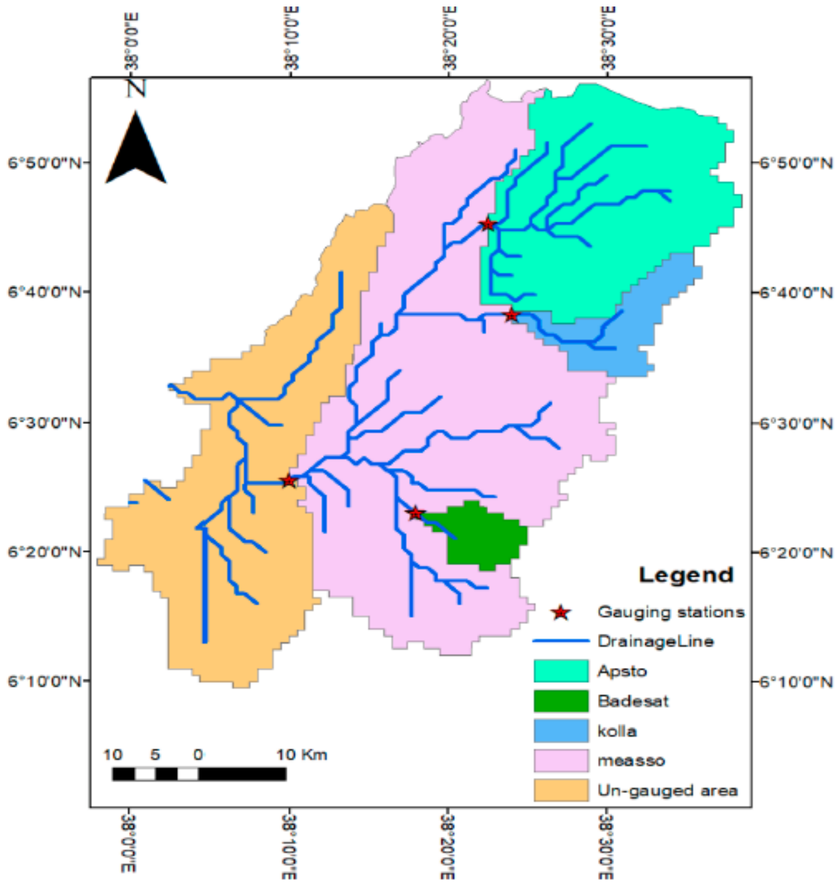


Figure 3: Gidabo river basin monitoring gauge stations

The procedure used to analyze water balance for managing a dam will vary depending on typical design of dam, river catchment area, local climate and rainfall intensity. The Gidabo Dam could be filled with water mainly from rainfall because Gidabo River, fed by small streams flowing into the dam. The spatial and temporal patterns of annual rainfall variability to show the amount of rainfalls based on the rainfall data monitored from the single rain gauge installed for covering the Dam catchment area. The overall methodology used to carry out the study was shown below in figure 4.

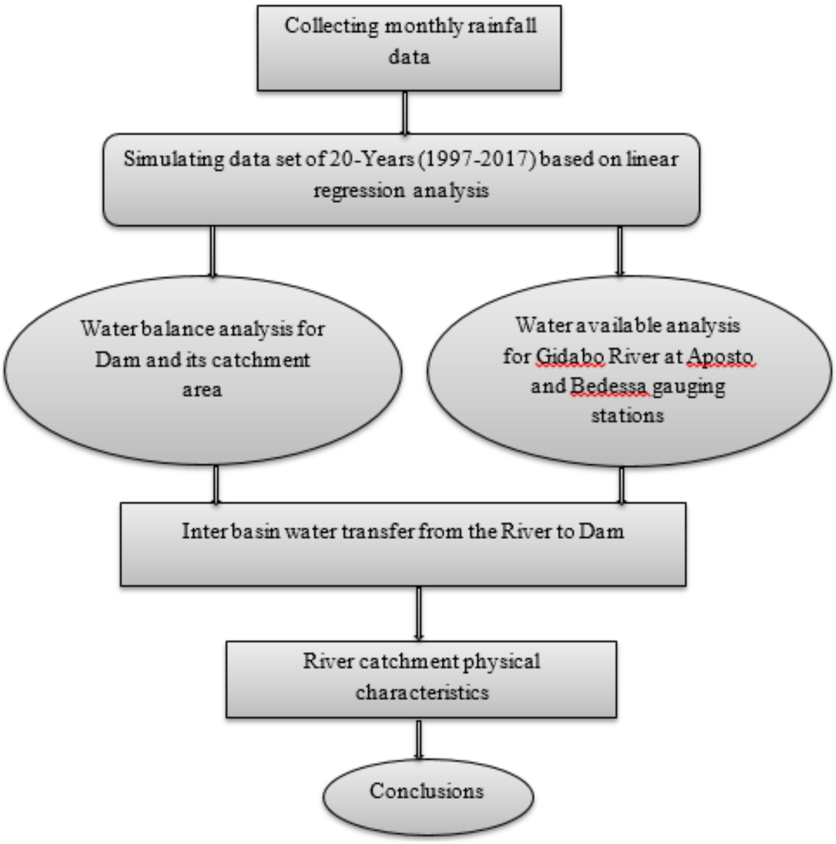


Figure 4: Flowchart of Gidabo dam water balance analysis

Rainfall Data

Climate data used for model input was collected from Ethiopian Meteorological Agency (EMA). These include rainfall, maximum and minimum temperature relative humidity. In and around Gidabo River Catchment, there are 24 stations; but, only some of them have reliable long-term data. Thesien polygon method was used to check whether the rainfall stations are influential or not. Using these criterion 13 stations was selected for further analysis the list of these stations displayed in. A monthly rainfall data of 20 years from selected meteorological stations starting from 1997-2017 was used.

Discharges for Gidabo River

The Gidabo River catchment area is one of the leading coffee production areas in Ethiopia with a basin size of 3,302 km2 (1,275 sq mi). The river is not navigable and it has no notable tributaries, but the river basin contains a sizable number of ~97 small rivers and streams in three sub-basins. The average annual discharge at its mouth amounts to 11 m3/s, with peak discharges reaching ~40 m3/s in spring and autumn, while in summer and winter the discharge can drop to 2-3 m3/s (Contributors, 2018). The river flows from the northeast and crosses the highway of Addis Abeba to Dilla at Aposto Town where it is gauged. The average flow of the river at the Aposto station is 17.35 m3/s (MOWR, 2010). The 17 years monthly mean stream flows from two stations i.e., Aposto station and Bedessa station of Gidabo River Catchment in period of 1989 - 2006 was used. The Digital Elevation Model (DEM) of 30m by 30m was collected from Ethiopian Construction Design and Supervision Works Corporation.

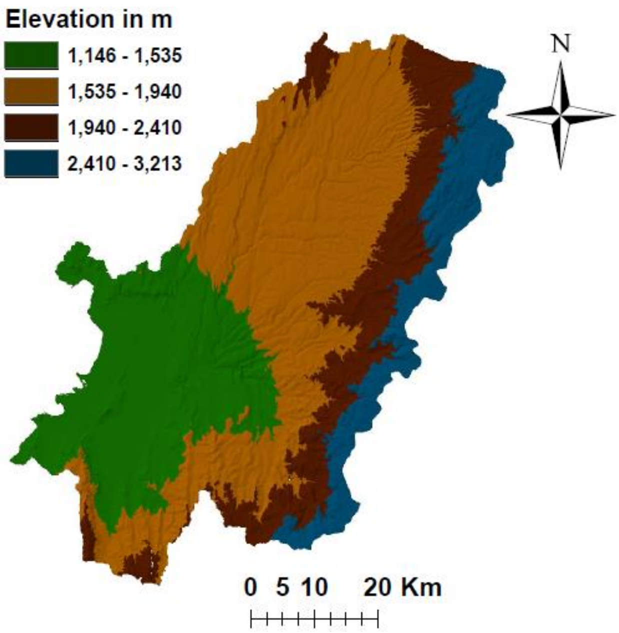


Figure 5: DEM of Gidabo River Catchment

The catchment areas of Gidabo River above the gauging stations are determined by the surface area of all lands which drains toward the river from above that point. River discharge at Aposto and Bedessa gauging stations depends on rainfall on the catchment areas and inflow or outflow of groundwater to or from the areas, stream modifications such as dams and irrigation diversions, snow and season, as well as evaporation in any temperature and evapotranspiration from the area's land and through plants. All this information must be used in a multiple regression analysis to build a regression equation of the form:

$$Q = d * P + e * S + f * N + g * T + h * IW + i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (1)$$

Where:
Q = River discharge (m^3/s)
P = Average monthly precipitation (mm)
S = Season along the year with S = 1 for summer, S = 2 for autumn, S = 3 for winter and S = 4 for spring N = Snow with N = 0 for no snow, N = 1 for snowfall and N = 2 for snowmelt
T = Temperature (°C)
IW = Water supply for irrigation (m^3/s)
d = -0.189m^3/s, e = 23.583m^3/s, f = 36.849m^3/s, g = 1.272m^3/s°C, h = -14.916 and i = -40.004m^3/s are all multiple regression coefficients.

Estimation of Water Balance for the Dam

Balancing reservoirs are required to balance supply with demand. Water balance basically looks at the balance between inputs and outputs, and thus the water balance equation is the basic formula to quantitatively study hydrology and water resources (Dawidek & Ferencz, 2014). This study used a water balance equation to calculate the variability of inflow available for Gidabo Dam, such that:

$$\text{Inflow to the dam} - \text{Outflow from the dam} = \text{Rise in the water surface of the dam} \ldots (2)$$

Computing of the Inter Basin Water Transfer

In this study, the seasonal patterns of river discharge for Gidabo River need to be reviewed to make it more appealing to inter basin water transfer, according to the amount of annual water resources available. As the causality of Gidabo catchment basin characteristics according to hydro morphological reference conditions was hardly considered in a deductive approach of the inter basin water transfer an integrated analysis of the potential water availability for the rationalization of water transfer properties from River to Dam can be developed on the basis of different alternative scenarios (Galia & Hradecký, 2014).

RESULTS AND DISCUSSION

Presentation of Hydrological Data for Water Balance Analysis

A plot of the rainfall data recorded from the Gidabo Dam station versus those derived from the calculations gives a linear expression of: $P_1 = 1.284\, P_2$ with $R^2 = 0.7125$ where P_1 is the rainfall monitored at the Dam rain gauge station (in mm month_1) and P_2 is the rainfall data calculated (in mm month_1). The results in figure 6 and 7 below shows the seasonal pattern average yearly rainfall modelling for Gidabo Dam station from making long-term forecasts of 20 years (1997–2017); thus, the inter-annual rainfall variability drives the Gidabo Dam inflow variability. As a whole, the intensity of rainfall shows a decreasing trend from year to year and may result in a decreasing trend of water volume in the reservoir, in which should be potentially sufficient water available for irrigation purposes. Figure 6 and 7 in below also shows the seasonal pattern of runoff inflow into the Dam for a period of 20 years (1997–2017). Inflow into the dam in year 1998, recorded at a rate of 199.3 m^3/s was the highest inflows recorded. The lowest inflow on the record, i.e., the minimum annual streams inflow available for the reservoir, was recorded at a rate of 79.6 m^3/s in year 1999. In terms of the seasonal pattern of runoff inflow into the Dam during the last 20 years (1997–2017), the figure shows a varying trend of the inflow. But it shows decreasing trend between 2001-2003 and again from 2006-2009. Therefore, the important economic concepts that need future research attention for a scheme of integrated economic-hydrologic water management include transaction costs, agricultural productivity effects of water allocation mechanisms, inter-sectoral water allocations, environmental impacts of water allocations and property rights in water for different allocation mechanisms.

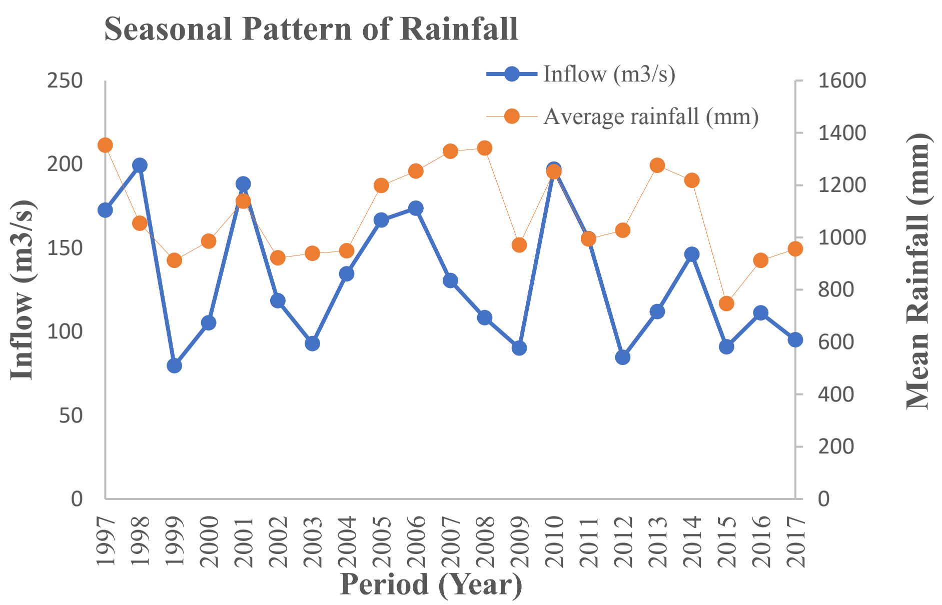


Figure 6: Patterns of inflow rainfall on the catchment area of Gidabo Dam.

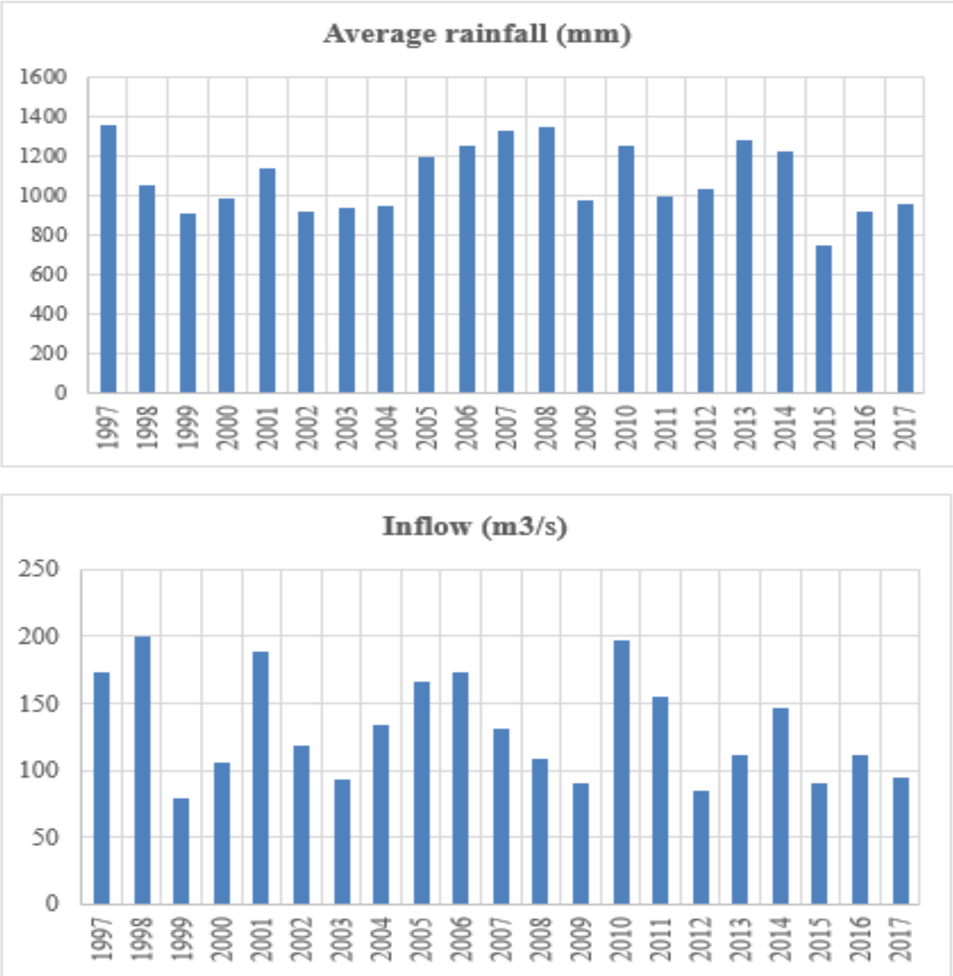


Figure 7: Extended term annual precipitation and Inflow graph (1997-2017)

Because people live mostly in the nearby of the dam, the water levels of the dam can be affected by water withdrawals for human needs. It is recognized that the withdrawal of water is one of the outflows released from the Dam.

The information about the volume of water lost through evaporation, to illustrate its significance to net water supply per year in comparison to the annual outflow from the dam, needs to be verified. The use of pan evaporation data could be useful for estimating the evaporation of the stored water, but transpiration and evaporation of the intercepted rain on aquatic vegetation are still difficult to estimate and would most likely be negligible. Even though the volume of water lost through evapotranspiration would be quite significant, the measurement of water loss from the dam based on the evaporation estimates does not accurately represent actual losses. However, the measurements and observations could confirm the significance of evaporation and help explain the influence of complex interactions among the hydro-meteorological factors that affect the water levels. For this study, evapotranspiration with a rate of 92 m^3/s of the stored water, corresponding to approximately 14.21% of the annual outflow, was estimated for the Gidabo Dam only based on the pan evaporation data. During the periods of high runoff in the years of 1998, 2001 and 2010, the water stored in the dam typically increased and overflow through the spillway occurred. There are rainy and dry seasons in the Gidabo sub-basin. The main rainy season is from April to October with a peak rainy season from April to May and a second peak rainy season from September to October. These two peak seasons are separated by the relatively small rainy season in June to August while the rest seasons from November to February are dry. The mean annual precipitation of the sub-basin varied from 954.98 to 1843.70 mm while mean monthly variation is between 36.82 mm to 187.93 mm as it shown in figure 8 below

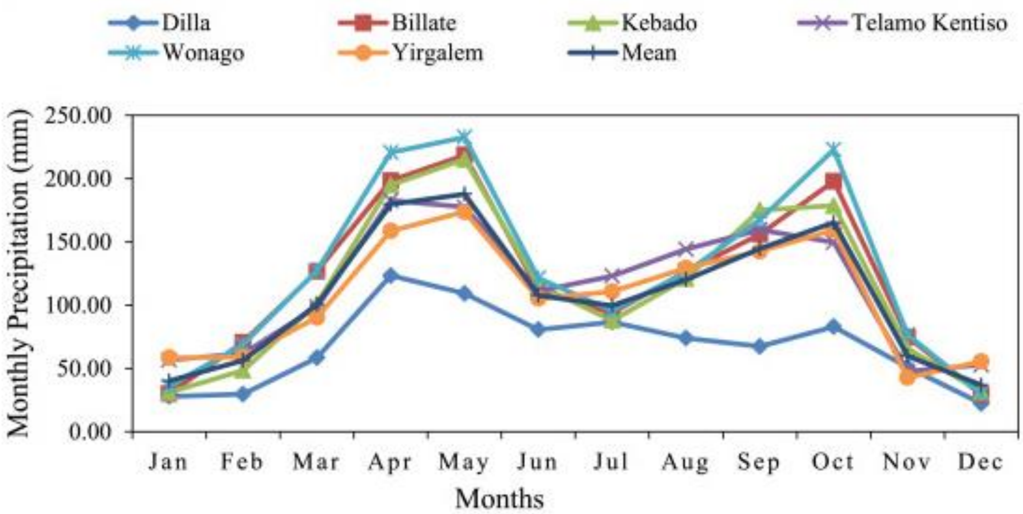


Figure 8: Spatial variation of mean monthly precipitation in Gidabo river sub-basin

As the total inflow from existing streams indicate, the composite inflow hydrograph resulting from triangular hydrographs at dam site by using standard dimensionless SCS unit hydrograph method has a peak flow of 6387 m3/s as shown on figure 9 below.

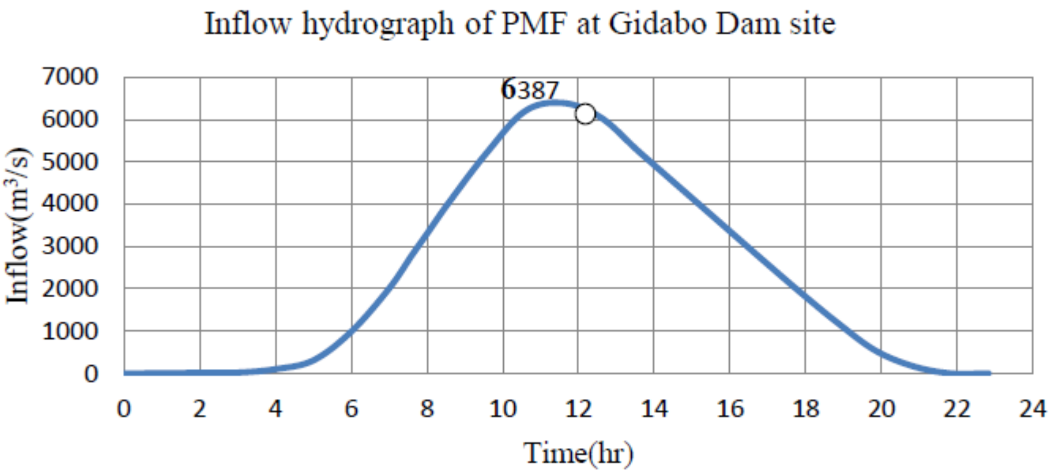


Figure 9: Total inflow hydrograph

According to the water balance analysis, a total volume of 6387.1m^3/s inflow into the dam was estimated from the inflow volume from streams and a total volume of 6170.1096 m^3/s outflow from the dam was estimated as the sum of outflow volumes due to evaporation (644.1375 m^3/s) and water withdrawals (5525.971m^3/s). The residual estimated storage of water that cannot be released from the dam should be 216.9904m^3/s as indicated in table 2.

Table 2: Water balance analysis for Gidabo Dam

Items	Volume	Unit
Total volume at FSL	123.674	Mm^3
Dam volume at max. level	102.4	Mm^3
Dam volume at normal level	62.318	Mm^3
Annual mean inflow from streams to dam	6387.1	m^3/s
Outflow volume due to evaporation	644.1375	m^3/s
Water withdrawals	5525.971	m^3/s
Total volume of outflow from the Dam	6170.1096	m^3/s
Residual volume storage	216.9904	m^3/s

Sub- Catchments of Gidabo River Catchment

The physical catchment characteristics of the two gauged sub-watersheds (Aposto and Bedessa) and Gidabo River Catchment outlet were determined from 30m DEM as shown in figure 10 below.

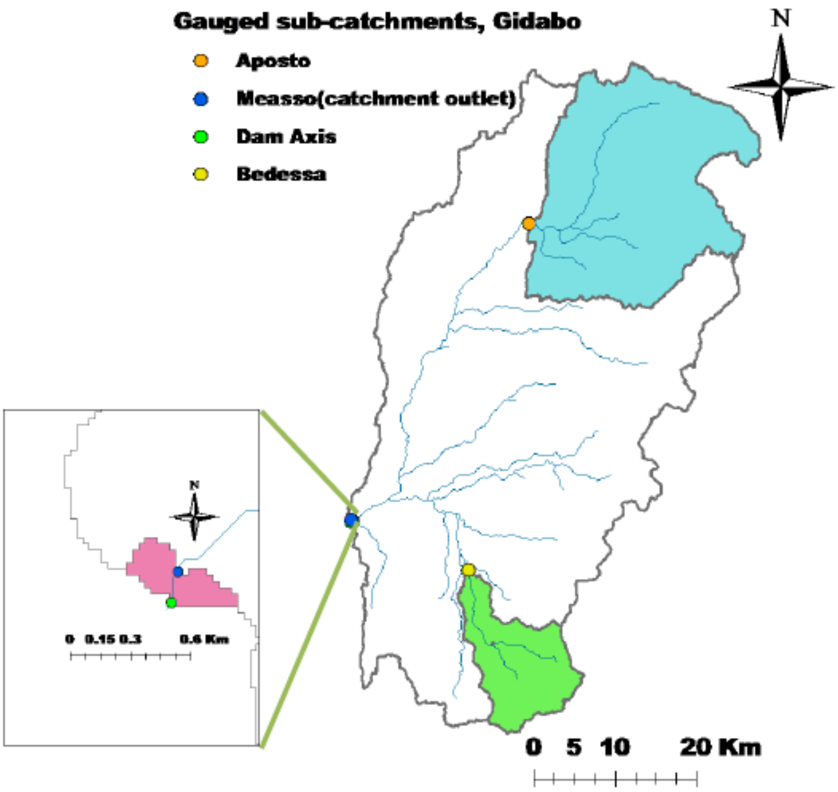


Figure 10: Sub-catchments in Gidabo River Catchment

Gidabo River Catchment Physical Characteristics

Generally, runoff in the watershed is affected by the physical catchment characteristics. These are climatic characteristics, geography and physiographic, land use and cover conditions. The climatic characteristic of Gidabo River Catchment is similar. The circularity index of both gauged catchment and Gidabo River Catchment is more or less similar. The result indicated that the catchment is elongated with smaller CI value. This result also approved by the elongation ratio. The slope of the Gidabo River Catchment also showed similarity. The drainage density of the Gidabo River Catchment also shows similarity with a low drainage density both for gauged catchment and the Gidabo River Catchment. This means the catchment drained poorly with a slow hydrologic response. The land use and land cover conditions in the Gidabo River Catchment are mainly dominated by forest land followed by crop land for gauged and for Gidabo River

Catchment. Generally, the results of selected physical characteristics of the catchments are shown in the table 3 below.

Table 3: Physical characteristics of Gidabo River Catchment

Characteristics	Apposto watershed	Bedessa watershed	Measo watershed (Gidabo outlet)
Area (km^2)	646	149.8	2947
Perimeter (Km)	174	90	416
Mean annual rainfall (mm)	1214	1495	1499
Elevation (m)	1848	1789	1851
Main stream slope (SS)	31	36.4	15
Sub-basin slope (%)	16	26	15
Land use (2018)			
FRSE (%)	75	61	55
PAST (%)	2	0.12	4
AGRL (%)	16	35	30
Drainage length (Km)	48.9	28.3	134
Drainage density	0.076	0.189	0.045
Catchment shape indices			
Circularity index (CI)	0.268	0.228	0.213
Elongation ratio (ER)	1.13	1.02	0.99

CONCLUSIONS

In this study the following points given as a conclusion. The points are:

1. Direct measurements and report data calculation was used to create a compilation of the long-term hydrological datasets for a period of 20 years (1997-2017).
2. The assessment of the trends in long-term series of hydrological data was of paramount scientific and practical significance for analyzing the amount of water available in Dam and the discharge of the river.
3. Since the amount of runoff in the catchment is affected by the physical characteristics of the catchment, identification of the physical characteristics of the catchment was of the basic thing in this study; accordingly, the climatic characteristic of Gidabo River Catchment is similar.
4. The slope of the Gidabo River Catchment also showed similarity.
5. The drainage density of the Gidabo River Catchment also shows similarity with a low drainage density both for gauged catchment and the Gidabo River Catchment; this means the catchment drained poorly with a slow hydrologic response.
6. The land use and land cover conditions in the Gidabo River Catchment are mainly dominated by forest land followed by crop land for gauged and for Gidabo River Catchment

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