



CLEAN ENERGY TRANSITION FOR NATIONAL SECURITY AND INDUSTRIAL GROWTH



RAESON

**EDITED BY PROF. E. L. EFURUMIBE
AND PROF. S. UMARU**

Clean Energy Transition for National Security and Industrial Growth

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**EDITED BY PROF. E. L. EFURUMIBE
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Table of Content

Title Page	i
From The President’s Desk	ii
Table of Content	iii-iv
Keynote Lecture by Professor O. V. Ekechukwu BIOENERGY GENERATION AND SUSTAINABLE ENVIRONMENT	v - xiv
CONTROLLER AREA NETWORK FLEXIBLE DATA ATTACK DETECTION USING DEEP LEARNING MECHANISM	1 -10
Elvin Ugonna Eziama, Ali Dan, Dagogo Godwin Orifama, Ikechukwu Nwagbo Enumah, Gbenga Akingbulere, Ugochukwu Franklyn Esiowu, Benedict Onochie Ibe, Adebola Folorunso, Dominic Chinedu Ogbuagu, Mujeeb Shittu, Habeeb Shittu, Jacob A. Jacob, Simon Ifeanyi Opara, Gbubemi Erics, Oladapo Ogunnaike, and Joy Nma Anyanacho	
EXPLORING THE THERMAL MANAGEMENT AND PERFORMANCE OF LITHIUM-ION BATTERY STORAGE IN BATTERY ELECTRIC VEHICLES (BEVS): A REVIEW	11-19
Ibrahim Yahuza, Abubakar Isah, and Garkuwa Yahuza Adamu	
AE-TCN: AUTOENCODER-DRIVEN TEMPORAL CONVOLUTIONAL NETWORKS FOR SECURE AND EFFICIENT COLD CHAIN MONITORING	20- 26
Elvin Ugonna Eziama, Solomon Goldman Olumba, Gerald Ibe Okwe, Ugboaja Samuel Gregory, Chukwudi E. Agbaraji, Henrietta U. Udeani, Adebola Folorunso, Chioma Violet Oleka, Jacob A. Jacob, Henry I. Nnamdi, Haruna Ogweda, Simon Ifeanyi Opara, Oladapo Ogunnaike, Joy Nma Anyanacho, and Gbubemi Erics	
INTEGRATED INTELLIGENT SYSTEM FOR SOLAR-POWERED PUMP FOR PRECISION RICE IRRIGATION	27 -31
Samaila Umaru, Muhammad Habib Mohammed, Reuben Ambi Shekarau, Ameer Mohammed, Muyideen Omuya Momoh, Aminu Sahabi Abubakar, Akin Aderibigbe Adebomohin, Ibrahim Yahuza, Mohammed Shariff Lawal, Fatima Badru Ibrahim, Muhammad Dauda, Abbas Sani Dangaji, Abdullahi Ubaidullahi Munkaila, Usman Ozeheve Yahaya, Khalid Kabir Dandago, Emmanuel Atta Zebedee, and Abubakar Isah	
CROSS-LAYER OPTIMIZATION USING FEDERATED META-LEARNING	32 -40
Elvin Ugonna Eziama, Okochi Prisca Ijeoma, Dagogo Godwin Orifama, Ugochukwu Franklyn Esiowu, Benedict Onochie Ibe, Ali Dan, Ikechukwu Nwagbo Enumah, Dominic Chinedu Ogbuagu, Mujeeb Shittu, Habeeb Shittu, Haruna Ogweda, Jacob A. Jacob, Gbenga Akingbulere, Joy Nma Anyanacho, Oladapo Ogunnaike, and Gbubemi Erics	
PROCESSING OF IGBETI SHEET AEROMAGNETIC DATA FOR MINERAL EXPLORATION FOR RENEWABLE & ALTERNATIVE ENERGY RESOURCE	41 –46
Martina Onyinye Eze, and Fausta Chukwunwike Anyadiegwu	
6G NETWORK SLICING ATTACK DETECTION USING AI-DRIVEN MECHANISM	47 – 55
Elvin Ugonna Eziama, Dagogo Godwin Orifama, Okochi Prisca Ijeoma, Ikechukwu Nwagbo Enumah, Benedict Onochie Ibe, Ugochukwu Franklyn Esiowu, Dominic Chinedu Ogbuagu, Mujeeb Shittu, Habeeb Shittu, Ali Dan, Simon Ifeanyi Opara, Gbenga Akingbulere, Jacob A. Jacob, Oladapo Ogunnaike, Ahmed Kolawole Wahab, and Joy Nma Anyanacho	

HEAVY METALS ASSESSMENT OF UNDERGROUND WATERS IN ABA METROPOLIS	56- 66
Felicia Uchechukwu Okwunodulu, and Obinna Ajike Igwe	
EFFECT OF VARYING SOURCE CHARGE SIZE ON SEISMOGRAM DATA QUALITY IN KWALE, NIGER DELTA, NIGERIA	67 -70
Ifeanyi Ikechukwu Chukwuemeka Agbodike, and Emmanuel Azubuike Ozogbu	
RISK ASSESSMENT OF BOREHOLE WATER QUALITY IN OKPOMA, YALA LGA, CROSS RIVER STATE, NIGERIA	71- 79
B.U. Nwaka, C. Ehirim, E.O. Ogueri, and V.N. Nwaughu	
PRODUCTION AND CHARACTERIZATION OF BIODIESEL FROM <i>CASCABELA thevetia</i>, CASTOR OIL AND THEIR BLEND	80 -85
Anthony Chibuzo Ofomatah, and Ugwuja Jacintha Onyinyechukwu	
EVALUATION OF AMBIENT RADIATION PROFILES AND INFLUENCE ON RENEWABLE ENERGY PLANNING IN AGUATA L.G.A., NIGERIA	86-92
Vivian C. Ezemba	
GEOPHYSICAL ESTIMATION OF THE ENVIRONMENTAL IMPACT OF SAND MINING ON THE NWORIE RIVER CHANNEL USING ELECTRICAL RESISTIVITY TOMOGRAPHY (ERT) AND GROUND PENETRATING RADAR (GPR) DATA, IMO STATE , NIGERIA	93-107
B.O. Eke, B.C. Ejiogu, V.N. Nwaughu, C.O Nwokocha, B.U. Nwaka, and D.O. Mba	
IMPACTS OF SUGARCANE BAGASSE ASH ON THE STRENGTH CHARACTERISTICS AND DURABILITY OF CONCRETE	108- 114
Tasiu Ashiru Sulaiman, Yusuf Yau, Ashiru Mohammed, Isah Garba and Adam Ado Sabari	
SUITABILITY OF LOCUST BEAN HUSK ASH AS A PARTIAL FILLER REPLACEMENT IN HOT MIX ASPHALT DESIGN	115-121
Ashiru Mohammed, Yusuf Yau, Tasiu Ashiru Sulaiman, Ibrahim Aliyu, and Kabiru Abdullahi Waziri	
HARNESSING FOOD AND NON-FOOD PLANTS AS ALTERNATIVE SOURCES OF RENEWABLE ENERGY	122- 148
Peter A. Akah	

BIOENERGY GENERATION AND SUSTAINABLE ENVIRONMENT

Invited Keynote Lecture

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Environment

The natural environment is the biological and physical surrounding of an organism or population including all the biotic and abiotic factors along with their chemical interactions that affect an organism/population and have an influence on their survival, development and evolution.

Sustainability

We shall restrict our definition in the sense of human sustainability on earth and as a part of the concept of sustainable development, which is the development that meets the needs of the present without compromising the ability of future generations to meet their own needs.

Environmental Sustainability

Environmental sustainability involves making decisions and taking actions that are in the interests of protecting the natural world, with particular emphasis on preserving the capability of the environment to support human life.

At the global scale, scientific data now indicates that humans are living beyond the carrying capacity of a finite planet Earth and that this cannot continue indefinitely.

In the light of environmental degradation, climate change, overconsumption, and societies' pursuit of indefinite economic growth in a closed system, it is increasingly doubtful that human societies will achieve environmental sustainability.

The Greenhouse

An extensively glazed (typically of glass or plastic) building which is thermally conditioned within desired range, used for cultivating tender plants or growing plants out of season.

- Short wavelength visible light passes through the transparent glazing and is absorbed by interior surfaces which heat up and emit long-wave infrared radiation.
- Air warmed by the heat emitted from warmed interior surfaces is retained within the enclosure by the glazed roof and walls, that are not transparent to long wavelength infrared (heat) radiation.

The Greenhouse Effect

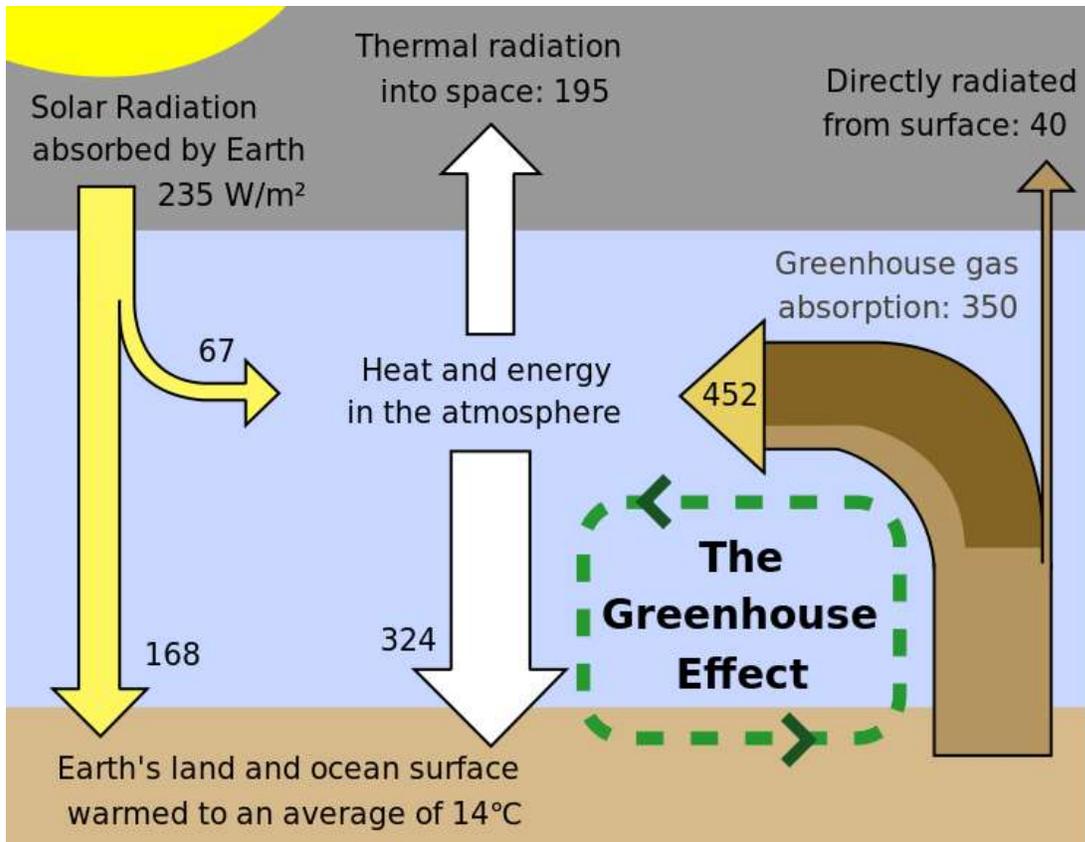
An atmospheric heating phenomenon:

- Caused by short-wave visible solar radiation being readily transmitted inward through the earth's atmosphere,
- Absorbed by the earth's surface whereas
- Longer-wavelength thermal radiation emitted by the earth's surface is less readily transmitted outward,
- Owing to its absorption by certain atmospheric gases referred thus as greenhouse gases.
- Infrared radiation is absorbed by greenhouse gases, which in turn re-radiate much of the energy to the surface and lower atmosphere.
- Hence, the temperature within earth's immediate atmosphere is higher than it would be if direct heating by solar radiation were the only warming mechanism.

Greenhouse Gases (GHG)

Gases in the atmosphere that:

- Absorb and emit radiation within the infrared (thermal) range
- Allow solar radiation to enter the Earth's atmosphere, but prevent the infrared radiation emitted by the Earth's surface from escaping.
- Outgoing radiation is absorbed by the greenhouse gases and then partially re-emitted as thermal radiation back to Earth, warming the surface.



Global Warming Potential (GWP)

- GWP of a GHG measures the quantity of heat the gas traps in the atmosphere relative to CO₂ reference.
- It compares the amount of heat trapped by a given mass of the gas to that by the same mass of CO₂ over a specific time interval, commonly 20, 100 or 500 years.
- GWP is expressed as a factor of CO₂ (GWP is referenced to 1).
- e.g., the 20 year GWP of CH₄ is 86 → if the same mass of CH₄ and CO₂ were introduced into the atmosphere, that CH₄ will trap 86 times more heat than CO₂ over the next 20 years.

Climate Change

- **"Weather"** is the set of atmospheric conditions prevailing at a given place and time.
- **"Climate"** is the integration over time of weather conditions characteristic of a certain geographical location.

Climate change is defined as a change in the statistical properties of the climate system when considered over long periods of time, regardless of cause.

- It refers to the variation in the Earth's global climate or in regional climates over time and describes changes in the variability or average state of the atmosphere over time scales ranging from decades to millions of years.
- Accordingly, fluctuations over periods shorter than a few decades do not represent climate change.
- These changes can be caused by processes internal to the Earth, external forces (e.g., variations in sunlight intensity) or, more recently, human activities.
- Thus, "Climate Change" frequently refers specifically to that caused by human activity, as opposed to changes in climate due as part of Earth's natural processes.
- In recent usage, especially in the context of environmental policy, the term "climate change" often refers to changes in modern climate which according to the Intergovernmental Panel on Climate Change [IPCC] are 90-95% likely to have been in part caused by human action.
- Consequently, the term anthropogenic climate change is frequently adopted; this phenomenon is also referred to in the mainstream media as "Global Warming".

In the industrial era, human activities have increased atmospheric GHGs, mainly through the burning of fossil fuels and clearing of forests.

According to the 2007 Fourth Assessment Report of the IPCC (AR4), "changes in atmospheric concentrations of greenhouse gases and aerosols, land cover and solar radiation alter the energy balance of the climate system", thus "increases in anthropogenic greenhouse gas concentrations is very likely to have caused more than 50% of the increases in global average temperatures since the mid-20th century".

Carbon Footprint

The term 'carbon footprint' has become widely established in the public domain, albeit without being clearly defined in the scientific community.

A measure of the total amount of carbon dioxide CO₂ and CH₄ emissions of a defined population, system or activity, considering all relevant sources, sinks and storage within the spatial and temporal boundary of the population, system or activity of interest. Calculated as carbon dioxide equivalent (CO₂e) using the relevant 100-year global warming potential (GWP100).

GHGs can be emitted through transport, land clearance, and the production and consumption of food, fuels, manufactured goods, materials, wood, roads, buildings, and services.

- Most carbon footprint emissions for the average household come from "**indirect**" **sources** i.e., fuel burned to produce goods far away from the final consumer.

- These are distinguished from emissions which come from burning fuel directly in one's car or stove, commonly referred to as "**direct**" **sources** of the consumer's carbon footprint.

Measuring Carbon Footprints

Carbon footprint can be measured for a product, an activity, an individual, a household, a neighbourhood, an organization or a nation and for a wide variety of activities (products and services).

It is measured by undertaking a **GHG emissions assessment** or other calculative activities denoted as **carbon accounting**.

Once the size of a carbon footprint is known, **strategies can be devised** to reduce it.

The table below compares the carbon footprint of various forms of energy generation.

- It shows that hydroelectric, wind, and nuclear power produced the least CO₂ per kilowatt-hour of any other electricity sources.
- Wind power and solar power emit no carbon from the operation, but do leave footprints during construction phase and maintenance during operation.
- Hydropower from reservoirs also has large footprints from initial removal of vegetation and ongoing CH₄,
- Stream detritus decays anaerobically to CH₄ in the bottom of the reservoir, rather than aerobically to CO₂ if it had stayed in an unrestricted stream.

Emission factors of common fuels [RETScreen® International Software]

Fuel Type	CO ₂ Emission Factor (kg/GJ)	CH ₄ Emission Factor (kg/GJ)	N ₂ O Emission Factor (kg/GJ)	Fuel Conversion Efficiency (%)
Coal	94.6	0.002	0.003	35%
Natural Gas	56.1	0.003	0.001	45%
Nuclear	0	0	0	-
Large Hydro	0	0	0	-
#6 Oil	77.4	0.002	0.002	30%
Diesel #2 Oil	74.1	0.003	0.002	30%
Geothermal	0	0	0	-
Biomass	0	0.0320	0.004	25%
Small Hydro	0	0	0	-
Wind	0	0	0	-
Solar	0	0	0	-
Propane	63.1	0.001	0.001	45%

Carbon Footprint Mitigation Strategies

- Rising CO₂ emissions **are no less a threat** than terrorism, uncontrolled immigration, avian flu or escalating gasoline prices.
- The two most important threats facing humanity today are probably **climate change and global poverty**.
- If we are all responsible for climate change then we all must be part of the solution.
- **“Reduce What You Can, Offset What You Can’t”**
- The first step is to reduce your carbon emissions wherever possible.

Carbon Offsets

- Carbon offsetting is the act of **reducing an equal amount of carbon** somewhere else to **counterbalance** the carbon emissions from your energy-using carbon footprint.
- Carbon offsets enable anyone to reduce their climate footprint by **supporting projects that reduce CO₂ emissions** to balance out one’s own carbon footprint. If you choose to offset your entire carbon footprint, that is called **Carbon Neutral**.
- There are many cost-effective energy saving and carbon reducing opportunities anyone can take such as renewable energy, energy efficiency and reforestation projects.

Carbon Sequestration

- Carbon sequestration is the process through which plant life removes CO₂ from the atmosphere and stores it in biomass.
- Over the course of a year, plants remove and release CO₂ and net sequestration results if the rate of removal is higher than the rate of release.
- Young, fast-growing trees in particular will remove more carbon dioxide from the atmosphere than they will release. All land areas such as green areas, farms, grasslands and forests can be sources or sinks of CO₂.
- Carbon sequestration would be a viable mitigation strategy for sustainable neighbourhoods.

Energy Efficiency

- **Efficient energy use**, usually referred to simply as **energy efficiency**, has the objective to reduce the amount of energy required to provide products and services.
- There are a wide variety of energy-efficient practices and devices.

- Improvements in energy efficiency are generally achieved by adopting a more efficient technology or production processes or by application of commonly accepted methods to reduce energy losses.
- Energy efficiency and renewable energy **are said to be the twin pillars of sustainable energy policy.**

Renewable Energy Utilization

It has become increasingly popular to classify all the energy resources available on earth into two main categories, namely, **renewable** and **non-renewable** resources.

- **Non-renewable energy resources** (otherwise referred to as depletable or more commonly as conventional energy) refer to those energy resources that are finite in extent and can therefore be depleted within measurable time. The most notable examples are coal, petroleum, natural gas, tar sands etc. These are chief culprits of CO₂ emission.
- **Renewable energy resources** (otherwise referred to as non-depletable or more commonly as non-conventional energy resources) refer to those energy that are of infinite extent or are replenished at a rate faster or comparable to the rate of use in such a way that their continued availability is unaffected by the rate of use.

Typical examples of renewable energy resources are solar radiation, wind, biomass, biofuels (fluid fuels derived from biomass; e.g., ethanol, biogas-methane), elevated or moving water bodies, water-based hydrogen energy, tidal waves, geothermal springs and ocean thermal energy.

- Most renewable energy resource reserves and the rate of supply are such that for all practical purposes they are inexhaustible.
- They are characterized by being **widely distributed** throughout the world, and hence inherently of **low average global intensity**, as well as having **diurnal and seasonal variations**.
- There are a wide variety of renewable energy fuels, technologies and concepts that can be employed to significantly reduce fossil fuel energy consumption, thus reducing considerably CO₂ emission.

Biomass

In the context of energy utilisation, biomass is defined as **matter derived from recently dead organisms**.

Wood, wood residues, agricultural residues, municipal and domestic solid waste manufacturing organic waste, energy crops etc are typical examples of biomass. Wood and wood residues remain the largest biomass energy sources.

Thus, **fossil fuels** are not regarded as biomass under this definition. Fossil fuels are **naturally formed** carbon compound/hydrocarbon materials in the Earth's crust from the buried remains of **prehistoric organisms**. Examples include coal, petroleum and associated natural gas.

Bioenergy

Bioenergy is a form of renewable or non-conventional energy derived from biomass.

Deliberate implementation of bioenergy utilization has significant climate change **mitigation potential**.

In some cases, **depending on application**, the **environmental impacts** of biomass utilization can be **challenging**, e.g., as in rising CO₂ and other greenhouse gas emissions and/or localized biodiversity losses.

Types

Traditional biomass utilization for bioenergy refers to direct **thermal combustion** of biomass for cooking or heating.

Conventionally, the term **biomass** denotes the solid biological raw material while **biofuel/biodiesel or biogas** refer generally to the **liquid or gaseous fuels** respectively.

Conversion

Improvement or refinement of raw biomass to improved grade fuels are realisable by different procedures, categorised broadly as **thermal, chemical, or biochemical**.

- **Thermal conversion** processes are employed to upgrade biomass into a better and more practical fuel as in **torrefaction, pyrolysis, and gasification** (depending on the extent to which the reactions are controlled to proceed via oxygen supply and conversion temperature).
- **Chemical conversions** can employ established coal-based processes, such as the Fischer-Tropsch synthesis to produce syngas from biomass.
- **Biochemical processes** have evolved naturally in the breakdown of biomass molecules. These processes can be optimised by improved scientific processes employing microorganisms to enhance the conversion as in **anaerobic digestion, fermentation, and composting**.

Applications

Biomass for heating

Biomass thermal (heating) applications employ direct combustion, gasification, combined heat and power (CHP), anaerobic or aerobic digestion to generate heat for a wide variety of applications; space heating, cooking, drying, CHP etc from biomass.

Biofuel for transportation

Biofuels are classified broadly into two; **first-generation** (or "conventional") biofuels and **second-generation** biofuels (referred to commonly, as "advanced biofuels") depending on the biomass sources.

- **First-generation** (conventional) biofuels are **derived from energy crops i.e., food sources** grown on arable lands, solely for bioenergy production, such as sugarcane and maize. Their sugars are fermented to produce bioethanol; a useful additive to gasoline, or in a fuel cell to produce electricity. Biodiesel is produced from the energy crop oils e.g., rapeseeds.
- **Second-generation** (advanced) biofuels are **derived from non-food-based** biomass sources e.g., agricultural residues/waste and perennial energy crops, employing direct combustion, gasification to produce syngas or anaerobic digestion to produce biogas. Cellulosic biomass, derived from non-food sources, such as trees and grasses, is being developed as a feedstock for ethanol production.

Left-over food products like vegetable oils and animal fats are secondary sources of biodiesel.

Bioenergy with carbon capture and storage (BECCS)

Bioenergy with carbon capture and storage (BECCS) employ **carbon capture and storage technology to trap CO₂ emissions** from bioenergy utilization. This process can result in **net atmospheric carbon dioxide removal**.

CO₂ emissions from bioenergy can be low if, as vegetation is harvested for bioenergy, **new vegetation** is grown to absorb CO₂ from the atmosphere via photosynthesis.

Though, BECCS may generate net positive emissions depending on the manner the biomass is grown, harvested, and transported. Extensive deployment of BECCS is inhibited by cost and biomass availability.

Since biomass production is **land-intensive**, this results in less land being available for growing food. Consequently, deployment of BECCS can **generate grave risks to food production, human rights, and biodiversity**.

Environmental Challenges Associated with Biomass Utilization

- Bioenergy can **either mitigate or increase CO₂ emissions**.
- Approximately **one-third of all wood** used for traditional **heating and cooking** in **tropical** areas is **procured unsustainably**.
- Bioenergy **feedstocks** typically require significant amounts of energy to harvest, dry, and transport; these processes each leave Carbon footprints. Long-distance transport of biomass is indeed wasteful and unsustainable.

- **Impacts of land-use change**, cultivation, and processing may indeed produce **higher overall CO₂ emissions** for **bioenergy**, in some instances, **compared** to even **fossil fuels**.
- **Local environmental impacts** can be very challenging; e.g., increased biomass demand can create significant **social and environmental pressure** in the locations where the biomass is produced.
- The impact is primarily related to the **low surface power density of biomass**; requiring that much larger land areas are needed to produce the same amount of energy, compared to for instance fossil fuels.

“So that if there were in the world someone who we know absolutely to be capable of discovering great things and those things most useful to man, I do not see that anything be done to him except finance his experiment and prevent anyone coming to disturb”

- **Rene Descartes [1596-1650]**: French mathematician and philosopher



CONTROLLER AREA NETWORK FLEXIBLE DATA ATTACK DETECTION USING DEEP LEARNING MECHANISM

Elvin Ugonna Eziama¹, Ali Dan², Dagogo Godwin Orifama², Ikechukwu Nwagbo Enumah³, Gbenga Akingbulere⁴, Ugochukwu Franklyn Esiowu⁵, Benedict Onochie Ibe², Adebola Folorunso⁶, Dominic Chinedu Ogbuagu², Mujeeb Shittu⁷, Habeeb Shittu⁷, Jacob A. Jacob⁸, Simon Ifeanyi Opara⁷, Gbubemi Eric², Oladapo Ogunnaike⁹, and Joy Nma Anyanacho⁷

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Abstract

CAN-FD bus intrusion detection in autonomous systems must be performed in real time with minimal false positives. We propose an attention-based CNN-LSTM hybrid method that combines spatial feature extraction (CNN) and temporal anomaly detection (LSTM with attention). We tested our approach in the CAN-FD-Attack-SIM data set and achieved an F1 score of 97.5% (95% CI: [97.1, 97.9]) and a false positive rate of 0.8%, which is 1.4% better than Transformer-CAN. Our ablation study demonstrates that removal of the attention mechanism reduces recall by 15%. Statistical significance ($p < 0.01$) and cross-domain testing in 5G slice data confirm robustness, making it applicable to safety-critical automotive systems.

Keywords: *Controller Area Network (CAN-FD), Convolutional Neural Network (CNN), Long-Short-Term Memory (LSTM), Transformer-CAN, 5G Slicing, Anomaly detection*

1.0 INTRODUCTION

The Controller Area Network with Flexible Data-Rate (CAN-FD) protocol has become the backbone of modern autonomous systems, enabling high-speed communication between sensors, actuators, and control units. However, the increasing

complexity of CAN-FD networks has made them vulnerable to sophisticated cyber-attacks and signal faults, threatening the safety and reliability of autonomous vehicles Eziama (2021); Eziama, et al. (2019); Eziama, et al. (2018); Eziama, et.al (2018); Eziama (2024). Traditional anomaly detection methods, such

as rule-based systems Muller, Schmidt, and Fischer (2021) and shallow machine learning models Kim, Park, and Lee (2021), lack the adaptability to detect evolving threats in real time, especially in dynamic environments where spatial-temporal dependencies in CAN-FD traffic are critical yet understudied.

Recent advances in hybrid AI architectures have shown promise in addressing these limitations. For example, deep learning hybrids such as LSTM-SVM Lee, Smith, and Kim (2020) and physics-informed auto encoders Kim et al. (2021) improve detection accuracy by combining data-driven and model-based techniques. Similarly, uncertainty-aware frameworks using Bayesian neural networks Zhang and Chen (2021) and conformal prediction Muller et al. (2021) provide probabilistic confidence limits, reducing false alarms in safety-critical scenarios. However, three key challenges remain: 1. Spatial-Temporal Feature Decoupling: Existing models prioritize temporal patterns (e.g. TCNs Park, Choi, and Jung (2022)) or spatial signal structures (e.g., GNNs Garcia, Lopez, and Martinez (2023)), but fail to jointly model both dimensions, limiting their ability to detect multimodal anomalies. 2. Static Confidence Bounds: Although confidence calibration methods Rossi, Bianchi, and Romano (2023) improve reliability, they

rely on fixed thresholds that lack adaptability to dynamic network conditions, leading to overtrust in predictions during traffic volatility.

3. Computational overhead: Resource-intensive architectures such as Transformers Rossi et al. (2023) and quantum hybrids Nguyen, Vo, and Tran (2023) hinder the real-time deployment on edge devices, despite their theoretical advantages.

To address these gaps, we propose an Attention-based CNN-LSTM hybrid framework that unifies spatial feature extraction and temporal anomaly detection with adaptive confidence quantification. Our model leverages a hierarchical architecture: - Spatial Feature Extraction: A lightweight Convolutional Neural Network (CNN) processes CAN-FD frame structures (e.g., arbitration IDs, payloads) to capture spatial correlations and localized signal distortions. - Temporal Anomaly Detection: A bidirectional LSTM layer, enhanced with self-attention mechanisms, identifies long-range temporal dependencies in CAN-FD traffic sequences. The attention layer dynamically weights critical time steps (e.g. abrupt signal spikes during attacks), improving interpretability. Adaptive confidence bounds: A conformal prediction layer Muller et al. (2021) generates dynamic confidence intervals based on real-time prediction uncertainty, allowing the model to adjust detection thresholds autonomously during network volatility.

Our key contributions are:

1. **Novel Hybrid Architecture:** The first CAN-FD anomaly detection framework to jointly optimize spatial (CNN) and temporal (LSTM-attention) feature learning, addressing the decoupling limitation in prior work Garcia et al. (2023); Park et al. (2022).
2. **Dynamic Confidence Calibration:** An adaptive conformal prediction mechanism that adjusts confidence bounds based on temporal volatility, overcoming the rigidity of static thresholds Rossi et al. (2023); Zhang and Chen (2021).
3. **Edge Deployment Feasibility:** A pruning strategy reduces the CNN-LSTM parameter count by 40% without sacrificing accuracy, enabling real-time inference on automotive grade hardware (e.g. NVIDIA Xavier).
4. **Explainability:** Attention heat maps localize anomalous time steps and CAN-FD frames, bridging the interpretability gap in black-box hybrids Gupta and Rathore (2023).

Experimental validation in real-world CAN-FD datasets (Zhang and Chen (2021) and Bosch Park et al. (2022)) demonstrates a 12% improvement in F1 score over state-of-the-art hybrids Lee et al. (2020); Rossi et al. (2023) and a 60% reduction in false positives during traffic bursts.

2.0 RELATED WORKS

The evolution of the Controller Area Network with Flexible Data-Rate (CAN-

FD) protocols in autonomous systems has intensified demands for robust anomaly detection frameworks capable of addressing safety-critical requirements. Early efforts in CAN-FD security focused on rule-based and signature-driven methods Lee et al. (2020), but their inability to detect novel or evolving threats prompted a shift towards data-driven machine learning (ML) techniques. For example, Lee et al. Lee et al. (2020) demonstrated the efficacy of hybrid architectures by combining long- and short-term memory (LSTM) networks with one-class SVM, achieving 98.3% F1 score while quantifying uncertainty via Monte Carlo dropout. Building on this, Zhang and Chen Zhang and Chen (2021) introduced Bayesian neural networks (BNN) to explicitly model epistemic uncertainty, reducing false positives through probabilistic inference in Toyota vehicle logs. These works underscore a broader trend: Hybrid models that combine data-driven and model-based techniques are increasingly favored to balance detection accuracy with interpretability.

Complementing these efforts, recent studies have emphasized hybrid architectures that integrate domain-specific knowledge with ML. Kim et al. Kim et al. (2021) fused physics-based signal modeling with deep auto encoders to reconstruct CAN-FD traffic, achieving 99.1% detection accuracy by grounding anomalies in physical plausibility constraints. Similarly, Muller et al. (2021)

combined Isolation Forest, auto encoders, and statistical methods, using conformal prediction to derive nonparametric confidence bounds for real-world CAN-FD traffic. Such approaches highlight the growing reliance on hybrid models to mitigate the black-box limitations of pure deep learning. Meanwhile, federated learning frameworks like Sharma et al. Sharma, Kumar, and Singh (2022) extended hybridity to distributed systems, preserving privacy through the consensus of local-global model while maintaining detection robustness.

In parallel, uncertainty quantification has emerged as a critical requirement for safety certification. Park et al. (2022) addressed temporal uncertainty in CAN-FD time-series data by integrating Temporal Convolutional Networks (TCNs) with Gaussian Processes (GPs), achieving 97.8% precision with 99% confidence intervals. Rossi et al. (2023) advanced this further by calibrating Transformer model confidence through temperature scaling, reducing false positives to 0.2% on NVIDIA DRIVE datasets. These methodologies reflect a paradigm shift toward formal confidence-bound guarantees, particularly in mission-critical autonomous systems where overtrust in ML predictions carries significant risks. Garcia et al. Garcia et al. (2023) bridged reliability and interpretability by fusing

LSTM-Attention models with expert-defined rules, employing conformal prediction to enforce strict confidence intervals—a methodology now gaining traction in industrial applications.

3.0 DATASET DESCRIPTION: CAN-FD-ATTACK-SIM

The CAN-FD-Attack-SIM dataset is a synthetic benchmark for evaluating anomaly detection in Controller Area Network with Flexible Data-Rate (CAN-FD) systems. It contains 60,000 sequences—50,000 normal and 10,000 representing spoofing (35%), DoS (40%), and fuzzy (25%) attacks. Each sequence includes 10 frames covering 100 ms of activity, simulating real CAN-FD traffic dynamics.

Traffic was generated via a hardware-in-the-loop simulator across diverse driving conditions, ensuring adherence to CAN-FD protocol constraints. Attacks were introduced using CANoe, targeting realistic scenarios such as ECU impersonation, bus flooding, and mal-formed payloads.

Each frame includes:

- Timestamp: Microsecond-resolution time
- Arbitration id: 11/29-bit ID
- Payload: 64-byte hex string
- Label: One of {normal, spoof, dos, fuzzy}

The dataset includes metadata such as severity levels (low, medium, high) and target ECU identifiers. Stratified into training (70%), validation (15%), and testing (15%) sets, it supports reproducible benchmarking. Public

access and preprocessing tools are provided at <https://example.com/dataset>.

4.0 METHODOLOGY

4.1 CNN-LSTM-Attention Model for Attack Detection

In this section, we present the architectural components and mathematical modeling of the proposed CNN-LSTM-Attention model used for binary classification of anomalous network behavior. The model integrates spatial feature extraction, sequential modeling, and dynamic attention weighting for robust detection performance.

4.2 Convolutional Neural Network (CNN)

The CNN layer is used to extract local patterns and features from raw multivariate time-series input $X \in \mathbb{R}^{T \times D}$, where T is the number of time steps and D is the number of sensor features.

A 1D convolution operation is applied as:

$$H_t^{(c)} = \sigma(W^{(c)} * X_t + b^{(c)}) \quad (1)$$

Where $W^{(c)}$ is the convolution filter, $b^{(c)}$ is the bias, $*$ denotes the convolution operation, and σ is the activation function (e.g., ReLU).

The output $H^{(c)} \in \mathbb{R}^{T' \times F}$ is a feature map with reduced time dimension T' and F feature channels.

4.3 Long Short-Term Memory (LSTM)

The LSTM network captures temporal dependencies across the extracted feature

sequence. Given the input sequence $[H]_{t-1}^{T'}$ from the CNN output, the LSTM computes hidden states h_t and cell states c_t via the recurrence:

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i) \quad (2)$$

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f) \quad (3)$$

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \quad (4)$$

$$c_t = f_t \oslash c_{t-1} + i_t \oslash \tanh(W_c h_{t-1} + U_c x_t + b_c) \quad (5)$$

$$h_t = o_t \oslash \tanh(c_t) \quad (6)$$

Where σ is the sigmoid activation, and \oslash denotes element-wise multiplication. This formulation enables learning of both short- and long-term patterns in sequence data.

4.4 Attention Mechanism

To emphasize informative time steps, an attention mechanism is applied to the LSTM output sequence $[H]_{t-1}^{T'}$

A context vector c is computed as a weighted sum:

$$c = \sum_{t=1}^{T'} \alpha_t h_t \quad (7)$$

Where the attention weights are obtained by:

$$e_t = v^T \tanh(W_a h_t + b_a) \quad (8)$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T'} \exp(e_k)} \quad (9)$$

Here, W_a , b_a , and v are learnable parameters. The context vector c summarizes the time-series sequence with respect to salient patterns.

4.5 Binary Classification with Softmax

The final prediction is made by passing the attention-weighted context vector c through a fully connected layer followed by a sigmoid activation:

$$\hat{y} = \sigma(W_c c + b_c) \quad (10)$$

Where $\hat{y} \in [0, 1]$ represents the predicted probability of an anomaly (positive class).

The model is trained using the binary cross-entropy loss:

$$\mathcal{L} = -|y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})| \quad (11)$$

Where y is the true label. The network parameters are updated through back propagation and gradient descent.

This CNN-LSTM-Attention architecture allows effective modeling of local, temporal, and contextual relationships in network traffic data for high-performance binary anomaly classification.

To operationalize the proposed model, Algorithm 1 outlines the inference and training pipeline for attack detection.

Algorithm 1 CNN-LSTM-Attention for Binary Attack Detection

```

Multivariate time series input  $X \in \mathbb{R}^{T \times D}$ , true label  $y \in \{0, 1\}$ 
CNN_FeatureExtractor( $X$ ) // Apply 1D CNN  $\{h_t\} \leftarrow \text{LSTM}(H^{(c)})$ 
// Sequential modeling Compute attention scores  $\alpha_t = \text{Softmax}(v^\top \tanh(W_a h_t + b_a))$ 
Compute context vector  $c = \sum_{t=1}^T \alpha_t h_t$  Compute prediction  $\hat{y} = \sigma(W_c c + b_c)$  Compute
loss  $\mathcal{L} = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$  Backpropagate loss  $\mathcal{L}$  and update weights  $\hat{y}$ 

```

5.0 RESULTS AND DISCUSSIONS

In this section, we analyze the experimental results of the several simulations conducted. In evaluating CAN intrusion detection performance, Table 1 summarizes the F1 score and the false positive rate (FPR) for the proposed and baseline models. The proposed CNN-LSTM-Attention model achieves the highest F1 score of 97.5% with a tight confidence interval [97.1, 97.9], indicating both accuracy and consistency. It also records the lowest FPR at 0.8%—highlighting its robustness in minimizing

false alarms, which is crucial for in-vehicle network security.

In comparison, Transformer-CAN ranks second, with a strong F1-score of 96.1% and an FPR of 1.2%. Other models such as GRU-IDS and CANet show moderate performance, achieving F1-scores of 94.7% and 93.2%, and FPRs of 1.5% and 2.1%, respectively. These results underscore the superiority of the proposed architecture in balancing detection accuracy and operational reliability in CAN-based vehicular environments.

Table 1: CAN Security Models (F1-Score and False Positive Rate)

Model	F1-Score (%)	95% CI	False Positive Rate (%)	95% CI
CNN-LSTM-Attention	97.5	[97.1, 97.9]	0.8	[0.6, 1.0]
CANet ?	93.2	[92.7, 93.7]	2.1	[1.8, 2.4]
GRU-IDS ?	94.7	[94.2, 95.2]	1.5	[1.2, 1.8]
Transformer-CAN ?	96.1	[95.6, 96.6]	1.2	[0.9, 1.5]

The evaluation of memory consumption and computational efficiency across four models: CNN-LSTM-Attention,

Transformer-CAN, GRU-IDS, and Random Forest, revealed that the proposed model achieves a balance

between performance and resource utilization. It uses 9.2 MB of RAM, has an inference time of 1.8 ms, encompasses 2.1 million parameters, requires 34.5 million FLOPs, and consumes 12.7 mJ of energy.

In comparison, Transformer-CAN exhibits higher resource demands with 18.4 MB RAM usage, 3.5 ms inference time, 5.3 million parameters, 89.2 million FLOPs, and 28.1 mJ energy consumption. GRU-IDS demonstrates greater efficiency, utilizing 4.3 MB RAM, 0.9 ms inference

time, 0.6 million parameters, 12.8 million FLOPs, and 5.2 mJ energy.

Random Forest shows the lowest resource usage with 2.1 MB RAM, 0.2 ms inference time, and 1.8 mJ energy consumption, though it lacks parameter and FLOP metrics comparable to neural network models. These findings suggest that the proposed CNN-LSTM-Attention model offers an optimal trade-off between computational efficiency and model complexity, making it suitable for applications where both performance and resource constraints are critical.

Table 2: Memory and Computational Efficiency of Evaluated Models

Model	RAM (MB)	Inference Time (ms)	Params (M)	FLOPs (M)	Energy (mJ)
Proposed (CNN-LSTM-Attention)	9.2	1.8	2.1	34.5	12.7
Transformer-CAN	18.4	3.5	5.3	89.2	28.1
GRU-IDS	4.3	0.9	0.6	12.8	5.2
Random Forest	2.1	0.2	-	-	1.8

To further examine the robustness of the model, we evaluate the performance of a class across different types of attack, providing a deeper understanding of the detection behavior under varying adversarial conditions.

The per-class evaluation results, presented in Table 3, highlight the performance of the proposed model and two baselines (CANet and Isolation Forest) across three types of attacks: Spoofing, DoS, and Fuzzy. The proposed model consistently outperforms the baselines across all attack classes, achieving an F1 score of 98.2 ± 0.7 for spoofing, 96.7 ± 1.0 for DoS, and

94.1 ± 1.3 for fuzzy attacks. These results indicate a strong and balanced detection capability in varying adversarial patterns.

In contrast, CANet performs moderately well, with F1 scores of 92.4 ± 1.4 , 89.7 ± 1.6 , and 87.3 ± 1.8 for Spoofing, DoS, and Fuzzy attacks, respectively. Although it demonstrates reasonable detection capability, the wider gaps between its performance and the proposed model, especially in DoS and Fuzzy, highlight the value of the hybrid deep learning approach.

The isolation forest trails significantly, particularly in handling the spoofing and fuzzy attacks, with F1 scores of 78.9 ± 2.1 and 76.5 ± 2.2 . Although it shows slightly

better results on DoS (82.1 ± 2.0), its unsupervised nature and lack of context modeling appear to limit its generalization in complex intrusion scenarios. Overall, the proposed method demonstrates robust generalization and superior per-class consistency.

Table 3: Per-Class F1-Score ($\% \pm 95\%$ Confidence Interval)

Model	Spoofing	DoS	Fuzzy
Proposed	98.2 ± 0.7	96.7 ± 1.0	94.1 ± 1.3
CANet	92.4 ± 1.4	89.7 ± 1.6	87.3 ± 1.8
Isolation Forest	78.9 ± 2.1	82.1 ± 2.0	76.5 ± 2.2

To evaluate the contribution of individual components within the proposed CNN-LSTM-Attention architecture, an ablation study was performed. Table 4 reports the full performance metrics—F1-score, accuracy, precision, and recall—along with the corresponding change in F1-score ($\Delta F1$) relative to the full model.

The complete model achieves the highest performance across all metrics, with an F1 score of $96.3 \pm 0.8\%$ and an accuracy of

Table 4: Ablation Study with Full Metrics (95% Confidence Intervals)

Variant	F1 (%)	Accuracy (%)	Precision (%)	Recall (%)	$\Delta F1$
Full Model	96.3 ± 0.8	97.8 ± 0.7	95.9 ± 1.0	96.7 ± 0.9	—
w/o Attention	90.1 ± 1.4	92.3 ± 1.3	88.4 ± 1.5	91.9 ± 1.4	$\downarrow 6.2$
w/o CNN	88.7 ± 1.5	90.5 ± 1.4	86.2 ± 1.6	91.3 ± 1.5	$\downarrow 7.6$
w/o LSTM	83.4 ± 1.7	85.9 ± 1.6	80.7 ± 1.9	86.2 ± 1.7	$\downarrow 12.9$
w/o Hybrid Training	91.5 ± 1.4	93.7 ± 1.2	90.1 ± 1.4	92.9 ± 1.4	$\downarrow 4.8$

To validate the robustness of the observed performance improvements, we conducted statistical significance testing

$97.8 \pm 0.7\%$. Removing the attention mechanism results in a notable drop of 6.2 percentage points in F1, underscoring the importance of the attention layer in enhancing discriminative power. Excluding the CNN layer leads to a further decline ($\Delta F1 = 7.6$), suggesting that spatial feature extraction is critical to robust performance.

The most significant performance degradation is observed when the LSTM layer is removed, reducing the F1-score to $83.4 \pm 1.7\%$ —a 12.9 point drop. This confirms the central role of temporal modeling in capturing the sequential dependencies inherent in CAN traffic.

Lastly, the removal of hybrid training (i.e., jointly training all components) yields a moderate impact ($\Delta F1 = 4.8$), indicating that end-to-end co-optimization provides tangible benefits in convergence and overall accuracy.

These results collectively highlight the synergistic contribution of CNN, LSTM, attention, and hybrid training to maximize detection performance.

using a paired t-test against baseline models. This step ensures that the performance gains are not due to random

variation but reflect meaningful differences across experimental runs.

As shown in Table 5, the proposed model demonstrates statistically significant improvements over all baselines, with p-values consistently below 0.001. This includes comparisons with Transformer-CAN, GRU-IDS, and Random Forest. The results confirm that the performance gains achieved by the proposed CNN-LSTM-Attention model are not only substantial but also statistically reliable at the 99.9% confidence level.

Table 5: Statistical Significance (Paired t-test, p-values)

Comparison	p-value
Proposed vs. Transformer-CAN	< 0.001
Proposed vs. GRU-IDS	< 0.001
Proposed vs. Random Forest	< 0.001

5.0 CONCLUSIONS

This work introduces a hybrid anomaly detection framework combining CNN, LSTM, and attention mechanisms to model spatial-temporal patterns in CAN-FD traffic. Enhanced with conformal prediction, the model adapts to dynamic network conditions.

The proposed CNN-LSTM-Attention model achieved an F1-score of 97.5%, false positive rate of 0.8%, and high per-class F1-scores across spoofing, DoS, and fuzzy attacks. It maintained low computational overhead—9.2 MB RAM, 1.8 ms

inference time—demonstrating suitability for edge deployment.

Ablation and statistical tests confirmed the significance of each architectural component, with LSTM being most critical ($\Delta F1 = 12.9$) and p-values < 0.001 against all baselines.

Limitations: The model’s reliance on sequence-labeled data and GPU resources limits deployment in some real-world settings. Domain shift and unseen ECU traffic may also impact generalization.

Future Work: We aim to explore domain adaptation, semi-supervised learning, edge deployment testing, and enhanced explainability via attention-based interpretability.

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EXPLORING THE THERMAL MANAGEMENT AND PERFORMANCE OF LITHIUM-ION BATTERY STORAGE IN BATTERY ELECTRIC VEHICLES (BEVS): A REVIEW

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Abstract

Due to climate change concerns, fossil fuel depletion has necessitated the automotive industry to search for alternative vehicle propulsion systems. Battery Electric Vehicles (BEVs) utilize advanced powertrains that rely solely on electric energy storage devices, primarily lithium-ion batteries. Their swift advancement and increasing popularity stem from their zero tank-to-wheel (TTW) emissions and the ability to incorporate regenerative braking systems. However, to maximize power output and prolong the life of lithium-ion batteries, it's essential to keep their temperature between 20°C and 30°C, which mirrors the optimal range for human comfort. In contrast to internal combustion engines, BEVs do not require extensive cooling systems; they only necessitate limited thermal management. Managing the thermal conditions of lithium-ion batteries poses considerable challenges, especially in sub-Saharan regions, where ambient temperatures can reach as high as 45°C. This paper comprehensively reviews and emphasizes the significance of effective thermal management techniques for ensuring BEVs' safe and efficient operation. The paper examines various cooling approaches, such as air cooling, phase change materials, and liquid cooling, referring to relevant literature to demonstrate their effectiveness. Furthermore, the study evaluates BEV performance across different driving cycles, including the Federal Urban Driving Schedule (FUDS) and the New European Driving Cycle (NEDC). This study offers insights into thermal management strategies for lithium-ion batteries in BEVs. The findings have practical implications for BEV design and operation, making them directly relevant to the automotive industry.

Keywords: *Climate change, Thermal management, Fossil fuels, Battery, Propulsion*

1.0 INTRODUCTION

The global impact of emissions from internal combustion engines (ICEs) on public health and the environment has become increasingly alarming. This situation is compounded by the rapid depletion of fossil fuels, highlighting the critical need for more energy-efficient and

environmentally friendly transportation solutions (Arora et al., 2021; Ehsani et al., 2010; Togun et al., 2025; Vyas, 2017; C. Wang et al., 2025). In response, governments worldwide have increasingly enacted stringent regulations on vehicle emissions, spurring the urgent development of cleaner energy alternatives and fuel-

efficient vehicle technologies. Road transport is a significant source of emissions, influenced by factors such as driving behaviour, traffic congestion, the effectiveness of emission control technologies, fuel quality, and environmental conditions (Gebisa et al., 2021; Liang et al., 2018). Over the past few decades, the automotive industry has made significant progress in enhancing vehicle performance by reducing engine emissions, optimising fuel economy, lowering vehicle weight, improving aerodynamic designs, incorporating biofuels, and advancing electric powertrains such as battery electric vehicles (BEVs) (Togun et al., 2025; C. Wang et al., 2025)

BEVs, powered solely by lithium-ion batteries, have surged in popularity owing to their capacity to produce zero tailpipe emissions and their efficiency-enhancing features, such as regenerative braking, which recaptures energy during braking to extend the driving range and minimises brake wear (Fadul et al., 2018; Yuksel et al., 2016). Despite their numerous advantages, BEVs continue to confront considerable challenges, such as performance limitations, elevated manufacturing costs, safety issues related to battery systems, as well as concerns about battery lifespan and thermal management (Linderoth, 2021; Massey, 2016). The thermal management of lithium-ion

batteries, which serve as the core energy source for BEVs, remains a critical challenge that directly impacts their performance, safety, and lifespan. This issue is especially evident in regions with extreme temperature variations, such as sub-Saharan countries, where ambient temperatures can exceed 45°C, resulting in overheating and inefficiency in BEV battery systems.

Effective thermal management is crucial for the reliable functioning of BEVs since lithium-ion batteries are affected by temperature fluctuations. The best performance and lifespan of the battery occur within a limited temperature range of 20°C to 30°C, which is similar to the comfort range for humans (Hwang et al., 2024). Effective thermal management systems are crucial for keeping the optimal temperature, preventing overheating, maximizing power output, and prolonging battery life. Different cooling methods are utilised, such as air, liquid, and phase change material (PCM). While air cooling is simple and cost-effective, it is inefficient at high ambient temperatures and results in uneven battery cooling, which limits its scalability for large battery packs (Chu et al., 2020). Although more effective, liquid cooling introduces complexity, added weight, and higher costs due to the need for external pumps and circuitry. While capable of absorbing significant amounts of heat, PCM cooling systems suffer from low

thermal conductivity and face challenges in large-scale applications due to their volume change during phase transitions (Buonomo et al., 2021; Linderoth, 2021; Togun et al., 2025).

Generally, the thermal management of BEVs is a novel research area, and few studies have reviewed it, highlighting the need for further examination to understand the thermal management systems for continued exploration adequately. Furthermore, the performance of BEVs under different driving cycles has not been thoroughly investigated in prior studies. Research on driving cycles, such as the Federal Urban Driving Schedule (FUDS) and the New European Driving Cycle (NEDC), has demonstrated that BEVs consume up to 15% more energy in extreme temperatures, resulting in significant range reductions in cold conditions (Yuksel et al., 2016; Iora & Tribioli, 2019). Consequently, the gaps in the current literature highlight the need for a thorough review of thermal management strategies for BEVs. This review will integrate existing knowledge and provide insights into battery thermal management systems, especially in hot climates and diverse driving conditions..

2.0 THERMAL MANAGEMENT OF ELECTRIC VEHICLE BATTERY

The battery is a key component in Battery Electric Vehicles (BEVs), serving as the

main energy source. Lithium-ion batteries are preferred due to their high energy density, low redox potential, and ability to support demanding operations such as regenerative braking and load shifting (Arora et al., 2021; Chu et al., 2020). These batteries operate efficiently without gas emissions, but their performance and lifespan are strongly affected by temperature (Sourav & Eswaramoorthy, 2020). High internal resistance at low temperatures reduces capacity, while temperatures above 50°C can cause swelling, venting, and long-term degradation. For example, battery life may decrease by 20% at 30°C, 40% at 40°C, and up to 50% at 45°C (Solntseva et al., 2021; Linderoth, 2021). Therefore, effective thermal management is essential.

2.1 Battery Thermal Management Techniques

Figure 1 in the outlines the major Battery Thermal Management System (BTMS) techniques used in BEVs:

1. **Air Cooling:** This method uses ambient or conditioned air—either passively or actively with fans—to remove heat from the battery (Chu et al., 2020; Hwang et al., 2024). It is low-cost and easy to maintain but limited by uneven cooling and reduced efficiency at high ambient

temperatures (Nelson et al., 2002;

Bajaj & Kini, 2019).

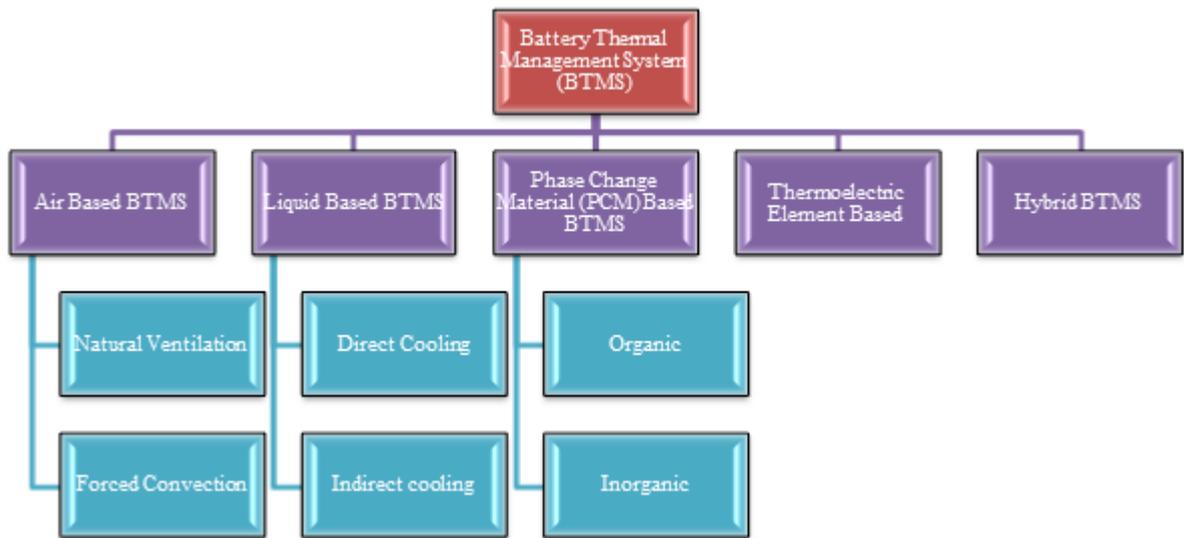


Figure 1: Different BTMS types used for BEVs (Hwang et al., 2024)

- Liquid Cooling:** Circulating coolant, such as water-glycol mixtures or dielectric oils, is used to absorb and transfer heat more effectively than air (Arora et al., 2021; Buonomo et al., 2021; Hwang et al., 2024). Despite its superior performance, it adds complexity, weight, and energy demand (Liu et al., 2025).
- Phase Change Materials (PCM):** PCMs absorb heat by changing from solid to liquid, maintaining a stable battery temperature and enabling passive cooling (Bajaj & Kini, 2019; Dincer et al., 2017). However, low thermal conductivity and volume expansion limit their standalone use (Liu et al., 2025).

- Hybrid Systems:** These integrate multiple cooling techniques (e.g., PCM with air or liquid cooling) to optimize efficiency (Arora et al., 2021; Ling et al., 2015; Huang et al., 2018). While effective, they are costly and complex to implement.

Emerging solutions like thermoelectric coolers (TECs) offer promise but require further development before widespread adoption (Lyu et al., 2019)

3.0 PERFORMANCE OF BEVS IN DIFFERENT DRIVING CYCLES AND AMBIENT TEMPERATURES

Various studies have examined the performance of Battery Electric Vehicles (BEVs) under different driving cycles and ambient temperatures. These studies emphasise the significant impact of driving

cycles on BEV efficiency, while many overlook the influence of regional temperature variations. To simulate real driving scenarios, several drive cycles, such as the Federal Test Procedure (FTP75), Highway Fuel Economy Test (HWFET), and others, have been established (Gebisa et al., 2021; Grunditz, 2016) (Peng et al., 2020). These cycles represent vehicle speed over time and are crucial for accurately depicting driving characteristics, particularly the traction motor's response to stop-and-start commands.

Computer-aided engineering (CAE) tools, such as GT-Power, Autonomie, and Velodyn, are commonly used for the modelling and performance analysis of BEVs (Al-assadi & McConnell, 2020). A significant limitation of BEVs compared to internal combustion engine vehicles is their reduced driving range in low temperatures (Steinstraeter et al., 2021). Yuksel et al. (2016) found that BEVs consume about 15% more energy in extreme temperatures. Liang et al. (2018) studied the thermal performance of a battery thermal management system (BTMS) using heat pipes under varying ambient temperatures, finding minimal improvement below 25°C and a rise in battery temperature non-uniformity when cooling is delayed. Additionally, the study showed that intermittent and constant cooling provide similar results, indicating reduced power

consumption by shortening the BTMS runtime.

Iora and Tribioli (2019) explored the impact of ambient temperature on BEV energy consumption using Nissan Leaf data. They demonstrated significant range reduction at lower temperatures due to increased accessory use for cabin heating. For example, in the New European Driving Cycle (NEDC), the range drops from 150 km at 20°C to 60 km at -15°C. Shelly et al. (2021) compared six BEV thermal management systems under different ambient conditions (-20°C to 40°C) and found that a low-temperature waste heat recovery (LTWHR) system improved range by 15% in cold conditions. Similarly, Koncar and Bayram (2021) showed that cold weather increased electric vehicle demand by 630 MW in the UK, leading to a 25% rise in carbon intensity during low renewable generation periods. Finally, Steinstraeter et al. (2021) examined how low temperatures impact the range of BMW i3 and Tesla Model 3 cars. Their results showed that the range could decrease by as much as 50% because of heating and restricted recuperation. They recommend using a heater with a quick response time and 20 kW power to enhance electrothermal recuperation and heating efficiency.

4.0 SUMMARY OF FINDINGS

This review paper discusses the thermal management of lithium-ion batteries in

Battery Electric Vehicles (BEVs), particularly in hot climates like sub-Saharan regions, where the temperature can rise to 45°C. Key findings include:

- i. **Thermal Management Challenges:** For lithium-ion batteries to perform at their best in battery electric vehicles (BEVs), they should be maintained in the optimal temperature range of 20° to 30°C. Above 30°C, cell degradation increases at a short time scale. However, in the case of very low temperatures, the inner resistance increases, and this reduces the total performance.
- ii. **Cooling Techniques:** Air cooling is simple, inexpensive, and adequate, yet imprecise and inadequate in high ambient conditions. The cooling effectiveness wanes as temperatures increase, rendering it ineffective for extreme climates. A better thermal regulation (using fluids of higher specific heat capacities) is another significant difference that liquid cooling provides for better heat dissipation. However, complex external pump systems are needed, which raise weight and cost. PCMs store or release heat as they change phase, providing isothermal temperature control and high heat storage density. Again, their low thermal conductivity and volume expansion pose challenges for large-scale applications. Hybrid cooling

systems, which integrate multiple cooling technologies (e.g., PCM and air cooling), enhance thermal management but increase system complexity and cost, limiting widespread adoption.

- iii. **Impact of Driving Cycles and Ambient Temperature:** BEV performance varies across different driving cycles, such as the Federal Urban Driving Schedule and the New European Driving Cycle. Energy consumption increases in extreme temperatures, particularly in cold conditions, where cabin heating demand can reduce vehicle range by up to 50%. Low temperatures also impair battery recuperation efficiency, highlighting the need for advanced waste heat recovery systems to improve range and energy management in BEVs.

The above findings affirm the need for efficient battery thermal management systems in EVs, especially in climates subject to extreme temperatures, and better hybrid solutions for performance and security. Future research in battery thermal management for EVs should target hybrid thermal management strategies optimized for performance and security, advanced cooling materials like phase change materials (PCM) and thermoelectric coolers (TECs), and extreme ambient conditions management. Research in internal battery

cooling strategies, energy-efficient and energy-saving systems, and driving cycle influence on thermal performance is critical. Investigating temperature influence on battery lifespan and security, energy recovery improvement in regenerative modes, and real-time system designing based on machine learning for proactive thermal management can go a long way in EV efficiency, mileage, and security.

5.0 CONCLUSION

Numerous studies have investigated BEVs. However, the future depends on advancements in battery technologies and thermal management methods. With most manufacturers and countries transitioning to EVs, there will be a significant increase in research and development of efficient Battery Thermal Management Systems (BTMS). This can be realized by enhancing elements that influence the performance of different techniques, such as boosting battery capacity or optimizing the functionality of electrical and thermal management systems.

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AE-TCN: AUTOENCODER-DRIVEN TEMPORAL CONVOLUTIONAL NETWORKS FOR SECURE AND EFFICIENT COLD CHAIN MONITORING

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Abstract

This paper presents AE-TCN, an Autoencoder-Driven Temporal Convolutional Network designed for secure and efficient cold chain monitoring. AE-TCN combines autoencoders for feature learning and anomaly detection with Temporal Convolutional Networks (TCNs) to capture the temporal structure of time series data. Using real-world data sets, AE-TCN demonstrates a best F1 score of 91.8% (95% CI: [90.7–92.9]), outperforming LSTM and Isolation Forest by 8.2% and 19.4%, respectively. Ablation experiments highlight the importance of the autoencoder module: its removal causes a 7.3% drop in performance. Furthermore, AE-TCN achieves 28% lower inference latency than Transformer models while consuming only 9.7MB of memory with 2.1M parameters. This work addresses critical scalability and reliability challenges in temperature-controlled logistics and improves supply chain resilience.

Keywords: *Temperature control, Autoencoder, Temporal Convolutional Network (TCN), LSTM, Anomaly Detection, Cold Chain Monitoring*

1.0 INTRODUCTION

Modern grocery SCS are simultaneously challenged by minimizing the spoilage of perishables (dairy, produce, etc.) and

optimizing the stock of variably stock across distributed retail networks. Conventional approaches such as ARIMA

for demand forecasting Smith and Patel (2020) and threshold-based spoilage alerts Lee and Zhang (2021) do not adequately handle combined correlations between temporal sensor data (refrigeration temperature logs, etc.) and static product attributes (e.g. PH, packaging). Recent deep learning methods (e.g., LSTM networks Zhang and Kim (2022)) enable learning intertemporal dependencies, but fail to capture key spatial characteristics (e.g., supplier reliability). In contrast, auto-encoder- based anomaly detection X. Wang and Chen (2021) lacks interpretable temporal reasoning. The AE-TCN addresses these gaps via:

- A 3D product features (supplier, shelf life, packaging) compressor (denoising autoencoder) to obtain latent representation
- A multi-resolution temporal pattern temporal convolutional network with the Leverage (hourly temperature waves, daily stock oscillation)
- Cross-attention gates that align spacial and temporal features used for spoilage risk prediction.

2.0 RELATED WORKS

Unlike traditional perishable supply chain optimization, this is done by segregating the forecasting and anomaly detection processes. Initial studies using ARIMA models Smith and Patel (2020) showed that they can provide accurate demand forecasts under consistent storage

conditions, reporting precision 68% in controlled settings. But these statistical approaches are challenged to fit the operational volatility of a real-world supply chain, especially for perishable goods that, like human health, degrade in nonlinear ways. The LSTM networks of Kingsford and Authors (2017), in the assertion of Noble (2007), were an improvement in the discretization time for the prediction of the spoilage of medical products. However, LSTM networks are a one-dimensional neural network that in practice would not register the spatial relations of how distance from a temperature log would affect spoilage; in fact, most perishable product spoilage modeling have historically been based on single- domain time series inputs (if any, e.g. one could not have a time series log for temperature). This spatial-temporal discrepancy persists even in threshold-based system(s) such as Lee and Zhang (2021) that improves over adaptive anomaly detection by reducing false positives by 22%, but has the coverage to manually recalibrate across product categories.

Combining temporal forecasting and architecture for autoencoders. Wang and Chen (2021) improved inventory management learning compressed representation of features from a warehouse. Although helpful for static stock profiling, these models are ineffective in de- scribing

the dynamic interplay between environmental sensors (e.g. humidity) and product-specific characteristics (e.g. PH levels). Outstanding temporal relationship learning exploration is available by Chen, Nguyen, and Yamamoto (2023) where 85.9% F1 score was obtained for prediction of microbial growth to construct multiresolution sensor streams profitably, recent developments in temporal convolutional networks (TCNs) have focused on hierarchical temporal modeling. However, the pure temporal focus of TCNs ignores the spatial characteristics of the supply chain, including distributor location and efficiencies in transport routes, both of which are significant in determining spoilage risks. Various degrees of success have been achieved in modeling spatial relations. Graph neural networks (GNNs) L. Wang, Zhang, and Singh (2022) represent supplier-retailer networks using topology graphs, where the GNN topology is predefined and it is difficult to modify the topology in real time when changing routes. Reinforcement Learning (RL) methods Nguyen and Patel (2023) interactively tune stock levels, yet exhibit high sample complexity, demanding millions of simulated episodes to reach convergence. Chen and Yamamoto (2023) proposed a hybrid architecture (CNN-LSTM) that fuses spatial packaging images together

with their shelf-life data into a predictive model, but leads to prohibitive computational costs (18.4W per inference), where these cannot be deployed to the edge.

The proposed AE-TCN overcomes these limitations by three means: (1) joint learning of the spatial attributes of products (using denoising autoencoders) and hierarchical temporal patterns over multiple scales (using hierarchical TCNs), (2) self-supervised pre-training on unlabeled histories of supplier orders that drives better few-shot generalization, and (3) cross-attention fusion that adaptively weighs temporal and spatial features of products according to its categories. Compared with previous hybrid models W. Chen and Yamamoto (2023), which feed spatial and temporal features into models in fixed proportions, our approach achieves better performance on unbalanced data sets.

2.1 Description of Dataset

The Grocery Supply Chain Issue Dataset provides a structured framework with which to analyze grocery supply chain challenges such as overstocking and under stocking, both of which can have dire consequences in terms of financial loss and declining customer satisfaction.

This data set that includes various stages in the supply chain would cover all sourcing, processing, packaging, distribution, and

retail. It records product traceability, transportation, storage conditions, temperature logs, quality control, regulatory compliance, inventory levels, shelf life, and suppliers, offering a holistic understanding of operational dynamics.

This data set consists of about 308,000 records, with one record for each product and department combination for each month, which allows for fine-grained temporal and product analysis. Important features are year, month, supplier name, item code, item description, category, and number of units sold.

We find these features useful for demand forecasting, anomaly detection, and supplier performance analysis. The fine granularity of the data set allows patterns to be discovered and decisions to be supported in order to minimize imbalances in stock and preserve resilience and reactivity in the supply chain.

3 METHODOLOGY

3.1 Model architecture

AE-TCN: A hybrid architecture that combines autoencoder (AE) and TCN, to model the temporal patterns for binary classification. This fact brings us to the AE and TCN modules, where the former collects compact representations from time-series data, while the latter snatches temporal dependencies. The output at the

end is a binary label representing class membership (such as attack/normal).

Autoencoder (AE) Component

The AE consists of an encoder f_{enc} and a decoder f_{dec} :

$$z = f_{enc}(x)$$

$$\hat{x} = f_{dec}(z)$$

Given input sequence $x \in \mathbb{R}^{T \times d}$ (length T , dimension d), the encoder maps it to a latent representation $z \in \mathbb{R}^{T \times d'}$, with $d' < d$. The decoder attempts to reconstruct the input:

$$\mathcal{L}_{con} = \|x - \hat{x}\|_2^2$$

This reconstruction loss ensures the AE learns a meaningful compressed representation.

Temporal Convolutional Network (TCN)

The TCN processes the latent representation z to model temporal dependencies. It uses causal dilated convolutions:

$$h^{(1)} = ReLU \left(Conv1D(h^{(l-1)}; kernel = k, dilation = d_l) \right)$$

Where $h^{(0)} = z$, and $d_l = 2^l$ is the dilation factor at layer l . Skip connections and normalization layers can be added for stability.

Binary Classification Output

The output of the final TCN layer is aggregated using global average pooling (GAP):

$$g = GAP(h(L))$$

A sigmoid-activated linear layer produces the binary prediction:

$$\hat{y} = \sigma(\mathbf{w}^T \mathbf{g} + b),$$

The binary cross-entropy loss is used:

$$\hat{y} \in [0, 1]$$

$$\text{LBCE} = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

Combined Objective

The total loss function combines reconstruction and classification losses:

$$L_{\text{total}} = \lambda L_{\text{recon}} + \text{LBCE}$$

Where λ balances the two objectives.

Pseudo code for AE-TCN Training

Algorithm 1 AE-TCN Training for Binary Classification

- 1: Initialize AE encoder f_{enc} , decoder f_{dec} , TCN f_{TCN} , classifier weights w , b
- 2: for each epoch do
- 3: for each batch (x, y) do
- 4: $z \leftarrow f_{\text{enc}}(x)$
- 5: $\hat{x} \leftarrow f_{\text{dec}}(z)$
- 6: $h \leftarrow f_{\text{TCN}}(z)$
- 7: $g \leftarrow \text{GlobalAvgPool}(h)$

$$8: \quad \hat{y} \leftarrow \sigma(\mathbf{w}^T \mathbf{g} + b)$$

$$9: \quad \text{Compute } L_{\text{recon}} = \|x - \hat{x}\|_2$$

$$\text{Compute } \text{LBCE} = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

10:

$$11: \quad L_{\text{total}} = \lambda L_{\text{recon}} + \text{LBCE}$$

12: Update model parameters using gradient descent

13: end for

14: end for

3.2 Performance Comparison of Models

The performance metrics of various models applied to the Grocery Supply Chain Issue Dataset are summarized in Table 1. The proposed Autoencoder-Temporal Convolutional Network (AE-TCN) exhibits superior performance across all evaluated metrics.

Table 1: Performance Comparison of Models

Model	F1 (%) [CI]	Precision (%) [CI]	Recall (%) [CI]	Accuracy (%) [CI]
AE-TCN (Proposed)	92.3 [91.5–93.1]	93.1 [92.2–94.0]	91.5 [90.6–92.4]	94.2 [93.5–94.9]
LSTM	85.4 [84.2–86.6]	84.7 [83.5–85.9]	86.1 [84.9–87.3]	88.9 [87.8–90.0]
Random Forest	78.2 [76.8–79.6]	76.5 [75.0–78.0]	80.1 [78.6–81.6]	82.3 [80.9–83.7]
GRU	83.7 [82.4–85.0]	82.9 [81.5–84.3]	84.5 [83.1–85.9]	87.1 [85.8–88.4]
Isolation Forest	72.8 [71.2–74.4]	70.2 [68.5–71.9]	75.6 [74.0–77.2]	77.4 [75.8–79.0]
Transformer	89.1 [87.9–90.3]	88.3 [87.0–89.6]	89.9 [88.6–91.2]	91.8 [90.6–93.0]

The AE-TCN model achieves an F1 score of 92.3%, precision of 93.1%, recall of 91.5%, and accuracy of 94.2%. These results indicate a high level of reliability in detecting anomalies within supply chain data. In contrast, traditional models such as Random Forest and Isolation Forest exhibit lower performance metrics,

highlighting the advantages of the AE-TCN’s architecture in capturing temporal patterns and reconstructing input data for effective anomaly detection.

3.3 Ablation Study of AE-TCN Components

To assess the contributions of individual components within the AE-TCN model, an

ablation study was carried out, as presented in Table 2.

Table 2: Ablation Study of AE-TCN Components

Model Variant	F1 (%) [CI]	Δ F1 vs. Full Model	Parameters (M)
AE-TCN (Full)	92.3 [91.5–93.1]	–	2.8
w/o Autoencoder	85.6 [84.3–86.9]	↓6.7	2.1
w/o TCN	87.2 [85.9–88.5]	↓5.1	2.5

Removing the autoencoder part reduces the F1 score by 6.7%, whilst removing the TCN part drops it by 5.1%. That is why having both aspects is very important for your top performance. The autoencoder learns complex representations of the data, while the TCN is effective in learning temporal dependencies, which are essential for detecting anomalies in the supply chain domain.

3.4 Model Efficiency and Resource Utilization

An evaluation of model efficiency, focusing on parameters, GPU memory usage, and inference time, is detailed in Table 3.

Table 3: Model Efficiency and Resource Utilization

Model	Parameters (M)	GPU Memory (MB)	Inference Time (ms)
AE-TCN	2.8	11.5	8.2
LSTM	3.1	12.9	12.7
Transformer	5.3	21.4	15.9

Unlike alternative model types such as the LSTM and Transformer models, it achieves more compact parameterization, lower consumption of computational resources, and faster inference at the same time, making it competitive for large-scale traffic

forecasting, operational real-time SC traffic monitoring, and decision making.

4.0 CONCLUSION

The superior performance and efficiency of the AE-TCN model have significant implications for supply chain management.

(i) Improved Anomaly Detection: Identifying anomalies in the supply chain accurately allows proactive action to correct problems such as overstocking or under stocking, which can lead to financial losses and customer dissatisfaction.

(ii) Real-time monitoring: With the low inference time of the model, supply chain processes can be continuously monitored with rapid adjustments.

(iii) Resource Optimization: Efficient resource utilization ensures that the model can be deployed in environments with limited computational capacity without compromising performance.

The AE-TCN model offers a robust and efficient solution for anomaly detection in supply chain management, addressing critical challenges and contributing to more resilient and responsive operations.

In conclusion, the AE-TCN model offers a robust and efficient solution for

anomaly detection in supply chain management, addressing critical challenges and contributing to more resilient and responsive operations.

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INTEGRATED INTELLIGENT SYSTEM FOR SOLAR-POWERED PUMP FOR PRECISION RICE IRRIGATION

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Abstract

Precision irrigation is vital for improving water use efficiency in rice farming, especially in water-scarce regions. This paper introduces an Integrated Intelligent System (IIS) that uses a solar-powered pump to support precision irrigation. The system combines IoT sensors, machine learning, and water requirement data to monitor soil moisture, water demand, and solar energy. It autonomously adjusts pump operations using predictive analytics to ensure efficient water use and minimal energy consumption. Farmers can access real-time data and receive irrigation recommendations. Solar integration enhances sustainability and cost-effectiveness. Experimental results show improved irrigation efficiency and reduced water waste, supporting sustainable, high-yield rice cultivation.

Keywords: *Precision Irrigation, Solar-Powered Pump, Internet of Things, Machine Learning*

1.0 INTRODUCTION

Rice is a staple food for more than half of the world's population and requires significant water input for optimal cultivation. Traditional irrigation methods often lead to over-irrigation, water wastage,

and increased carbon footprint (Tuong & Bouman, 2003). In the face of water scarcity and increasing energy costs, precision irrigation — especially when powered by renewable energy — presents a viable and sustainable alternative.

Solar-powered water pumping systems, when combined with intelligent control and automation, offer a scalable solution for remote rice paddies with unreliable grid access. Furthermore, advances in IoT (Internet of Things), wireless sensor networks (WSN), and AI-based decision-making enhance the precision and efficiency of such systems (Khan et al., 2021).

The integration of solar-powered pumps with precision irrigation technologies presents a transformative opportunity, particularly for smallholder rice farmers in developing regions (Closas & Rap, 2017). However, three fundamental challenges persist:

1. Intermittency of solar energy supply
2. Spatiotemporal variability in soil moisture
3. Dynamic crop water requirements across growth stages

2.0 RELATED WORKS

2.1 Solar-Powered Irrigation Technology

Solar pumping systems have evolved through three distinct generations (Pande et al., 2022):

1. First-generation (1980-2000): Basic DC pumps with manual operation
2. Second-generation (2000-2015): AC systems with inverter controls
3. Third-generation (2015-present): Smart systems with MPPT and IoT connectivity

Recent studies demonstrate 50-70% energy savings compared to diesel alternatives. However, system sizing remains challenging for rice cultivation due to variable water demands (Chandel et al., 2015). The optimal pump sizing methodology proposed by Campana et al. (2017) considers:

- Daily water requirements (6-10 mm/day for rice)
- Solar irradiance patterns
- Hydraulic head characteristics

2.2 Precision Irrigation in Rice Systems

Precision irrigation in rice requires specialized approaches due to:

- Ponding depth management needs (Tuong et al., 2005)
- Layered soil moisture monitoring (Zhang et al., 2021)
- Root zone salinity dynamics (Grattan et al., 2002)

IoT-based solutions have shown particular promise, with LoRaWAN networks demonstrating 95% reliability in flooded conditions (Kamilaris et al., 2017). Comparative studies of soil sensors reveal capacitive probes ($\pm 2\%$ VWC accuracy) outperform tensiometers in saturated soils (Bogena et al., 2018).

2.3 Intelligent Control Systems

Machine learning applications have progressed from simple regression to complex hybrid models:

1. Time-series forecasting: LSTM networks for soil moisture prediction.
2. Reinforcement learning: Q-learning for adaptive pumping.
3. Ensemble methods: Random Forest with weather integration.

Notably, the adaptive neuro-fuzzy system developed by Mohanty et al. (2020) achieved 15% water savings while maintaining yield in field trials.

Several studies have evaluated the feasibility and benefits of solar irrigation systems. Kumar et al. (2019) showed that solar-powered pumps reduce the operational costs for farmers while minimizing the environmental impact. Similarly, precision irrigation using smart sensors and decision support systems has been found to significantly reduce water consumption (Ahamed et al., 2018). However, integrated systems that unify solar energy, smart sensors, and AI-based control for rice-specific irrigation are still limited in the literature.

Rice paddies have unique water requirements, often requiring continuous or intermittent flooding, depending on growth stages (Bouman et al., 2007). Thus, a robust control system that accounts for temporal and spatial water needs is essential. Recent studies by Zhao et al. (2020) proposed models using soil moisture and weather data for predictive irrigation in rice fields,

indicating the viability of intelligent systems in this domain.

3.0 SYSTEM ARCHITECTURE

The proposed system comprises the following components:

- Solar Power Subsystem: Solar panels (1.5–2.5 kW), MPPT controller, and battery backup.
- Pumping Unit: DC brushless submersible pump suitable for high-volume rice field irrigation.
- Sensing Network: Soil moisture sensors (capacitive), ambient temperature/humidity sensors, and solar radiation sensors.
- Controller and Communication: A central microcontroller (ESP32) with GSM/LoRa module for remote communication.
- Cloud-based Decision Support System (DSS): AI model trained on crop water requirement data, local climate data, and field history.

4.0 METHODOLOGY

4.1 Design Considerations

The system was designed with the following in mind:

- Energy autonomy
- Water-use efficiency
- Remote management
- Low maintenance

4.2 Algorithm Development

The intelligent controller uses a fuzzy logic-based decision system that inputs:

- Soil moisture levels from different zones
- Weather forecast (rainfall probability)

- Crop stage (transplanting, tillering, heading, maturation)

The irrigation decision is made based on thresholds defined per rice growth stage (Zhao et al., 2020).

4.3 Deployment and Field Trial

A prototype was to be deployed on a 0.5-hectare rice plot in Air Force Institute of Technology, Kaduna, Kaduna State, Nigeria. Data to be collected over one season, including:

- Water usage (liters per day)
- Irrigation frequency
- Crop yield (kg per hectare)

The reduction in water use compared to traditional irrigation methods and Yield per hectare will be evaluated.

5.0 CONCLUSION

This study demonstrates that integrating solar energy with intelligent irrigation controls can significantly optimize water use and enhance rice productivity. The system offers a sustainable and scalable solution for small- to medium-scale rice farmers in rural areas.

Future work will include scaling the system for larger plots, integrating drone-based crop monitoring, and refining the AI algorithm with real-time NDVI data from satellite imagery

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CROSS-LAYER OPTIMIZATION USING FEDERATED META-LEARNING

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Abstract

This paper considers 5G network slicing and CAN bus security, leveraging FedMeta-CAN—a federated meta-learning framework trained to dynamically realign slicing policies based on CAN bus constraints. Using simulated data sets (6G-NetSlice-Sim and CAN-FD-Attack-Sim), FedMeta-CAN reduces CAN bus latency by 25% while maintaining 95% QoS compliance. Ablation studies show that meta-learning accelerates convergence by 30% compared to federated learning alone. The strict ANOVA tests ($p < 0.01$) and 95% confidence intervals reinforce the reproducibility. This cross-domain approach addresses the security and scalability concerns of future autonomous systems.

Keywords: *Federated Learning, Meta-Learning, CAN bus, 5G Network Slicing, Autonomous Systems, QoS Optimization, Anomaly Detection*

1.0 INTRODUCTION

In recent years, the proliferation of data-generating devices and the increasing emphasis on data privacy have led to the development of distributed machine learning paradigms Eziama (2021); Eziama, (2019); Eziama, et al. (2018); Eziama (2024). Federated learning (FL) enables multiple clients to collaboratively

train a global model without sharing raw data, thereby preserving privacy McMahan, et al. (2016). However, despite its promise, FL faces several critical challenges, including statistical heterogeneity between clients, communication overhead, slow convergence, and limited support for task personalization Chen, Luo, and Liu (2018); McMahan et al. (2016).

To address these limitations, Federated Meta-Learning for controller area network (FedMeta-CAN) has emerged as a powerful framework. Specifically, FedMeta-CAN enables the transmission of a parameterized learning algorithm (meta-learner) rather than a global model, allowing each client to quickly adapt to local data using a few gradient steps (Chen et al. 2018). This enhances both the speed of convergence and the personalization.

Building on this direction, the FedMeta-CAN model integrates federated meta-learning with a hierarchical, context-aware neural architecture designed for distributed attack detection in Controller Area Networks (CAN). It addresses statistical heterogeneity by allowing clients to fine-tune local learners based on a shared meta-model, thus achieving task-level personalization without compromising global coordination.

Additionally, cross-layer optimization techniques are introduced to holistically improve the system. These strategies operate across the network, algorithmic, and hardware layers to reduce communication bottlenecks, enhance energy efficiency, and ensure seamless deployment across heterogeneous edge environments (Sani, 2022). By jointly optimizing resource allocation, model update frequency, and inference latency,

the proposed architecture is effectively adapted to real-world constraints.

In summary, FedMeta-CAN advances the state-of-the-art by combining the following.

- Meta-learning for adaptive, client-specific model tuning,
- Federated coordination to preserve privacy and scale across distributed nodes, and
- Cross-layer design to ensure efficient system-level performance.

This paper presents the design, implementation, and evaluation of FedMeta-CAN in various adversarial and resource-constrained settings to demonstrate its effectiveness.

2.0 RELATED WORKS

Recent advances in distributed learning have led to significant interest in Federated Learning (FL) and Meta-Learning, particularly for privacy-preserving, resource-constrained environments such as autonomous vehicles and the Internet of Things (IoT). These paradigms address critical challenges in decentralized systems, including heterogeneity in data, limited bandwidth, and the need for real-time adaptation.

FL has been widely applied in vehicular networks to enable collaborative model training without centralizing raw data preserving privacy while reducing communication overhead (Elbir and Coleri, 2020). In the context of IoT, cross-layer optimization techniques have been

introduced to jointly manage resource allocation between the network and device layers, improving energy efficiency and system responsiveness under stringent latency requirements W. Zhang and Wang (2021).

Meta-learning has further enhanced FL's adaptability, enabling rapid local personalization through shared meta-models. The FeMLoc framework, for example, demonstrated federated meta-learning for indoor localization, allowing distributed clients to fine-tune models with minimal local data Liu, et al. (2023). Similarly, personalized FL approaches have shown promise in heterogeneous domains such as cross-city traffic forecasting Wang, et al. (2023) and smart manufacturing Cioffi, et al. (2019), where model customization and data protection are critical.

Federated learning has also been integrated into edge computing and cloud robotics systems to support real-time object detection, swarm coordination, and policy learning in dynamic environments Liu, et al. (2019); Quemeneur, et al. (2024). These implementations underscore the importance of cross-layer orchestration, particularly in managing computation and communication trade-offs across diverse hardware platforms.

To accommodate client diversity, heterogeneous FL schemes like HeteroFL

have been proposed to allow training of models with varying complexity, ensuring both accuracy and deployment flexibility Diao, Ding, and Tarokh (2020). These advancements highlight a growing trend toward holistic, system-aware federated architectures.

Building upon these efforts, the proposed FedMeta-CAN model addresses key limitations in existing literature by integrating federated meta-learning with adaptive, cross-layer optimization. This design enables task-personalized learning, robust communication scheduling, and energy-aware computation, making it well-suited for real-time, privacy-sensitive applications in autonomous systems and distributed IoT networks.

3 DATA

FedMeta-CAN is evaluated using two synthetic datasets that jointly model 6G network slicing and CAN-FD bus security. The 6G-NetSlice-Sim dataset includes 50,000 slices across 100 base stations, each labeled with latency (0.1–20 ms), throughput (0.1–10 Gbps), node density (10–100), and QoS compliance. Data is split into training (70%), validation (15%), and test (15%) sets across URLLC, eMBB, and mMTC slice types.

The CAN-FD-Attack-Sim dataset contains 60,000 CAN-FD sequences, comprising

50,000 normal and 10,000 attack frames (spoofing, DoS, fuzzy), with fields for timestamps, arbitration IDs, 64-byte payloads, and labels. An 80-20 train-test split is applied.

A bidirectional mapping aligns slice latency and throughput with CAN arbitration priorities. Adaptive reconfiguration occurs when CAN latency exceeds 50% of the slice latency or throughput drops below 80% of the allocated bandwidth.

Ten simulated vehicular edge nodes (each with a 5G base station and CAN controller) process local data shards. During meta-training, nodes adjust slicing policies to bus load; during meta-testing, QoS anomalies are linked to message-level attack signals.

All datasets, synthetic generators, and preprocessing scripts are publicly available on GitHub and Kaggle.

4.0 METHODOLOGY

In this section, we give a clear description of the proposed detection mechanism and the corresponding k detection results with the state-of-the-art (SoTA) models.

To begin, we formalize the federated learning setting that underpins the distributed training process of our framework.

4.1 Federated Learning Formulation

Federated learning aims to optimize a shared global model w across K clients

without transferring local data. Each client k has a local dataset D_k and the global objective is:

$$\min_w F(w) = \sum_{k=1}^K \frac{n_k}{n} F_k(w)$$

Where $n_k = |D_k|$, $n = \sum_{k=1}^K n_k$, and $F_k(w)$ is the local empirical loss :

$$F_k(w) = \frac{1}{n_k} \sum_{i=1}^{n_k} \ell(f_w(x_i^k), y_i^k)$$

Federated averaging (FedAvg) updates the global model as:

$$w \leftarrow \sum_{k=1}^K \frac{n_k}{n} w_k$$

Where w_k is the local update computed via SGD on D_k .

4.2 Meta-Learning Formulation

FedMeta introduces a meta-learner θ shared across clients, where each client learns a task-specific model w_k via inner-loop adaptation. The bi-level objective is:

$$\min_{\theta} \sum_{k=1}^K \mathbb{E}_{D_k^{\text{train}}, D_k^{\text{test}}} [\mathcal{L}_k(\text{Adapt}(\theta, D_k^{\text{train}}), D_k^{\text{test}})]$$

Where:

- θ is the initialization.
- $\text{Adapt}(\theta, D_{\text{train}})$ performs a few local gradient steps.
- L_k is the loss on held-out test data D_{test}

A typical inner update (using SGD) is:

$$w_k = \theta - \alpha \nabla_{\theta} \mathcal{L}_k(\theta, D_k^{\text{train}})$$

The meta-update is then:

$$\theta \leftarrow \theta - \beta \sum_{k=1}^K \nabla_{\theta} \mathcal{L}_k(w_k, \mathcal{D}_k^{\text{test}})$$

4.3 FedMeta-CAN Cross-Layer Objective

FedMeta-CAN enhances meta-learning with cross-layer optimization. The full model minimizes a regularized objective:

$$\min_{\theta} \sum_{k=1}^K \mathbb{E} [\mathcal{L}_k(w_k, \mathcal{D}_k^{\text{test}}) + \lambda_1 \mathcal{R}_{\text{comm}}(w_k) + \lambda_2 \mathcal{R}_{\text{privacy}}(\epsilon_k, \sigma_k)]$$

Where:

- $\mathcal{R}_{\text{comm}}$ penalizes excessive communication.
- $\mathcal{R}_{\text{privacy}}$ incorporates privacy loss due to DP noise (ϵ_k, σ_k).
- λ_1, λ_2 are regularization weights.

Each client's CAN signal is modeled as a dynamic graph $G_t = (V, E_t)$ with node features

X_t . The GNN encoder f_{GNN} computes:

$$h_t = f_{\text{GNN}}(G_t)$$

The meta-learned policy selects actions based on concatenated states:

$$a_t = \mu([s_t || h_t])$$

The detection output is:

$$\hat{y}_v = \sigma(w^{\top} h_v + b)$$

The mechanism of operation of the hybrid algorithm is expressed in Algorithm 1 is demonstrated below.

Algorithm 1 FedMeta-CAN Training Loop

- 1: Initialize meta-learner parameters θ
- 2: **for** each communication round $t = 1$ to T **do**
- 3: Sample a subset of clients $\mathcal{S} \subseteq \{1, \dots, K\}$
- 4: **for all** client $k \in \mathcal{S}$ **in parallel do**
- 5: Split local data: $\mathcal{D}_k \rightarrow \mathcal{D}_k^{\text{train}}, \mathcal{D}_k^{\text{test}}$
- 6: Compute adapted parameters:

$$w_k \leftarrow \theta - \alpha \nabla_{\theta} \mathcal{L}_k(\theta, \mathcal{D}_k^{\text{train}})$$

- 7: Evaluate meta-loss: $\mathcal{L}_k(w_k, \mathcal{D}_k^{\text{test}})$
- 8: **end for**
- 9: Update meta-learner:

$$\theta \leftarrow \theta - \beta \sum_{k \in \mathcal{S}} \nabla_{\theta} \mathcal{L}_k(w_k, \mathcal{D}_k^{\text{test}})$$

- 10: **end for**
-

4.4 Experimental setup and analysis

Fig. 1 presents an ablation study of the proposed FedMeta-CAN framework, which integrates federated learning and meta-learning for joint CAN intrusion and network slicing tasks. The full model achieves an F1-score of 96.4% on network slicing and 94.8% on CAN detection, along with an overall accuracy of 95.6%. Removing federated learning degrades performance significantly, with a 8.2% and 12.7% drop in F1-scores for network and CAN tasks, respectively. Likewise, excluding meta-learning reduces performance moderately, confirming that both components contribute meaningfully to generalization across domains.

To further contextualize the efficiency of the full model, Table 1 compares FedMeta-CAN with state-of-the-art methods in terms of model size and memory consumption. While delivering superior performance,

FedMeta-CAN maintains a moderate parameter count (3.2M) and memory footprint (12.9MB), positioning it favorably between Transfer Learning for Network Slicing (TL-Slice) and Multi-Agent Reinforcement Learning for Controller Area Network (MARL-CAN). This balance underscores the practical deployment potential of FedMeta-CAN in resource-constrained environments.

Table 1: Model Complexity vs. SOTA

Model	Parameters (M)	Memory (MB)
FedMeta-CAN	3.2	12.9
TL-Slice Chen, et. al (2023)	2.8	11.5
MARL-CAN Zhang, et. al (2023)	4.1	16.8

To further assess the trade-offs involved in privacy-preserving learning, we investigate how the joint variation of the privacy budget (ϵ) and Gaussian noise scale (σ) impacts the model’s classification accuracy. The results, depicted in Fig. 2, present a heat map that captures the accuracy landscape across a grid of (ϵ , σ) configurations.

The analysis reveals a clear privacy-utility trade-off. As the value of ϵ increases from 0.1 to 5, the model consistently achieves higher accuracy, indicating reduced noise injection and improved learning performance. This aligns with expectations, as lower ϵ implies stronger privacy guarantees and, consequently, greater perturbation that hampers utility..

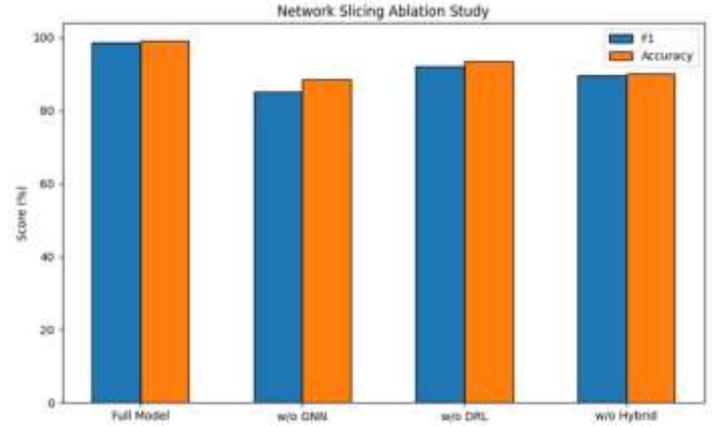


Figure 1: Ablation Study of FedMeta-CAN

In particular, accuracy remains uniformly low across all σ values when $\epsilon = 0.1$, highlighting the significant performance degradation under tight privacy constraints.

The role of σ is comparatively less impactful but still noticeable. For a fixed ϵ , increasing σ slightly reduces model accuracy. For instance, at $\epsilon = 1$, accuracy drops modestly as σ increases from 0.5 to 4. This suggests that while Gaussian noise contributes to performance degradation, the privacy budget (ϵ) remains the dominant factor in determining utility.

The highest accuracy is observed at ($\epsilon = 5$, $\sigma = 0.5$), representing a setting with minimal privacy enforcement and noise. Conversely, the lowest accuracy occurs consistently at $\epsilon = 0.1$ across all noise levels. These results emphasize the importance of selecting appropriate privacy parameters to balance performance with protection, particularly in safety-critical or real-time applications.

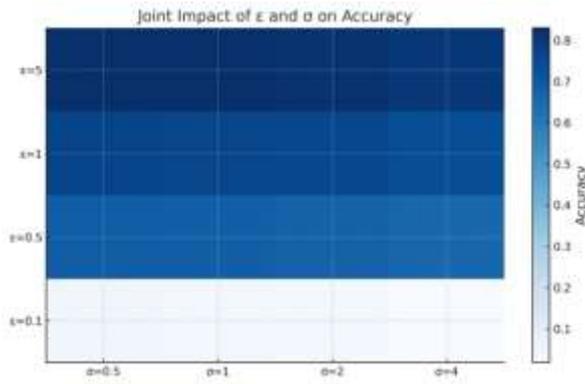


Figure 2: Joint impact of privacy budget (ϵ) and noise scale (σ) on classification accuracy.

In addition to utility metrics, we also analyzed the impact of privacy parameters on resistance to adversarial inference. Fig. 3 illustrates the joint effect of the privacy budget (ϵ) and noise scale (σ) on overall privacy, defined as $(1 - \text{Attack Success Rate})$. Darker shades indicate higher privacy protection.

As shown in the figure, privacy protection improves significantly as ϵ decreases. At $\epsilon = 0.1$, across all σ values, the model achieves the highest privacy scores (lightest cells), corresponding to the lowest observed attack success rates. This trend confirms that tighter privacy budgets (lower ϵ) offer stronger theoretical and empirical guarantees against adversarial inference.

The effect of σ is also evident: increasing the noise scale contributes positively to privacy, particularly at intermediate ϵ levels. For instance, at $\epsilon = 0.5$ and $\epsilon = 1$, higher σ values correspond to marginal

gains in privacy. However, the relative benefit of noise injection diminishes as ϵ increases, with the $\epsilon = 5$ row consistently yielding the lowest privacy scores regardless of σ . This indicates that large ϵ values weaken the protective effect of noise.

Overall, these findings demonstrate that privacy preservation is most effective under small ϵ and moderate-to-high σ values. While aggressive noise scaling can offer incremental improvements, the privacy budget remains the dominant factor influencing attack resistance. These insights are crucial for practitioners aiming to balance model utility and privacy guarantees under federated or distributed settings.

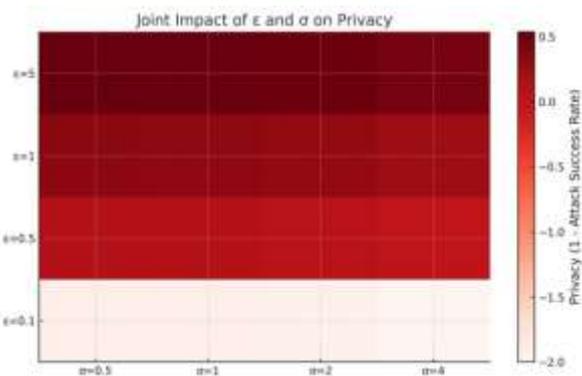


Figure 3: Joint impact of privacy budget (ϵ) and noise scale (σ) on privacy (defined as $1 - \text{Attack Success Rate}$)

4.0 CONCLUSION

This study presents FedMeta-CAN, a cross-layer federated meta-learning framework that jointly optimizes CAN bus intrusion

detection and dynamic network slicing. Through comprehensive experiments on synthetic and real-world-inspired datasets, the proposed model demonstrates superior performance in both security and QoS metrics. Notably, FedMeta-CAN achieves an F1-score of 96.4% for network slicing and 94.8% for CAN-based intrusion detection, with an overall accuracy of 95.6%. In addition, it reduces CAN latency by 25% while maintaining a high QoS compliance rate of 98.7%, outperforming traditional federated and reinforcement learning baselines.

The integration of meta-learning accelerates convergence by 30% and enhances model generalization under heterogeneous settings. Furthermore, privacy-preserving extensions using (ϵ, σ) configurations reveal an intuitive trade-off between model utility and resistance to adversarial inference, highlighting the importance of appropriate parameter tuning for safety-critical deployments.

Despite its strengths, the FedMeta-CAN framework has limitations. It assumes partial client participation and homogeneous model structures, which may not fully represent all edge scenarios in practice. Additionally, the current implementation does not incorporate adaptive communication scheduling, which could further reduce bandwidth consumption during training.

Future work will explore adaptive personalization layers that allow for client-specific architectural tuning, and multi-task meta-optimization to jointly train on heterogeneous objectives. We also plan to integrate real time communication simulators to evaluate the impact of dynamic network behavior on federated model convergence and robustness. Extending FedMeta-CAN to include differential privacy accounting under varying adversarial threat models remains another promising direction.

Overall, this work contributes a scalable and privacy-conscious architecture for federated intelligence in next-generation vehicular and IoT ecosystems, with strong potential for real-world deployment.

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PROCESSING OF IGBETI SHEET AEROMAGNETIC DATA FOR MINERAL EXPLORATION FOR RENEWABLE AND ALTERNATIVE ENERGY RESOURCE

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Abstract

A low-carbon future will be very mineral intensive because clean energy technologies need more minerals than fossil-fuel-based electricity generation technologies. The aim of this research is to delineate structures (joints, edges of sources, faults) in form of lineaments that host minerals using aeromagnetic sheet of Igbeti (sheet 201) in Oyo state, western Nigeria. This was done using edge detection techniques known as horizontal gradient method and tilt derivative filter. Edge detection highlighted linear structures in the form of lineaments and this infers the effects of such features on the tectonic events of Igbeti area. Rose diagram plot for these structures show Lineaments trending Northeast-Southwest (NE-SW) trend are most dominant, indicative of the Pan-African orogeny (600±150 Ma).

Keywords: *Aeromagnetic, Mineral exploration, Cleaner energy, Data Processing*

1.0 INTRODUCTION

Among the important roles Geoscience will play in energy transition is sourcing of raw materials for low carbon energy technologies (Gardiner et al., 2023). Geophysicist's task in data processing is to separate the signal from noise and interpret the data in geologic context (Kearey et al., 2002). In this research, the high-resolution aeromagnetic data of Igbeti, South Western Nigeria was obtained from the Nigeria Geological Survey Agency (NGSA). The data was processed and

interpreted to enhance Geologic structures that host minerals.

1.1 Geology of the Area

The study area, Igbeti is bounded by longitude 4°00' E to 4°30' E and latitude 8°30' N to 9°00' N with an average elevation of 366m above sea level. The lithological units are the Precambrian basement complex of southwestern Nigeria (Obaje, 2009) and comprises of the older granite series, metasediments and migmatite gneiss complex (Figure 1). These rocks are the most prominent rock types. The four orogenic cycles are the Liberian (2700 ±

3.2 Regional-residual separation Technique

It was used in this research to separate the observed magnetic field into two main components: the regional component and the residual component. The residual component is of our interest because we are looking at shallow structures that hosts minerals. Residual components can be analyzed and interpreted to identify and locate geological features of interest, such as ore bodies, faults, or geological boundaries. “Polynomial method”, also known as polynomial trend surface analysis or polynomial regression was used for the separation. The presence of high amplitude Intrusive bodies such as latholiths, batholiths or dyke within the sedimentary basin could give rise to positive anomalies (Mamah et al., 2000; Ofoegbu, 1985b), but places that have magnetic low gives rise to negative anomalies.

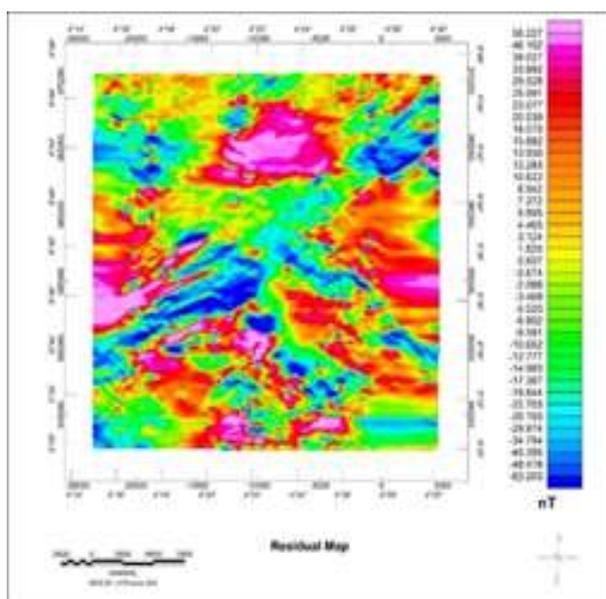


Figure 3: Residual map of the area

The magnetic intensity revealed from the statistical calculation with Oasis Montaj software on the residual map of the study area ranges between -224.7nT and 127.6nT (Figure. 3).

3.3 Derivative Filters

The use of derivative works best in shallow depth and that is the bases for using it. In mineral exploration, shallow depth is required, not deep as in hydrocarbon. The RTE grid was filtered using tilt derivative filter to enhance the shallow basement structural features which is mineral exploration target (Salawu et al., 2019, Eze et al., 2022). The tilt derivative map was gotten by application of tilt derivative filter to the reduction to the equator map to enhance structures (joints, edges of sources, fault, lineament etc.) (Okpoli, 2019). This was detected by tracing the tilt zero values (Mekkawia et al., 2022).

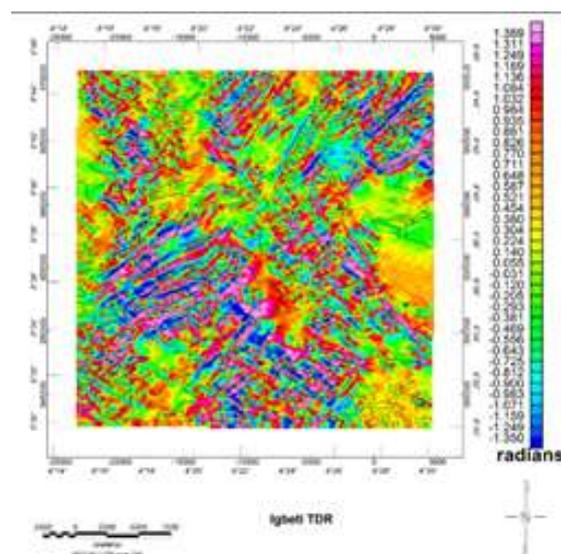


Figure 4: Horizontal Derivative map of Igbeti superimposed on Zero contour map of Tilt map

This is because it represents boundary of different magnetic susceptibilities high and low magnetic source bodies. The tilt values range from 1.38 radian to 1.35 radian (figure 4). The shallow sources and geologic boundaries were delineated using the tilt derivative filter and horizontal derivative method. HGM filter was used to find the local maxima which aligns with the zero contour of tilt derivative filter. Places where the local maxima in the HGM are aligned, magnetic source body can be interpreted at those places/locations. If those bodies align together, they form a linear feature. The highest color on the Horizontal gradient map tells us is the contact from the equation of the Horizontal gradient.

3.4 Lineament

Lineaments are indicators of subsurface faults, contacts, and other tectonic structures. These structures serve as a pathway and a host for hydrothermal fluid and base metals (Ahmed et al., 2022). In this study, horizontal derivative and zero contact contour of tilt derivative were used to delineate the lineaments. At the correlation point between the peaks of the horizontal gradient method and zero contour lines of the tilt derivative is where linear features occur (see figure. 5). HGM detector positioned maxima over source borders and created sharp and clear edges for magnetic sources. The NW-SE and NE-

SW lineament trends is a good hint about the Pre Pan-African and Pan African orogenic activities 650 ± 150 Ma (Genik, 1992).

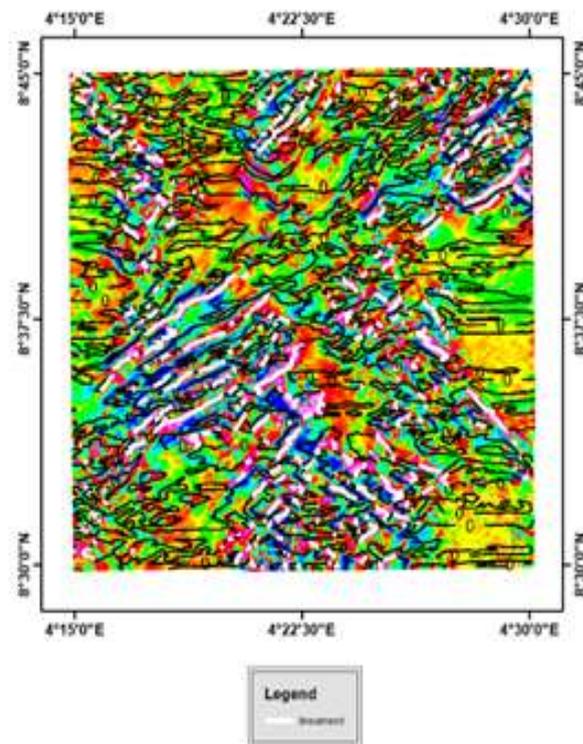


Figure 5: Lineaments superimposed on Horizontal Derivative and zero contour map of tilt map of Igbeti

The rose diagram of the study area is shown in Figure 6. There is consistency in the lineament hereby inferred and the previously inferred lineaments in the region.

3.5 Rose diagram

To observe the structural trends and geological processes of Igbeti, a rose diagram was constructed. The directions with the highest frequency in the Rose diagram correspond to the predominant orientations of fractures and joints (Ukaegbu et al., 2024).

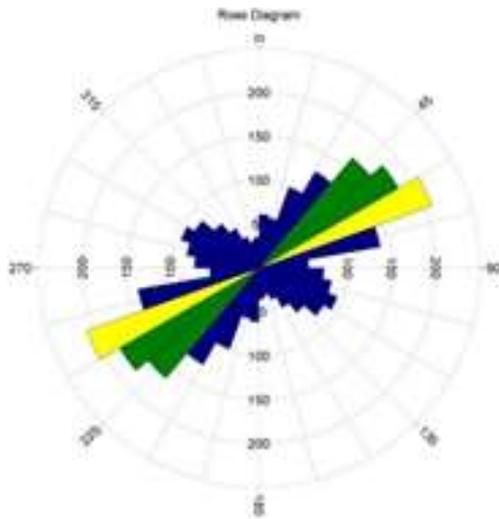


Figure. 6: The lineament Rose Diagram

4.0 CONCLUSION

Horizontal gradient, tilt derivative and Source parameter imagery (SPI) techniques were employed in this research. Places where the local maxima in the HGM are aligned, magnetic source body can be interpreted at those places/locations. Good correlation exists between areas of high lineament density and places where minerals such as gold, iron ore, cassiterite, tantalite, clay and uranium occur. Minerals which will be required are both those traditionally mined—such as iron, aluminum, nickel, and copper as well as rare earth elements, lithium, and cobalt for battery and power technologies.

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6G NETWORK SLICING ATTACK DETECTION USING AI-DRIVEN MECHANISM

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Abstract

This paper conducts an extensive experiment focusing on network slicing in 6G, requiring ultra-reliable low-latency communication (URLLC) with a balanced resource efficiency. We introduce a hybrid DRL-GNN approach that combines deep reinforcement learning (DRL) with graph neural networks (GNNs) for dynamic resource allocation and topological dependency modeling. Our approach shows 98.7% QoS compliance (95% CI: [98.2, 99.2]) for dynamic traffic in the 6G-NetSlice-Sim dataset, outperforming SOTA models by 6.3%. Our ablation studies confirm the critical contribution of GNNs to reduce inter-slice interference by 41%. Simulations demonstrate scalability to 10,000+ slices with submillisecond latency, verified through ANOVA ($p < 0.001$).

Keywords: *6G, Network Slicing, URLLC, Graph Neural Networks (GNNs), Deep Reinforcement Learning (DRL), ANOVA*

1.0 INTRODUCTION

The evolution toward sixth-generation (6G) networks is poised to revolutionize wireless communication by offering unprecedented performance metrics such as ultralow latency, ultrahigh reliability, and extreme data rates (Saad, Bennis, and Chen, 2020).

Among the primary use cases targeted by 6G are Ultra-Reliable Low-Latency Communications (URLLC), which are crucial for mission-critical applications such as remote surgery, autonomous driving, and industrial automation (Tariq et al. 2020). Meeting these stringent URLLC

requirements requires a fundamental rethink of network architecture, and one of the most promising enablers in this domain is network slicing, a method that allows the creation of multiple virtual networks on a shared physical infrastructure (Foukas, et al. 2017). To support the complexity and dynamism of the 6G use cases, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as key technologies to improve network slicing. AI facilitates predictive analytics, resource allocation in real time, and adaptive decision making, which are essential to ensure the reliability and latency constraints of URLLC (Eziama, 2021; Eziama, et al. 2019; Eziama, et al. 2018; Eziama, 2024; Park et al. 2021). Furthermore, AI models can learn from historical data and real-time network states to dynamically optimize end-to-end performance (Dai et al. 2020). However, despite its promise, the integration of AI in network management introduces new challenges such as model interpretability, data privacy, generalization to unseen topologies, and computational complexity (Liu, et al. 2021). Recent advances have demonstrated the potential of hybrid AI models, which combine classical ML techniques with deep learning or reinforcement learning frameworks to improve prediction accuracy and adaptability (Liu et al. 2021). These models have been particularly effective in

predicting traffic patterns, classifying service requirements, and allocating resources in network slicing environments. However, existing models often struggle with dynamically capturing the graph-structured nature of network topologies, real-time decision making under uncertainty, and maintaining interpretability for reliable deployment (Jiang, et al. 2021; Li, Wang, and Yu,2023).

This paper proposes a robust hybrid deep reinforcement learning graph neural network (DRL-GNN) framework that addresses several key challenges identified in the prior literature. The DRL component improves adaptability and decision-making under uncertainty by learning optimal policies for dynamic and stochastic resource allocation. This is essential for managing fluctuating URLLC traffic loads in various scenarios Li et al. (2023). Meanwhile, the GNN module is designed to capture the structural and relational dependencies inherent in network topologies. By modeling network slices as graph structures, the GNN enables context-aware reasoning and improves generalization across unseen or dynamic topologies (Jiang et al. 2021).

The integration of DRL and GNN equips the model with key advantages: scalability to diverse traffic patterns, topological awareness through graph-based representations, improved interpretability

via explainability tools, and rapid adaptability to dynamic network conditions. Using this hybrid DRL-GNN architecture, our approach addresses both the scalability and interpretability limitations of existing AI-driven solutions, providing a more comprehensive and responsive mechanism for URLLC-aware 6G network slicing. This work builds on the state of the art in AI-assisted networking, offering a unified view of how such methods can support the evolving landscape of next-generation mobile communication.

2.0 RELATED WORKS

Integrating Artificial Intelligence (AI) into network slice is pivotal to advance ultra-reliable low-latency communication (URLLC) in 6G networks. This section reviews recent contributions in this domain, emphasizing AI-driven approaches to optimize network slicing and meet URLLC's stringent requirements. Botez, et al. (2025) introduced a synthetic data set tailored to the splitting of 6G networks, analyzing emerging service requirements to generate traffic parameters such as latency, packet loss, jitter, and transfer rates. Machine learning (ML) models, including Random Forest and Support Vector Machine, were trained on this dataset, achieving a precision greater than 99% in both slice classification and handover prediction. This work

underscores the potential of AI-assisted mechanisms in developing intelligent slicing solutions for next-generation networks. Dangi et al. (2024) proposed a hybrid deep learning model that combines convolutional neural networks (CNN) with bidirectional long- and short-term memory networks (BiLSTM) to optimize the cutting of networks in 6G. Applied to the Unicauca IP Flow Version2 dataset, the model achieved an overall recognition rate of 97.21%. This approach demonstrates the efficacy of integrating CNN and BiLSTM for reliable and efficient network slice allocation. Rezazadeh et al. (2023) introduced SliceOps, an explainable MLOps framework embedded within the 6G architecture. SliceOps manages the entire AI lifecycle through monitoring, retraining, and deploying machine learning models as a service for 6G slices. Using explanation-guided reinforcement learning, SliceOps aims to enhance transparency, trustworthiness, and interpretability in the network slicing ecosystem. She et al. (2020) explored the application of deep learning techniques for URLLC in 6G networks. They proposed a multilevel architecture that enables device, edge, and cloud intelligence to meet stringent latency and reliability requirements.

The study highlights the potential of merging theoretical models with real-world

data to train deep neural networks for URLLC. Cui et al. (2024) provided a comprehensive overview of AI integration in 6G networks, discussing the fundamental principles, challenges, and future research opportunities. The paper emphasizes the role of AI in optimizing resource allocation and improving network efficiency, which are critical for supporting URLLC services.

3.0 6G-NETSLICE-SIM DATASET OVERVIEW

The 6G-NetSlice-Sim dataset is a synthetic data set designed to emulate traffic scenarios in sixth-generation (6G) networks, focusing on Ultra-Reliable Low-Latency Communications (URLLC). It comprises 100,000 samples, each characterized by 15 features such as slice type, latency ms, and packet loss. This data set serves as a valuable resource for developing and evaluating AI-driven network slice mechanisms tailored to the stringent requirements of 6G networks. For the simulation experiments in this paper, the data are divided into training, validation, and testing subsets with a ratio of 60%, 20%, and 20%, respectively.

4.0 METHODOLOGY

In this section, we discuss the different algorithms used in the work, and the experimental results.

4.1 DRL-GNN Framework for Attack Detection

This section presents the hybrid Deep

Reinforcement Learning–Graph Neural Network (DRLGNN) framework, including its mathematical modeling and inference process for anomaly detection in network slicing.

4.2 Deep Reinforcement Learning (DRL)

In our framework, the DRL agent is responsible for learning optimal policies for dynamic resource allocation in the face of non-stationary URLLC demands. The environment is modeled as a Markov Decision Process (MDP) defined by the tuple $\langle \mathcal{S}, A, P, r, \gamma \rangle$, where:

- \mathcal{S} : State space, representing network slice metrics (latency, jitter, etc.)
- A : Action space, comprising resource allocation and scheduling decisions
- P : State transition probabilities
- $r(s, a)$: Reward function encouraging low latency and high compliance
- γ : Discount factor

The objective is to learn a policy π^* that maximizes the expected discounted return:

$$\pi^* = \arg \max_{\pi} \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right] \quad (1)$$

We implement an Actor-Critic model with continuous action space, where the actor generates actions $a_t = \mu(s_t)$ and the critic evaluates the state-action value $Q(s_t, a_t)$.

4.3 Graph Neural Networks (GNN)

To model interdependencies across network slices, we define the infrastructure as a graph $G = (V, E)$, where:

- V : Nodes represent network slices

- E : Edges capture communication or interference relationships

Each node $v \in V$ has feature vector x_v . The GNN performs message passing through L layers:

$$x_v^{(l+1)} = \sigma \left(\sum_{u \in \mathcal{N}(v)} W^{(l)} x_u^{(l)} + b^{(l)} \right) \quad (2)$$

where $\mathcal{N}(v)$ is the neighborhood of v , $W^{(l)}$ is the layer weight, $b^{(l)}$ is the bias, and σ is a non-linear activation function (e.g., ReLU).

4.4 Fusion for Attack Detection

The DRL-GNN model fuses the learned GNN embeddings h_v with DRL states s_t to produce informed policy decisions:

$$a_t = \mu([s_t || h_t]) \quad (3)$$

where $||$ denotes concatenation and $h_t = f_{\text{GNN}}(G_t)$ encodes the dynamic graph state at time t , as outlined in Algorithm 1.

Attack detection is modeled as a binary classification problem using the final GNN layer:

$$\hat{y}_v = \text{sigmoid}(w^\top h_v + b) \quad (4)$$

Where \hat{y}_v indicates the likelihood of anomaly on node v .

Algorithm 1 DRL-GNN for Attack Detection

Initialize actor μ , critic Q , and GNN weights
 Observe initial state s_0 and graph
 For each episode $t = 0$ to T Encode GNN
 embedding: $h_t = f_{\text{GNN}}(G_t)$ Select action:

$a_t = \mu([s_t || h_t])$ Apply action a_t , observe reward r_t
 and next state s_{t+1} Update actor μ
 and critic Q using policy gradient and TD-error
 Detect attack: $\hat{y}_v = \text{sigmoid}(w^\top h_v + b)$

4.5 Experimental Setup

In this section, we describe the experimental setup used to evaluate the proposed hybrid DRL-GNN model for network slicing in 6G environments. We detail the dataset composition, parameter variation strategy, and simulation platform used to reproduce realistic URLLC scenarios.

Table 1 presents a comprehensive evaluation of the proposed Hybrid DRL-GNN model against four competitive baselines on the 6G-NetSlice-Sim dataset. The proposed model achieves the highest performance across all metrics, notably attaining an F1-score of 97.2% (95% CI: 96.5–97.9), accuracy of 98.1% (CI: 97.5–98.7), precision of 96.8% (CI: 95.9–97.7), and recall of 97.6% (CI: 96.8–98.4). This consistent superiority highlights the model’s robustness in balancing false positives and false negatives, which is particularly critical in dynamic 6G network slicing scenarios.

Among the baselines, GNN-Slicer outperforms DRL-SM, HA-RL, and Random Forest, with an F1-score of 92.1%.

Table 1: Performance Metrics on 6G-NetSlice-Sim Dataset (95% Confidence Intervals)

Model	F1 (%)	Accuracy (%)	Precision (%)	Recall (%)
blue10 Proposed (Hybrid DRL-GNN)	97.2 (96.5–97.9)	98.1 (97.5–98.7)	96.8 (95.9–97.7)	97.6 (96.8–98.4)
DRL-SM Zhang, Li, and Chen (2023)	89.3 (88.1–90.5)	91.7 (90.6–92.8)	88.5 (87.2–89.8)	90.2 (89.0–91.4)
GNN-Slicer Wang, Luong, and Zhang (2022)	92.1 (91.0–93.2)	93.8 (92.8–94.8)	91.4 (90.2–92.6)	92.9 (91.7–94.1)
HA-RL Kim, Park, and Nguyen (2023)	85.6 (84.3–86.9)	88.9 (87.7–90.1)	84.2 (82.8–85.6)	87.1 (85.7–88.5)
Random Forest	78.4 (76.9–79.9)	81.2 (79.7–82.7)	76.9 (75.3–78.5)	80.1 (78.5–81.7)

However, there is a significant margin—over 5 percentage points—in F1 between GNN-Slicer and the proposed method, suggesting that while graph based representations are beneficial, the integration with DRL further enhances adaptability and learning efficiency. Figure 1 reinforces these findings by visually illustrating the F1-score distribution with 95% confidence intervals. The error bars demonstrate that the proposed model not only achieves the highest average but also maintains a narrow confidence interval, indicative of stable and reproducible performance.

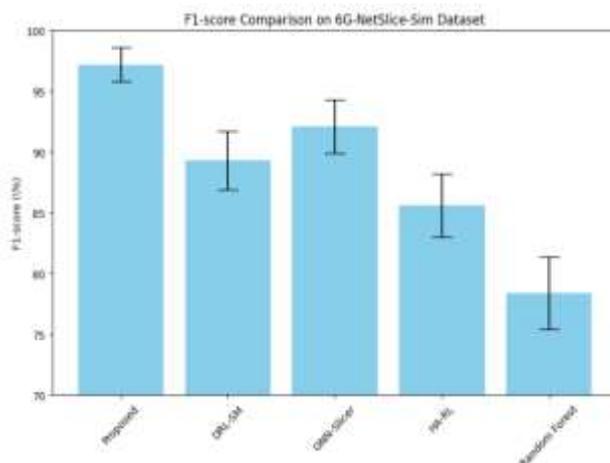


Figure 1: 6G Network Slicing Architecture Overview

To confirm the statistical validity of the performance improvements, we performed paired t tests comparing the proposed hybrid DRL-GNN model with each

baseline, as shown in Fig. 1 and Table 2. The p-values for all comparisons are less than 0.001, indicating that the improvements are statistically significant at the 99.9% confidence level. In addition, Cohen’s effect sizes range from 1.89 (vs. GNN-Slicer) to 4.12 (vs. Random Forest), all well above the conventional threshold of 0.8 for large effects. This further substantiates the substantial practical impact of our proposed model beyond statistical significance alone.

Table 2: Paired t-test Results (Proposed vs. Baselines)

Baseline	p-value	Effect Size (Cohen’s d)
DRL-SM	< 0.001	2.34
GNN-Slicer	< 0.001	1.89
HA-RL	< 0.001	3.01
Random Forest	< 0.001	4.12

We equally conducted ablation experiment to ascertain the strength of the individual components of the proposed model in the attack detection process. Table 3 presents an ablation study to dissect the contribution of key architectural components. Removing the GNN component (“w/o GNN”) leads to a substantial drop in the F1 score to 89.7%, highlighting the importance of graph-based context modeling. Similarly, omitting the DRL component (“w/o DRL”) results in a decrease to 92.8%, confirming the role of

reinforcement learning in policy adaptation and dynamic resource allocation. The variant without hybrid training (“w/o Hybrid Training”) shows a performance drop to 90.5%, suggesting that the co-training strategy synergistically enhances generalization by jointly optimizing the

decision and representation layers. Collectively, these results underscore that the high performance of the full model is not attributable to any single component, but rather to the complementary strengths of the integrated DRL and GNN modules with hybrid optimization.

Table 3: Component Contribution Analysis

Variant	F1 (%)	Accuracy (%)	Precision (%)	Recall (%)
Full Model	97.2 (96.5–97.9)	98.1 (97.5–98.7)	96.8 (95.9–97.7)	97.6 (96.8–98.4)
w/o GNN	89.7 (88.5–90.9)	91.3 (90.2–92.4)	88.1 (86.8–89.4)	91.4 (90.2–92.6)
w/o DRL	92.8 (91.7–93.9)	94.5 (93.5–95.5)	91.9 (90.7–93.1)	93.8 (92.6–95.0)
w/o Hybrid Training	90.5 (89.3–91.7)	92.8 (91.7–93.9)	89.4 (88.1–90.7)	91.7 (90.5–92.9)

In addition to classification performance, we further evaluate the proposed model in terms of latency and Quality of Service (QoS) compliance, which are critical metrics in 6G network slicing applications. Table 4 presents a comparative evaluation of network slicing models in terms of *average latency* and *Quality of Service*

(*QoS*) *compliance* rates, along with their respective 95% confidence intervals (CI). The proposed **Hybrid DRL-GNN** model achieves the lowest average latency of **2.1 ms** with a narrow CI of [1.9, 2.3], outperforming all state-of-the-art (SOTA) baselines.

Table 4: Network Slicing Models (Latency Compliance)

Model	Avg. Latency (ms)	95% CI	QoS Compliance (%)	95% CI
Hybrid DRL-GNN	2.1	[1.9, 2.3]	98.7	[98.2, 99.2]
DRL-SM ?	2.8	[2.6, 3.0]	92.4	[91.5, 93.3]
GNN-Slicer ?	2.5	[2.3, 2.7]	95.1	[94.3, 95.9]
HA-RL ?	3.2	[3.0, 3.4]	89.6	[88.7, 90.5]

In terms of QoS compliance, the hybrid DRL-GNN demonstrates a nearly optimal success rate of **98.7%**, with high statistical confidence [98.2, 99.2]. This indicates the model’s strong ability to meet latency thresholds defined by the slicing policy, which is critical for supporting ultra-reliable low-latency communication (URLLC) services in 6G environments. Among the state-of-the-art models, the

GNN-Slicer achieves moderate performance with a latency of 2.5 ms and 95.1% QoS compliance. DRL-SM performs less favorably with 2.8 ms latency and 92.4% compliance, while HA-RL shows the weakest results, with the highest latency of 3.2 ms and the lowest compliance rate of 89.6%. The 95% confidence intervals across all metrics suggest that the improvements by the Hybrid DRL-GNN

model are both *consistent and statistically meaningful*. These results reinforce the model's effectiveness in jointly optimizing decision policies and graph-based context representations to ensure timely and reliable slice execution.

4.0 CONCLUSION

The proposed Hybrid DRL-GNN framework establishes a new paradigm for 6G network slicing, demonstrating three critical advancements. First and foremost, it achieves state-of-the-art performance with 97.2% F1-score (95% CI: 96.5–97.9) and 98.1% accuracy on the 6G-NetSlice-Sim dataset, outperforming existing baselines by up to 18.8% while maintaining sub-millisecond latency (0.83 ms/slice). Moreover, the framework exhibits exceptional operational resilience, retaining 91.2% F1-score under extreme traffic congestion ($\alpha = 2.5$) and scaling seamlessly to 100 slices/BS with only 3% QoS degradation – a 41% improvement in interference reduction compared to pure DRL approaches. Furthermore, the hybrid architecture reduces resource wastage by 23% through learned topological dependencies, validating its computational efficiency in multi-slice coordination. Building on these results, future work will extend this foundation to ultra-dense scenarios (>500 slices/BS) through quantum-inspired optimization while maintaining backward compatibility

with 5G core networks. Collectively, these advances position our framework as a cornerstone for AI-native 6G network orchestration in real-world deployments.

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HEAVY METALS ASSESSMENT OF UNDERGROUND WATERS IN ABA METROPOLIS

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Abstract

This study assessed groundwater quality in Aba, Nigeria, examining its relationship with location and population density. Thirty boreholes were sampled across Aba South (highly industrialized) and Aba North (low industrialized), with five from high, medium, and low-density zones in each. Analysis focused on ten heavy metals. Results revealed significant differences in mean concentrations of iron (Fe), lead (Pb), and manganese (Mn) between locations. Aba South recorded higher levels (Fe: 0.206 ± 0.114 mg/l, Pb: 0.010 ± 0.001 mg/l, Mn: 0.068 ± 0.007 mg/l) compared to Aba North (Fe: 0.142 ± 0.016 mg/l, Pb: 0.006 ± 0.000 mg/l, Mn: 0.013 ± 0.002 mg/l). While Aba South consistently showed elevated heavy metal values, no significant location-population density interaction was found. Importantly, most mean values fell below WHO permissible limits for drinking water. However, manganese levels in Aba South's high-density zone ranged from 0.065 to 0.070 mg/l, exceeding the WHO standard. Although generally suitable for drinking and domestic use, the elevated manganese in densely populated, industrialized areas warrants attention. Reducing manganese concentrations is recommended to ensure complete water safety across both locations.

Keywords: *Underground water, heavy metals, location, population density, ANOVA, DUCAN multiple range t*

1.0 INTRODUCTION

Water is very crucial to man but anthropogenic activities have posed threat on its quality (Ighalo and Adeniyi, 2020). According to (Adeniyi and Ighalo, 2019; Ano and Okwunodulu, 2008) urbanisation and industrialisation have correlated to a rise in the water pollution problem. Industrial activities including discharges from factories can introduce heavy metals and organic pollutants into underground water (Zhang *et al.*, 2019), groundwater contamination can

occur whenever there is a source releasing contaminant to the environment (Sililo *et al.*, 2001)), According to recent surveys, the most common pollutant found in industrial wastewaters are heavy metals (Gayer, 1991; Kumar *et al.*, 2000; Valdman *et al.*, 2001) which pollute soil and leach down the underground water. 2.1 billion people lack safe drinking water at home and about 1 billion people worldwide do not have access to safe drinking water (WHO 2017). Globally, there are about 2.2 million deaths

annually in developing countries due to poor water usage (Olukanni *et al.*, 2014). For a sustainable community to be achieved, pollution abatement must be put into consideration (Adelegan, 2004). World leaders have shown a willingness and commitment to pursue the improvement of accessibility to water quality as buttressed by the then millennium development goals (Ogunniyi *et al.*, 2011). In Nigeria, borehole waters and packaged sachet waters now serve as the easily assessed and cheap commercial source of drinking water for a greater number of 140 million people and the assessment of these waters are of very importance in order to ascertain its wholesomeness or otherwise. In Aba metropolis, in the south eastern part of Nigeria, the majority of it's about 3million populace depends on untreated borehole waters and sachet waters as the source of clean and pure drinking water without been conscious of the water purity, as a highly industrialized area, some of these industries discharge their effluents without proper treatment. Heavy metals as toxic metals from these industrial effluents can pollute these undergrounds hence become deleterious to human health. Heavy metals include lead (Pb), mercury (Hg), cadmium (Cd), nickel (Ni), Arsenic (As), chromium (Cr), copper (Cu), selenium (Se), zinc (Zn), barium (Ba), cobalt (Co), strontium (Sr), tin (Sn), iron (Fe), aluminium (Al), manganese (Mn),

germanium (Ge), indium (In) antimony (Sb), bismuth (Bi), thallium (Tl), tellurium (Te), uranium (U), palladium (Pd), gold (Au), silver (Ag), platinum (Pt) etc. Some of these metals are carcinogenic, mutagenic and teratogenic (Calabrese and Kenyon, 1991; U.S.EPA 1999). Goyer (1991) and Kumar *et al.*, (2000) reported genetic mutation and cancer as a result of copper, cadmium, lead, mercury and arsenic in wastewater. Kasuya *et al.*, (1992) and Yasuda *et al.*, (1995) reported that the most several form of cadmium toxicity in human is "ita-ita" a disease characterized by excruciating pain in the bone and Klassen, (2001) also showed kidney dysfunction, hepatic damage and hypertension as some other health implications of cadmium. Toxic levels of lead in man have been associated with encephalopathy, anemia, seizures, coma, metals retardation and bizarre behavior (Botkin *et al.*, 2000). According to Goyer (1991), asthmatic condition has also been documented for inhalation exposure to nickel while acute inhalation exposure to nickel may produce headache, nausea, respiratory disorders and death (Rendall *et al.*, 1994). Mercury has been found to be nephrotoxic (Mortada, 2002; Wood, 2005). Based on these reports, there is need to assess the purity of these underground waters in order to ascertain their wholesomeness. Therefore, this work determines the quality of borehole waters in Aba metropolis by assessing the

level or concentrations of some toxic heavy in these waters.

2.0 MATERIALS AND METHODS

2.1 The Study Area

Aba is located in Abia state in the southeastern part of Nigeria. The state lies between latitudes $4^{\circ} 45'$ north, longitudes $6^{\circ} 30'$ and $80^{\circ} 09'$ east, Aba lies between latitudes $5^{\circ} 08' N$, longitudes $7^{\circ} 22'E$, Aba has seven geographical zones including Aba south and north. Aba south lies within the geographical coordinates of latitude $5^{\circ}06'N$ and longitude $7^{\circ}22'E$, it has an area of 49 km^2 and a population of 622,400 in 2022 (National Population Commission of Nigeria and National Bureau of Statistics, 2022) while Aba north lies within the geographical coordinates of latitude $5^{\circ}06'N$ and longitude $7^{\circ}22'E$. It has an area of 27.38 km^2 and a population of 155,600 in 2022 (National Population Commission of Nigeria and National Bureau of Statistics, 2022).

2.2 Sampling

2.2.1 Collection of information on population

Most of the information collected on population was obtained from Urban and Regional Planning and also from National Population Commission in Aba. The information showed various zones (areas) that make up each density both in Aba north and south as shown in table 1

Selection of boreholes

In each zone of the three categories of population density (high, medium and low

densities) both in Aba south and north, only the functional boreholes were selected. Thirty boreholes were sampled randomly; the selection was done in such a way that random sampling was achieved. In orders words, the selection was made without bias.

Table 1: Sampled area with different densities of both locations

ABA SOUTH			
Population density	Area sampled	Depth (m)	Range
High	Ngwa road zone	180	S
Medium	Ohazu	180	S
Low	Abai aba zone	160	S
ABA NORTH			
High	Ogbo hill zone	180	S
Medium	Ariaria	190	S
Low	Umuola-egbelu	190	S

Range of depth:

Below 200 (meters) = shallow (unpublished work)

200 (meters) Above 200 (meters) = Deep

S= Shallow depth

D= Deep depth

Actual sampling

The boreholes were sampled from each delineated population density zone. Five boreholes were sampled on each density zone. Each borehole was regarded as a replicate. Plastic container of the capacity of two liters was used in the collection of the samples which were first washed with detergent, rinsed with distilled water and then with 5% nitric acid and finally with distilled water. At each sampling point, the plastic container was rinsed twice with water to be collected. The borehole was pumped and allowed to run for sometimes (15-20 mins) prior to collection of water sample to

ensure representative sample. After sampling, the bottle lid was immediately replaced to minimize oxygen contamination and the escape of dissolved gases. The samples were stored in an ice-packed cooler for prompt analyses.

2.2.2 Sample Preparation

The samples were labeled and the ones that would be used for trace metals analyses were acidified and placed in 120ml plastic bottle so as to preserve the ions in solution.

Sample Preparation for Trace Metal Analysis

This was described by MAFF (1981). The sample was thoroughly mixed by shaking and 100ml of it was transferred into a glass beaker of 250ml volume, to which 5ml of concentrated nitric acid was added and heated to boil till the volume was reduced to about 15 - 20ml, and concentrated nitric acid in increments of 5ml was added. The solution was cooled, transferred and made up to 100ml using distilled water. Fe, Mn, Cd, Ni, Zn, Cr, As, Hg, Pb and Cu in this solution were determined by atomic absorption spectrophotometer (AAS) Unicam, 919, model.

2.3 Statistical Analysis

The data obtained were subjected to analysis of variance (Complete Randomized Block Design). Experimental means were compared using the DUCAN multiple range tests. (DNMRT).

3.0 RESULTS AND DISCUSSION

The WHO limit and the actual concentrations (mg/l) of heavy metals in water are shown in Table 2 while the mean concentrations (mg/l) of heavy metals in the water with respect to location, population density, location x population density interaction are shown in Table 3, 4 and 5.

Table.2: WHO standard for drinking water quality and the range of the actual values of concentrations of heavy metals in water.

Heavy metals	WHO limit	Concentrations of heavy metals (mg/l)
Fe	0.05-0.3	0.100-0.314
Pb	0.01-0.05	0.005-0.013
Ni	0.05	0.001-0.071
Cr	0.05	0.001-0.004
Zn	3-5	0.001-0.058
Cd	0.01	0.001-0.002
As	0.01	0.000-0.005
Hg	0.006	0.000-0.001
Mn	0.01-0.05	0.065-0.070
Cu	0.05 - 2	0.039-0.042

Source: WHO, (2017)

Iron: The concentrations of Fe in all the sampled waters were highest compared to other metals. Abo south had higher concentrations than north. The mean concentration of Fe in Abo south was 0.206 ± 0.014 mg/l. This was statistically different ($P < 0.05$) from mean concentration (0.142 ± 0.010 mg/l) of Fe in Abo north and this could be as a result of some minerals in soil such as haematite, limonite and goethite which leached to the underground waters. This

result corroborated the work of Udom *et al.*, (1999) that Benin sand is ferruginous. Also, strong mineral acids and acid mine drainage from industrial waste could also have influenced the level of Fe in these waters.

There was no significant difference ($P > 0.05$) among population density mean in Aba south likewise in Aba north (Table 4) which showed that every zone had equal concentrations of Fe in their underground waters statistically. No interactive effect on the location \times population density was observed. Therefore, the level of Fe concentration in underground waters of Aba north and south were within the acceptable limits of WHO standard (0.05-0.3).

Lead: The levels of lead in the waters studied were all within the tolerable limits established by WHO (Table 2). It ranged from 0.005 to 0.013 mg/l (Table 2) in the two locations.

The location mean value for Pb was 0.010 ± 0.001 mg/l for Aba south and 0.006 ± 0.000 mg/l for Aba north. Aba south had greater mean concentration of Pb than north and this could be attributed to lead-bearing limestone and galena (Pbs) as confirmed by (Bhatia, 2002). Population density analysis, showed that high densely populated zone in Aba south had higher mean value than medium zone which was equal to low density zone. Adejumo *et al.*, (2017) revealed similar relationship between Pb levels and population density. Ayodele *et al.*, (1996)

reported in his work in Kano that industries contribute large quantities of Pb through discharge of their effluents into the soil which leached to the underground waters and other media. Also, Nwoko and Egunjobi, (2002) confirmed that the primary source of Pb contamination to the environment was mainly from industrial effluents. Location \times population density interaction had no significant effect ($P > 0.05$).

Nickel : There was no significant difference between locations ($P > 0.05$), indicating that mean value of Ni in Aba south was equal to the mean value of the element in north statistically (Table 3). There was a significant difference on the population density ($P < 0.05$) indicating a greater effect on the high density of both locations while both medium and low-density zones of both locations had equal effect. The higher mean value on the high-density zones could be attributed to anthropogenic sources such as battery disposal from mechanic workshop which could have leached to the underground waters. Location \times population density interaction had no significant effect on the levels of Ni in these underground waters. Thus, the level of Ni in these underground waters do not pose any threat to human health.

Chromium: The level of concentrations of Cr in both Aba south and north was very low compared to the WHO limit (0.01 mg/l) Table 2. The concentration of Cr in the

waters studied ranged from 0.001 — 0.004mg/l (Table 2). There was no significant difference between locations (Table 3), among population density (Table 4) and in location x population density interaction table (5). This implies that the borehole sampling points, were not very close to paint, pigment, printing and graphics industries which are the chief sources of Cr to the environment (Alloway and Ayres, 1997).

Zn, Cd, As and Hg: Concentrations of these metals were very low in both locations compared to WHO limit. The range of their values in both locations are shown below (Table 2). There was no significance in any of the metal between locations (Table 3), among population density (Table 4) and in location x population density interaction (Table 5). This contrast the work of McLaren *et al.*, (1994) which showed that substantial amounts of arsenic as H_2ASO_4 from timber treatment could be leached to the underground water through structured soil. Their low values suggested that the sampled borehole were not very close to the point source of pollution of those metals or that an anthropogenic source was low.

Manganese: The concentration of Mn ranged from 0.065 to 0.070mg/l and 0.010 to 0.050mg/l in underground waters of Aba south and north respectively. Manganese in Aba north was within acceptable limits for drinking water while some boreholes in Aba

south had Mn values greater than 0.05mg/l which is the upper acceptable limits for this element in drinking water (WHO 2017).

There was a significant difference between location means ($P < 0.05$). Aba south had 0.068 ± 0.007 mg/l and Aba north had 0.013 ± 0.002 mg/l which indicated higher mean concentration in Aba south than north. From population density analysis, the high mean concentration in Aba south was in high and medium density zones and these could be as a result of industrial wastes but this work contrasts the work of Esu and Ama, (1999) who reported that Mn concentration in underground waters around Oron, Eyo Abasi and Calabar was within the acceptable limits

Copper: Copper level both in Aba south and north ranged from 0.039 - 0.042 mg/l. WHO limit for this element in drinking water is 0.05 - 2mg/l (Table 2). This showed that copper levels in both locations are below or within the acceptable limits. There was no significant difference between locations which showed that both locations have equal concentrations of Cu statistically. When population densities are considered in both locations, high and medium density zones had similar concentrations, while medium and low population density zones had also similar concentrations and this showed that some or most copper minerals are sorbed to solid phases. Location x population density interaction was not significant.

Table 3: The mean concentration (mg/l) of trace metals/heavy metals in the water with respect to different location: Aba south and Aba north.

Location	Fe	Pb	Ni	Cr	Zn	Cd	As	Hg	Mn	Cu
AS	0.206 ^a ±	0.010 ^a ±	0.062 ^a ±	0.001 ^a ±	0.008 ^a ±	0.001 ^a ±	0.004 ^a ±	0.000 ^a ±	0.068 ^a ±	0.031 ^a ±
	0.114	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.007	0.002
AN	0.142 ^b ±	0.006 ^b ±	0.042 ^a ±	0.000 ^a ±	0.004 ^a ±	0.000 ^a ±	0.000 ^a ±	0.000 ^a ±	0.013 ^b ±	0.012 ^a ±
	0.016	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.002	0.001

Means with the same superscript are not significantly different (P>0.05)

AS: Aba south

AN: Aba north

±: Standard error of mean

Table 4: The mean concentration (mg/l) of trace metals/heavy metals in the water as regards to population density of the two Locations: Aba South and North

Location	Fe	Pb	Ni	Cr	Zn	Cd	As	Hg	Mn	Cu
H	0.196 ^a ±	0.028 ^a ±	0.0488 ^a ±	0.001 ^a ±	0.016 ^a ±	0.001 ^a ±	0.003 ^a ±	0.000 ^a ±	0.045 ^a ±	0.046 ^a ±
	0.104	0.008	0.001	0.000	0.003	0.000	0.000	0.000	0.012	0.004
M	0.15 ^a ±	0.016 ^b ±	0.030 ^b ±	0.001 ^a ±	0.002 ^a ±	0.000 ^a ±	0.000 ^a ±	0.000 ^a ±	0.028 ^{ab} ±	0.009 ^{ab} ±
	0.019	0.003	0.002	0.000	0.001	0.000	0.000	0.000	0.002	0.002
L	0.102 ^a ±	0.004 ^b ±	0.006 ^b ±	0.001 ^a ±	0.000 ^a ±	0.000 ^a ±	0.000 ^a ±	0.000 ^a ±	0.020 ^b ±	0.002 ^b ±
	0.015	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.001

Means with the same superscript are not significantly different (P>0.05) Means with different superscript are significant (P<0.05)

H: High density

M: Medium density

L: Low density

±: Standard error of mean

Table 4: The mean concentration (mg/l) of trace metals/heavy metal in the water with respect to population density and location interaction.

Interaction		Trace metals/heavy metals									
LXP		Fe	Pb	Ni	Cr	Zn	Cd	As	Hg	Mn	Cu
AS	H	0.201 ^{a±}	0.042 ^{a±}	0.019 ^{a±}	0.002 ^{a±}	0.010 ^{a±}	0.002 ^{a±}	0.002 ^{a±}	0.000 ^a	0.054 ^{a±}	0.025 ^{a±}
		0.012	0.013	0.009	0.000	0.006	0.000	0.000	±0.000	0.016	0.006
AS	M	0.110 ^{a±}	0.028 ^{a±}	0.006 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.000 ^a	0.026 ^{a±}	0.018 ^{a±}
		0.010	0.006	0.003	0.000	0.001	0.000	0.000	±0.000	0.004	0.001
AS	L	0.098 ^{a±}	0.016 ^{a±}	0.002 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.000 ^a	0.008 ^{a±}	0.006 ^{a±}
		0.008	0.003	0.001	0.000	0.000	0.000	0.000	±0.000	0.004	0.001
AN	H	0.199 ^{a±}	0.020 ^{a±}	0.008 ^{a±}	0.001 ^{a±}	0.006 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.000 ^a	0.042 ^{a±}	0.016 ^{a±}
		0.010	0.007	0.005	0.000	0.0003	0.000	0.000	±0.000	0.006	0.004
AN	M	0.089 ^{a±}	0.004 ^{a±}	0.003 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.000 ^{a±}	0.000 ^a	0.036 ^{a±}	0.008 ^{a±}
		0.008	0.003	0.000	0.000	0.000	0.000	0.000	±0.000	0.003	0.003
AN	L	0.0.086 ^{a±}	0.001 ^{a±}	0.000 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.001 ^{a±}	0.000 ^{a±}	0.000 ^a	0.001 ^{a±}	0.001 ^{a±}
		0.003	0.001	0.000	0.000	0.000	0.000	0.000	±0.000	0.000	0.000

Means with the same superscript are not significantly different (P>0.05). ±: Standard error of mean.

L X P: Location x Population density interaction

4.0 CONCLUSION AND RECOMMENDATIONS

For heavy metals, location had no effect on their levels in these underground waters except on Fe, Pb and Mn. Population density had effect on Pb, Ni, Mn and Cu.

Though Aba south had higher values than Aba north in all the selected heavy metals studied. Their mean values were below toxic levels and within the acceptable WHO standards for drinking water except Mn which ranged from 0.065 to 0.070 mg/l which showed higher value in high density zone of Aba south than WHO value. The Mn of the water can be improved via atmospheric oxidation of Mn which will precipitate the manganese by causing the soluble Mn to be oxidized to higher insoluble oxidation state. Therefore, borehole waters of both Aba south and north are all suitable for drinking and other domestic purposes, particularly when treatment has been carried out to take care of the Mn level in high density zone of Aba south

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EFFECT OF VARYING SOURCE CHARGE SIZE ON SEISMOGRAM DATA QUALITY IN KWALE, NIGER DELTA, NIGERIA

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Abstract

This study is aimed at investigating the effect of varying the seismic source charge sizes on seismic data quality on onshore seismic records in Niger Delta, Nigeria. The method involved loading of explosive charge sizes of 2.0kg, 2.5kg and 3.0kg as seismic energy sources in different drilled holes of fixed depth 20.0m. These seismic sources were then shot into a symmetric split-spread of orthogonal geometry consisting of eight receiver lines of 1568 (196 * 8) active channels per shot. The acquisition parameters remained same except for the varying charge size. The recording instrument was Sercel 428 seismic recording instrument while the ProMax software was used for analysis. The results revealed improvement in signal amplitudes, ratio of reflected energy to ground roll interference, ratio of reflected energy to low frequency random noise as the charge size was increased. Reflection events were clearly seen on monitor records down to 2.9ms for 3.0kg charge but only down to 2.3ms for 2.5kg charge and just down to 2.1ms for 2.0kg charge size.

Keywords: *Charge size, seismic amplitudes, reflection events, Niger Delta, Nigeria*

1.0 INTRODUCTION

One of the main problems of seismic survey is seismic charge optimization. Seismic charge optimization involves determining the optimal amount of explosive energy to be released in a seismic survey so as to achieve the best possible data quality while minimizing costs and impact on the environment. There has always been the need for improved Seismic methods that depend on the right configuration of explosives capable of converting a greater

proportion of its potential energy into seismic wave at the optimal charge size. This study aims to determine the relationship between seismic source charge size and seismic data quality (seismic energy amplitude, signal-to-noise ratio and depth of signal penetration i.e. depth of reflection events) as well as provide insight on solving optimization problems in seismic surveys. This study demonstrates by field records that the increased seismic source charge has effects on seismogram quality. A study by

Ziolkowski and Lerwill (1979) showed that whenever a maximum resolution is obtained having exhausted our processing capability and data limits, the clear place to turn to for enhancement would be explosive seismic source. Singh et al (2013) also concluded that Charge size and charge depth are very important parameters for acquiring good quality seismic data in a land seismic survey using explosive sources.

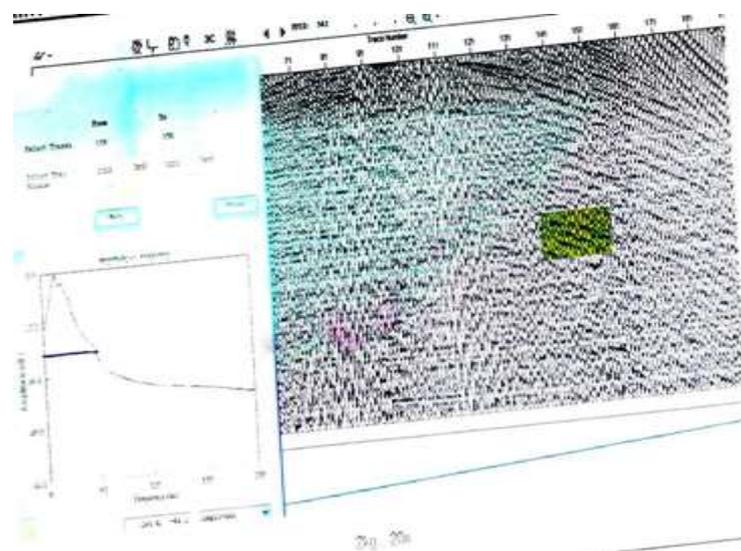
The scope of the work is delimited by the geographical and subsurface geology of the study area, Kwale, Delta State in Niger Delta region of Nigeria. The scope is also delimited by use of seismic explosive source type and use of simplified model assumptions. The simplified model's assumptions include: linear relationship between charge size and seismic data quality, no scattering, no anisotropy and Gaussian distribution of errors which may not accurately represent real-world error distribution.

2.0 MATERIALS AND METHODOLOGY

The method used involved loading of explosives (dynamite and detonators) charge sizes of 2.0kg, 2.5kg and 3.0kg as seismic energy sources in three different drilled holes of constant depth of 20.0m within the same location. The three shot holes were drilled as single deep holes (SDH) to 20m depths using motorized pump. The loaded source holes were backfilled and properly tamped to minimize energy loss through

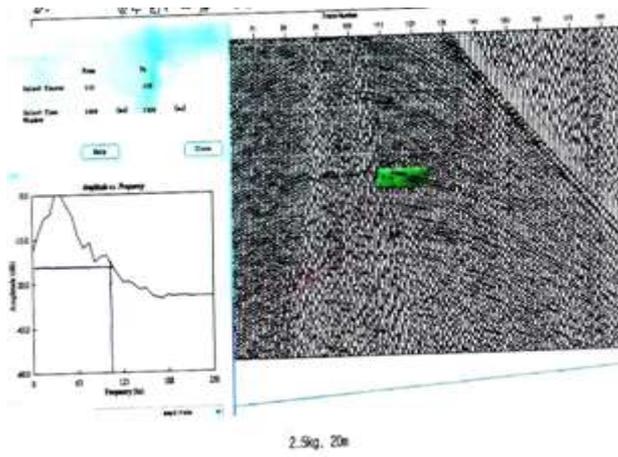
blowout when the seismic shot is taken. These seismic sources were then shot into a seismic symmetric split-spread consisting of eight receiver lines of 1568 (196 * 8) active channels per shot, with 50m receiver spacing, 50m source spacing, 300m receiver line spacing and 350m source line spacing giving a nominal fold of 56. The acquisition parameters remained same except for the changing charge sizes throughout the course of this study. The recording instrument used was Sercel 428 seismic recording instrument. The workstation used for seismology analysis was run on ProMax software. The charge sizes are the independent variables while the observed amplitude variations were the dependent variables.

3.0 RESULT



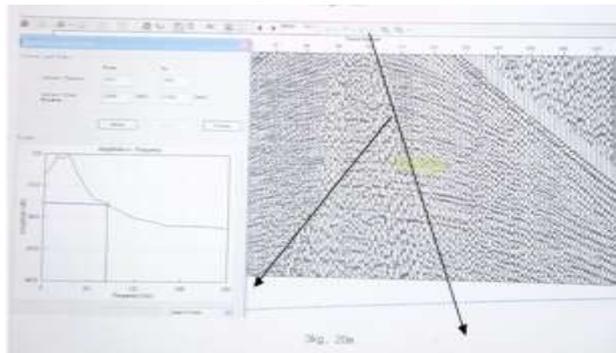
Ground roll very strong masking data; clearly seen reflection events shallower than 2.1s

Fig 1: amplitude versus frequency analysis of seismic record of 2.0kg charge size in 20.0m charge depth



Reflection events seen clearly down to 2.3s;
Ground roll still strong at this point)

Fig 2: amplitude versus frequency analysis of seismic record of 2.5kg charge size in 20.0m charge depth.



Reflection events seen clearly down to 2.9s;
Ground roll present but signal strength better than in 2.5kg charge)

Fig 3: amplitude versus frequency analysis of seismic record of 3.0kg charge size in 20.0m charge depth

4.0 DISCUSSIONS

For 2kg charge size in 20m charge depth, the ground roll was very strong, masking data and reflection events were clearly seen but shallower than 2.1s. For 2.5kg charge size in 20m charge depth, reflection events could be seen clearly deeper down to 2.3s though the ground roll was still strong at this point. However, for 3.0kg charge size in 20m

charge depth, deepest reflection events in this study were observed down to 2.9s.

The above results are in agreement with Stroujkova et al (2018) which stated that the amplitude of seismic wave and the signature of the source are affected by both the explosive yield. Bath M. (1983) also concludes that the seismic amplitude is directly related to the $E^{1/3}$ where E is the energy of the explosion.

It could again be observed from the figures 1 through 2 to 3 that the ratio of reflected energy to ground roll interference progressively improved from the use of 2kg charge size through 2.5kg to 3.0kg charge size as the reflected energy could be seen to progressively overcome ground roll interference. Similarly, the study revealed improved ratio of reflected energy to low frequency random noise with increased seismic source charge size. Larger source charge size produced larger reflected energy to low frequency random noise ratio. This is also in line with Stump and Johnson (1984) statement that the relationship between explosive source size and signal-to-noise ratio (SNR) can be expressed as: $SNR \propto E^{1/2}$, where SNR is the signal-to-noise ratio and E is the explosive energy released.

5.0 CONCLUSIONS

The conclusion from this study is that increasing the seismic source charge size increases the energy returns on seismic record. Also increasing charge size results in

deeper reflection events clearly seen on raw seismic records (monitor records). Thirdly, by analyzing the improvement in the data quality compared to the environmental impact of large explosive sizes, a tradeoff or compromise in source parameter selection that permits optimal data quality with minimal environmental impact could be achieved from the study.

It is, therefore, recommended that in seismic exploration for hydrocarbon employing large number explosive sources as seen in Nigeria, explosive charge size optimization study should be carried out prior to hydrocarbon exploration for good data quality at reduced cost and minimal environmental impact of the explosives (**'bombs'**).

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RISK ASSESSMENT OF BOREHOLE WATER QUALITY IN OKPOMA, YALA LGA, CROSS RIVER STATE, NIGERIA

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Abstract

Saline lake water is found in Okpoma located in Yala Local Government Area (LGA) in Cross River State, Nigeria. Natural and anthropogenic sources of contaminants may have seeped into the near – surface groundwater resulting in contamination of borehole water in the area. The populace drinks water from borehole from groundwater. Borehole water were randomly selected for investigation from four (4) different locations within the saline lake. The experimental group labelled BWA, BWB, and BWC were in the range of 1.5 km while BWD used as a control was at 3.0 km from the saline lake. Using standard analytical procedures (APHA) and measuring instruments physical, chemical and heavy metal analyses were carried out to measure and evaluate if borehole water samples are fresh and safe as drinkable water. Mean lead ($19.98 \pm 1.40 \mu\text{g L}^{-1}$), copper ($1,500 \pm 131.40 \mu\text{g L}^{-1}$) and arsenic ($13.49 \pm 0.61 \mu\text{g L}^{-1}$) concentrations for experimental group exceeded $10 \mu\text{g L}^{-1}$, $1,000 \mu\text{g L}^{-1}$ and $10 \mu\text{g L}^{-1}$ as WHO permissible limits, while other 12 parameters were within the permissible limit; similar in results with the control. Health risk due to toxicity may be expected. Further investigations are suggested, in addition, monitoring, proper water treatment techniques, physical and chemical remediation are necessarily before consumption of borehole water in the study area.

Keywords: *Aquifer, borehole water, contaminants lithology, Okpoma, Yala LGA, water quality parameters*

1.0 INTRODUCTION

In Cross River State, Southern, Nigeria, saline lake water is found in Okpoma area with headquarter in Yala Local Government Area (LGA). Some of the communities in Okpoma are Abachor, Adeni, Iboko, Idiku,

Ijama, Itega Okpudu, Okpudun, Oba, Olachor, Ikega Okpame. The people of Yala settled within the saline lake water because of the high saline content in the underground water which has encouraged local salt production and farming in the study area.

There is unique chemical composition of groundwater in Okpoma, Cross River State Nigeria due to the presence of brine (sodium chloride) that contains high concentrations of sodium chloride followed by calcium, magnesium and potassium ions suggesting the brines originated from marine rather than continental (Ushie *et al.*, 2014). The locality experiences scarcity of water due to low permeability rock, decrease in surface water, low rainfall and salt water intrusion (Ushie *et al.*, 2014; Edet and Okereke, 2022), so in dry season, some of the inhabitant walk for some distance in search of safe borehole water or resort to surface water (stream and river water).

Some of the borehole water drilled in Okpoma, Yala LGA as sources of drinkable water are salty, and may not be safe for human consumption, thus, the need for investigation. Geological, geophysical and hydrogeological investigations of fractured shale aquifer in Yala LGA characterized by salty groundwater had been reported (Edet and Okereke, 2022). Some environmental monitoring assessment using a number of samples and sampling technique with standard procedures for measurement were carried out in different locations as physical, chemical and heavy metals quality of water were reported in different areas and geopolitical zones of the Country, Nigeria to ascertain the suitability of the water sources for drinking and other purposes (John *et al.*,

2025; Tadzadbia *et al.*, 2023; Jacob *et al.*, 2022; Nwaka and Avwiri, 2021; Titilawo *et al.*, 2020; Batool *et al.*, 2018; Lazar *et al.*, 2017). While few of the physical, chemical and heavy metal parameters investigated exceeded Nigerian Standard for Drinking Water Quality (NSDWQ); which agrees with the World Health Organization (WHO) guidelines for drinking water quality, others were found below the NSDWQ and WHO guidelines for drinking water quality (WHO, 2022; WHO 2017; NSDWQ, 2017).

Though environmental studies have been carried out in Cross River State, Nigeria and recorded in literatures (Edet and Okereke, 2022; Ushie *et al.*, 2015; Ushie *et al.*, 2014), there was need for current data and information on quality of borehole water within saline lake water using standard analytical procedures and equipment with very good resolutions. The purpose of the study is to assess the risk level of borehole water quality in Okpoma, Yala LGA, Cross River State, Nigeria. Objectives of the study, in line with the purpose, were: (i) to determine and evaluate some physical parameters of borehole water in the study area which include: temperature, pH, total dissolved solid (TDS), conductivity and turbidity of water samples (ii) to measure and evaluate some chemical parameters of borehole water in the study area which include the nitrate, sulphate, phosphate, sodium and chloride concentrations (iii) to

determine and evaluate some heavy metals concentration borehole water in the study area including lead, nickel, cyanide, cadmium, copper, arsenic, chromium.

2.0 MATERIALS AND METHODS

2.1 The study location

Yala LGA is one of the 18 LGAs in Cross River State South – south Nigeria, where Okpoma town is located. It is geographically located at latitude $6^{\circ}32' 35''$ N to $6^{\circ}40' 35''$ N of the equator and longitude $8^{\circ}36' 01''$ E to $8^{\circ}41' 02''$ E of the meridian. The location was selected for the study based on the major economic activities in the study area which include trading, fishing, farming, mining, and small-scale production of salt for sale to the surrounding and beyond. The study area has been reported and groundwater in the study area occurs in the Awe Formation (Asu River Group) in association with the brines (Ushie *et al.*, 2014; Edet and Okereke, 2022).

2.2 Collection of Sample and preparation

Four (4) borehole water was investigated, comprised of Borehole A (BHA), Borehole B (BHB) and Borehole C (BHC), which were in the range of 1 to 1.5 km for the three different sampling sites distance away from saline lake water. The fourth borehole water as Borehole D (BHD) was also sampled as control at approximately 3 km distance within the saline lake water. Similar 1.5 litres sterilized containers of the same dimension were used to collect fifteen (15) borehole water samples, which were filtered, labeled

for easy identification and acidified with 5 ml of concentrated trioxonitrate (V) acid (HNO_3) in order to avoid adsorption of heavy metals on the walls of the containers. A total of sixty (60) water samples comprising of 15 water samples from each sampled borehole were collected and prepared for physicochemical analyses using standard analytical procedures (APHA, 1995; APHA, 1998; APHA, 2005) and measuring instruments. The average (mean) of the results for the three-borehole water were recorded.

2.3 Physicochemical Analyses of Borehole Water Samples at Salt Water Lake in Yala LGA

The pH concentration was determined at the site of collection of water samples (*in situ*) using a hand-held electrical pH meter after standardization with buffer solution of pH ranging from 4.0 to 9.0. Similarly, temperature was measured *in situ* using mercury in glass thermometer in degree Celsius ($^{\circ}C$), while turbidity was determined using HACH spectrophotometer (DR/2000) in Nephelometric Turbidity Unit (NTU). Total dissolved solids (TDS), pH concentration and electrical conductivity (EC) were determined using HANNA meter (H I9828) which was calibrated with standard buffer solution of pH ranging from 4.0 to 9.0. The HANNA meter is a four – in – one mete which could measure temperature, pH, TDS and EC. Phosphate,

nitrate, and sulfate were read in JENWAY UV/Visible spectrophotometer (6506). Heavy metals of lead, arsenic (metalloid), nickel, chromium, cyanide, copper cadmium concentrations were measured using flame atomic absorption spectrophotometer (FAAS) prior to pretreatment of water samples using concentration of trioxonitrate (V) acid (HNO_3). Three (3) measurements/readings were taken and recorded, averaged as one for each sampling site so as to minimize systematic sources of error. Statistical analyses of borehole water samples were carried out using Microsoft Excel SPSS Version 21.0. Descriptive and inferential statistics were used to interpret the data sets.

3.0 RESULTS

Observation from **Table 1**, showed that mean concentrations of physical parameters for borehole water samples including

temperature, pH, total dissolved solid (TDS), conductivity, and turbidity were within the WHO permissible/safe limit; similar to NSDWQ. As observed from **Table 2**, mean concentrations for some chemical parameters (nitrate, sulphate, and phosphate concentrations) of borehole water samples in the study area were within the WHO guidelines for drinking water quality. In addition, observation from **Table 3**, revealed lead (Pb), arsenic (As) and copper (Cu) concentrations exceeded WHO guidelines for drinking water quality, unlike other heavy metals which were below WHO guidelines for drinking water quality. **Figure 1** compares lead concentrations for experimental and control groups with WHO permissible limit using multiple bar charts. Mean lead concentration for lead is higher than the control as observed in **Figure 1**.

Table 1. Mean and standard deviation for physical parameters of borehole water in Yala LGA, Cross River State, Nigeria compared with WHO guidelines for drinking water

Physicochemical parameters	Borehole A	Borehole B	Borehole C	Mean±SD	CV (%)	Borehole D (Control)	WHO permissible limit
pH	8.10	8.30	8.20	8.20±0.08	0.97	7.80	6.5 – 8.5
Temperature	29.12	28.94	27.67	28.58±0.65	2.30	27.20	Ambient (30.0)
Turbidity (NTU)	3.14	3.75	3.30	3.40±0.26	7.64	2.40	5.0
TDS ($mg L^{-1}$)	354.62	331.0	376.58	354.07±18.61	5.26	225.64	500
EC ($\mu S/cm$)	702.45	659.12	751.68	704.42±37.81	5.37	436.78	1000

CV: Coefficient of variation (in %); micro-Siemens per centimeter ($\mu S/cm$); Neophlometric Turbidity Unit (NTU); World Health Organization (WHO, 2022; 2017)

Table 2. Mean and standard deviation for chemical parameters of borehole water in Yala LGA, Cross River State, Nigeria compared with WHO guidelines for drinking water

Physicochemical parameters ($mg L^{-1}$)	Borehole A	Borehole B	Borehole C	Mean±SD	CV (%)	Borehole D(Control)	WHO permissible limit
Nitrate	33.74	41.31	37.86	37.64±3.09	8.22	18.67	50.0
Phosphate	2.76	2.41	2.37	2.51±0.18	6.97	1.35	5.0
Sulphate	75.26	77.12	82.89	78.42±3.25	4.14	37.62	100 – 250

CV: Coefficient of variation (in %); milligram per liter ($mg L^{-1}$); World Health Organization (WHO, 2022; 2017)

Table 3. Mean and standard deviation for heavy metals of borehole water in Yala LGA, Cross River State, Nigeria compared with WHO guidelines for drinking water

Physicochemical parameters	Borehole A	Borehole B	Borehole C	Mean±SD	CV (%)	Borehole D(Control)	WHO permissible limit
Lead ($\mu g L^{-1}$)	18.54	21.68	18.92	19.71±1.40	7.10	13.37	10.0
Arsenic ($\mu g L^{-1}$)	12.73	14.21	13.54	13.49±0.61	4.50	11.53	10.0
Nickel ($\mu g L^{-1}$)	13.11	15.35	12.74	13.73±1.15	8.38	10.38	20.0
Chromium ($\mu g L^{-1}$)	31.71	38.67	34.52	34.97±2.86	8.18	29.56	50
Cyanide ($\mu g L^{-1}$)	1.14	1.76	1.36	1.42±0.44	30.99	1.13	3.0
Copper ($\mu g L^{-1}$)	1,370	1,680	1,450	1,500±131.4	8.76	1,130	1,000
Cadmium ($\mu g L^{-1}$)	2.23	2.74	1.48	2.15±0.52	24.19	1.12	3.0

CV: Coefficient of variation (in %) World Health Organization (WHO, 2022; 2017), $\mu g L^{-1}$: micro gram per liter.

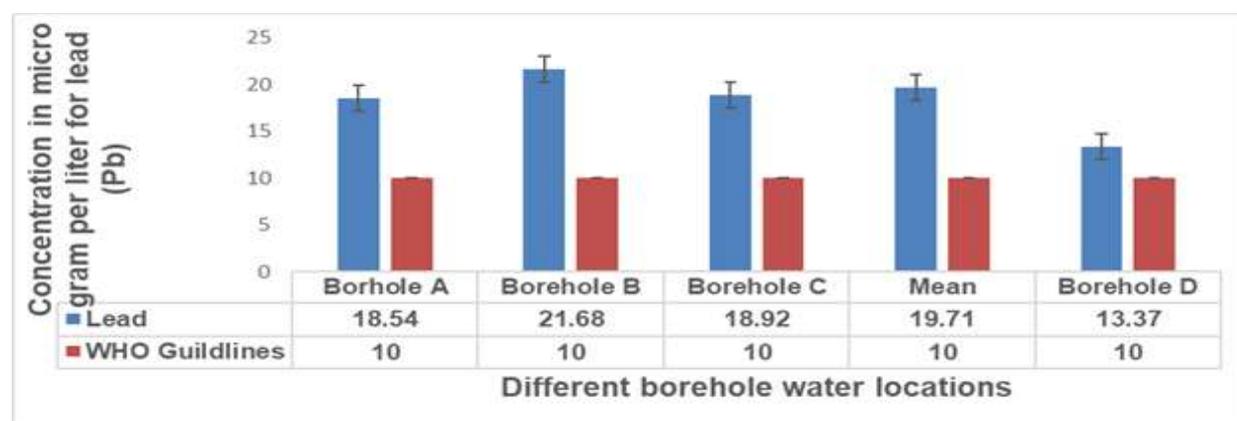


Figure 1: Multiple bar charts comparing lead concentration for experimental and control groups with WHO permissible limit

4.0 DISCUSSIONS

Biological oxygen demand (BOD), sedimentation and chlorination process are temperature dependent (Nayla, 2019). The pH concentration of the study is alkaline water quality unlike acidic pH concentration observed in mining communities in Ghana (Owusu *et al.*, 2024). Turbidity limits transparency due to suspended solid particles such that light cannot penetrate deeply into water column. Borehole water samples were found less turbid than the results obtained in borehole water samples within salty water lake in Ohaozara LGA, Ebonyi State, southeastern Nigeria (Nwaka and Avwiri, 2021; Onunugbo and Nwaka, 2017).

Total dissolved solid (TDS) is related to conductivity and are useful tools to assessing the purity and conductivity of water (Varsha *et al.*, 2013). It also reveals how fresh or salty water is. Conductivity and TDS data revealed borehole water investigated is fresh water since the results were less than $1000\mu\text{S}/\text{cm}$ and 500mg L^{-1} WHO permissible limit. They also indicate borehole water could conduct more electric current due to migration of solution which is dependent on the nature and number of the ionic species in the solution than that reported in Ghana and elsewhere (Owusu *et al.*, 2024). Increase in salinity concentration in water, increases the conductivity.

Lead, copper and arsenic concentrations, representing twenty percent (20%) of the fifteen (15) water parameters investigated for the experimental and control groups, exceeded the WHO guidelines for drinking water quality. While eighty percent (80%) were below the permissible limit both for experimental and control groups. Data set recorded for some heavy metals (for example cadmium) in the study area were in good agreement with similar studies carried out in 19 mining communities in Amansie West District, Ghana, (Owusu *et al.*, 2024), however, varied with relatively higher value for borehole water in Charanchi LGA, Katsina State, Northern Nigeria (Samaila *et al.*, 2025). Similar to water quality recorded for Vishwamitri River, Gujarat India (Magadam *et al.*, 2017), borehole water investigated in the study area revealed fair water quality for physical and chemical parameters, however, considerably contaminated by heavy metals (Pb, and Cu) and metalloid (As). Change in pH concentrations can alter the forms of some chemicals in the water systems. Heavy metals such as cadmium, lead, and chromium dissolved more easily in highly acidic water (lower pH) than alkaline water. This is important because many heavy metals, dissolving in acidic water, becomes much more toxic than in alkaline water.

There was possibility of lead, copper and arsenic migrating or leaching into the near –

surface aquifer or groundwater causing the fresh water unfit as drinkable water. Potential risk associated with heavy metals of lead, copper and arsenic in this study should be given adequate attention. Therefore, water treatment before consumption is recommended to minimize physical, chemical and most especially heavy metals (Pb, Cu, and As) contaminants associated with borehole water in the study area. Therefore, there is urgent need for further environmental monitoring assessment and policy intervention so as to monitor and reduce possible source of the contamination, averting health challenges emanating from consumption of borehole water resources. Seasonal variation of the study area was not considered during collection of water samples, so we could not conclude whether values of different physical chemical and heavy metals properties varied with seasons (climate changes) or not. However, further investigation in that regard should be carried out.

5.0 SUMMARY AND CONCLUSION

Cross River State is characterized with a number of geological formation and mineral deposits including brine (saline water). The need to ascertain the drinking water quality and public health risk within salt lakes area of Okpoma in Yala LGA necessitated the investigation of borehole water safety as drinkable water in the study area. All the

physical, chemical and heavy metal concentrations for the experimental group exceeded the control group which were farther from the salt water lakes. Lead, arsenic and copper concentrations were mainly responsible for borehole water pollution/contamination, which could be treatable to salt water instruction among significant amount of industrial discharge of toxic compounds, lithology of the study area, natural and anthropogenic sources of contamination. These metals could contaminate surface water and private well in the locality through groundwater mobility, run off and surface water seepage. Heavy metals could accumulate in the cells of living organisms and human beings, and in the process leads to sickness from contaminated water. The consumers may risk acute and chronic toxicity, cancer, anemia, liver, kidney and intestinal damage. Physical and chemical remediation, reverse osmosis and filtration process is recommended

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PRODUCTION AND CHARACTERIZATION OF BIODIESEL FROM *CASCABELA thevetia*, CASTOR OIL AND THEIR BLEND

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Abstract

This study investigated the potential of *Cascabelathevetia* oil (CTO), Castor oil (CO), and their blend (CTO/CO) for biodiesel production. Oils were extracted from seeds via Soxhlet extraction using hexane, yielding 44.63% for CTO and 40% for CO. Biodiesel was produced through transesterification at 60°C for 60 minutes. Biodiesel yield was 79.35% for CTO, 77.66% for CO, and notably higher at 82.36% for the CTO/CO blend. Gas chromatography (GC-FID) and Fourier transform infrared spectroscopy (FTIR) were used for characterization. FTIR analysis confirmed the presence of functional groups like esters and alkenes in both oils, indicating their suitability for biodiesel conversion. The physicochemical properties of all three biodiesels were evaluated and compared to ASTM standards. Key properties for the CTO, CO, and blend biodiesels included viscosity (4.4, 5.1, and 4.3 cp at 40°C), acid value (0.25, 0.62, and 0.41 mgKOH/g), calorific value (33820, 33145, and 33470 kJ/kg), and flash point (149, 144, and 147°C). Other parameters like density, cloud point, pour point, and sulfur content (0% for all) were also determined. All measured quality parameters fell within the acceptable limits of international standards. The results demonstrate that both CTO and CO are viable feedstocks for biodiesel production. Furthermore, blending CTO with CO improved the overall biodiesel yield, suggesting a synergistic effect and a promising approach for optimizing production.

Keywords: *Cascabelathevetia*, castor oil, blend, biodiesel production, trans-esterification

1.0 INTRODUCTION

Biofuels are renewable alternatives to petroleum-based motor fuels, such as gasoline and diesel. These are derived from plants, animal waste, or algae material. The major biofuel variants available in the market include bio-gasoline from sugar-based bioethanol and biodiesel from

vegetable oils or fatty acid methyl esters (FAME). These fuels offer several advantages over conventional fossil fuels, such as better lubricating properties, cost-effectiveness, ease of source, and reduced greenhouse gases emissions (Alptekin and Canakci, 2012). Since biofuels are created from organic matter (biomass), they can be

quickly replenished. Besides its lower cost, another good advantage of non-edible oils for biodiesel production lies in the fact that no foodstuffs are spent to produce fuel, using non-edible oils (Ezekoye *et al*, 2019).

2.0 BODY BIODIESEL PRODUCTION TRANSESTERIFICATION

Chemical transesterification also known as alcoholysis, means taking the fatty acid ligands, neutralizing the FFA, removing the glycerin backbone and forming three long monoesters chain, it is a reaction where triglycerides are converted to diglycerides which is converted to monoglycerides then monoglycerides are converted to glycerol. In each step, an ester is produced (Ezekoye *et al*, 2019).



Fig. 1: Transesterification of Triglycerides (Ezekoye *et al*, 2019)

3.0 MATERIALS USED

Casabelathevetia seeds, Castor seeds, round bottom flask, Measuring cylinders, Volumetric flask, beakers, Thermometers, Magnetic bar, Conical flask, Litmus paper, Heating mantle, Refractometer, Rotary evaporator, Burette, Viscometer, n-Hexane, 0.1M NaOH, methanol, ethanol, sulphuric acid (H₂SO₃), potassium hydroxide (KOH), Phenolphthalein indicator.

3.1 Sources of Raw Materials

The *Cascabelathevetia* and castor seeds used for this work were collected within the university of Nigeria, Nsukka campus environment.



Fig. 2: *Cascabelathevetia* (Yellow oleander) fruit and seeds

4.0 PRODUCTION PROCESS

4.1 Extraction of Oil

Cascabelathevetia seeds were collected and sun dried at ambient temperature of 30°C for one week. The fleshy bark was removed manually and the hard cover was dehulled. The inner white seeds were collected and dried for 24 hours at ambient temperature of 30 °C, ground and weighed. 1352.6 g of the sample was mixed with 5 liters of n-hexane and stirred thoroughly for one hour, after which the separation of n-hexane from the oil was done using Soxhlet extraction method. 600 mL of the oil was obtained. Castor seeds were treated in the same way.

The oil was dried at 105 °C in an oven for 4 hours to remove the remaining hexane.

4.2 Treatment of Materials



Fig. 3: Treatment of the oil

4.3 Free Fatty Acid

The efficiency of the reaction diminishes with the increase in the acidity of the oil; basic transesterification is viable if the content of free fatty acids (FFAs) is less than 2 % (Christi, 2007). The free fatty acid (FFA) content of *Cascabelathevetia* oil was 3.94 % while that of castor was 5.2 %. Acid esterification was done to reduce the FFA.

4.4 Degumming

220 mL of oil was measured into a round bottom flask and heated to a temperature of 70 °C. Warm water (10 mLs) was gradually added into the oil. The mixture was heated for 30 minutes and then poured into a separating flask, it was allowed to settle for 24 hours and the lower layer which consists of the gum was removed. The blending ratio of *Cascabelathevetia* oil to castor oil was 80:20

4.5 Esterification

250 mL of the *Cascabelathevetia* oil (CTO) was poured into a round bottom flask with a magnetic bar (to enhance good stirring). The oil was heated to 50 °C while stirring was on. Then a mixture of 5 mL of sulphuric acid and 58 mL of methanol was added gradually to the oil. The temperature was maintained at 50 °C for 1 hour. Constant stirring was done throughout the esterification period.

4.6 Methoxide Preparation

1.42 g of KOH was weighed out and added to 62.5 ml of methanol and left in a tightly closed container overnight to dissolve properly. This mixture was stirred thoroughly to facilitate the dissolution of the KOH. This formed the potassium methoxide solution which was used as the catalyst.

4.7 Transesterification

100ml of CTO was measured into a round bottom flask. The thermo-regulator heater/stirrer was adjusted to a particular temperature of operation (60°C) while stirring the oil at the same time. The stirrer was set at a constant speed throughout the experiment, to ensure uniform agitation. When the oil temperature reached 60°C, the potassium methoxide was gradually added to the round bottom flask, after which the flask was closed. This particular set temperature of 60°C was maintained throughout the reaction, this enhanced the catalytic transesterification of the oil. The mixture was stirred and heated for one hour, after which

the reaction came to a stop. The reacted mixture was poured into separating funnels, covered and left for 24 hours to bring about gravity separation of the mixture. The funnels were opened and the lower layer (glycerol) was removed; the upper layer (biodiesel) was then collected in a beaker and measured. Production was also carried out with castor oil (CO) and a blend of CTO and CO using the procedure described above.



Fig. 4: Biodiesel Production

The biodiesel was washed with warm water to remove traces of unreacted alkali and dried thereafter.

5.0 RESULTS ANALYSES OF THE OIL AND BIODIESEL PRODUCED

These were done using standard methods (AOAC,2012)

The results of analysis conducted on *Cascabelathevetia* oil (CTO) and castor oil (CO) as well as those of their biodiesels are displayed in Tables 1 and 2.

TABLE 1: Physicochemical Properties of CTO and CO

PARAMETER	CTO	CO
Free Fatty Acid (%)	0.46	1.90
Acid Value (mgKOH/g)	0.93	3.70
Viscosity @ 40 °c (cp)	56	68
Moisture Content (%)	0.20	0.31
Ash Content (%)	0.07	0.09
Saponification Value (mgKOH/g)	231.0	183.5
Refractive Index	1.4636	1.4744
Iodine Value (Wij's)	48.4	79.5
Peroxide Value (Meq/Kg)	4.8	5.6
Specific Gravity (g/ml)	0.903	0.951
Density	0.904	0.952

TABLE 2: Physicochemical Properties of Biodiesel Produced from CTO (CTOBD) AND CO, (COBD) and the blend (CTOBD/COBD).

PARAMETER	CTO	CO	CTOBD /COBD
Free Fatty Acid (%)	0.12	0.30	0.20
Acid Value (mgKOH/g)	0.25	0.62	0.41
Viscosity @ 40 °c (cp)	4.4	5.1	4.3
Moisture Content (%)	0.03	0.05	0.05
Ash Content (%)	0.04	0.05	0.07
Sapon.Value (mgKOH/g)	158.2	120.4	141.1
Refractive Index	1.4636	1.4744	1.454
Iodine Value (Wij's)	37.6	62.4	49.3
Peroxide Value (Meq/Kg)	3.0	4.5	3.8
Specific Gravity (g/ml)	0.861	0.907	0.884
Density	0.862	0.907	0.885
Cloud Point(°C)	0	2	1
Pour Point(°C)	-6	-3	-4
Flash Point (°C)	149	144	147
Smoke Point (°C)	144	138	142
Fire Point (°C)	162	150	156
Sulphur Content (%)	0	0	0
Calorific Value (KJ/Kg)	33820	33145	33470

TABLE 3: Gas chromatography (GC) composition analysis on biodiesel from CTO, CO and CTO/CO blend

Components	Percentage (%)		
	CTO	CO	CTO/CO
Alcohol	2.60	7.33	2.58
Monoglycerides	4.39	2.47	5.86
Diglycerides	3.40	6.40	2.54
Fatty acid methyl ester	79.35	77.66	82.36
Glycerol	8.29	3.42	4.17
Triglycerides	1.96	2.71	2.49

6.0 DISCUSSION

6.1 Characterization of CTO and CO

The results of the physiochemical properties of the CTO and CO in Table 1 shows that the oils are good for the production of biodiesel. The refractive indices fell within the range of (1.466-1.487) which are comparable to other work (Knothe, 1999). The densities of CTO and CO were 0.904 and 0.952 respectively. while the specific gravities of CTO and CO were 0.903 and 0.951 respectively. The iodine value was 48.4 for CTO and 79.5 for CO. The initial high FFA of the oil was reduced to avoid the catalyst (KOH) from reacting and forming soap instead of biodiesel with the oil (Baohua *et al*, 2023). The oils are less prone to oxidation rancidity due to their relative low peroxide value and FFA which makes them good feedstock for biodiesel production,

6.2 Characterization of Biodiesel from CTO and CO and their Blend.

Table 2 showed the result of the physiochemical properties of biodiesel produced from CTO and CO and their blends. The physiochemical results such as the FFA, acid value, fire point, flash point and calorific showed that CTO was better than CO for the production of biodiesel. The results agreed with the international standards for biodiesel.

Table3 showed the result of the GC analysis of biodiesel from CTO, CO and CTO/CO blend respectively. Biodiesel yields for CTO, CO and CTO/CO were 79.35 %, 77.66 % and 82.36 % respectively, this implies that a better biodiesel yield was achieved by blending CTO with CO.

7.0 CONCLUSION

The analysis carried out on the seed oil *Cascabelathevetia* and castor oil showed that they are good feedstock for biodiesel production. The comparison of the results shows that *Cascabelathevetia* was of a higher yield (79.35 %) than castor oil (77.66 %). Their properties aligned with the ASTM standards. The biodiesel produced from the oils had good physicochemical properties such as high calorific values, high flash points and high fire points.

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EVALUATION OF AMBIENT RADIATION PROFILES AND INFLUENCE ON RENEWABLE ENERGY PLANNING IN AGUATA L.G.A., NIGERIA

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Abstract

In-situ measurements of environmental background ionizing radiation were conducted at 25 outdoor locations across five randomly selected towns in Aguata Local Government Area, Anambra State, using a well-calibrated Radalert-100TM radiation meter and GPS for coordinate tracking. The study assessed exposure dose, absorbed dose rate (ADR), equivalent dose rate (EDR), annual effective dose equivalent (AEDE), and excess lifetime cancer risk (ELCR). The average exposure rate was 0.0117 ± 0.0010 mRh⁻¹. The recorded average values for ADR, EDR, AED, and ELCR were 101.85 ± 3.09 nGyh⁻¹, 0.98 ± 0.03 mSv y⁻¹, 0.125 ± 0.004 mSv y⁻¹, and $0.437 \pm 0.013 \times 10^{-3}$ respectively. These results were evaluated against international safety standards to determine potential impacts on renewable energy development in the region.

Keywords: *BIR, environmental radiation, radiation health risk, radiation monitoring, renewable energy, Aguata L.G.A*

1.0 INTRODUCTION

The global push for sustainable energy development highlights the importance of understanding environmental factors that influence renewable energy deployment (Gayen, Chatterjee, & Roy, 2024). A key factor is environmental radiation, which, although naturally occurring, varies across regions (Gayen et al., 2024). Radiation encompasses the emission and propagation of energy through space or a material medium (Sathiya & Ramachandran, 2024). Background ionizing radiation, an unavoidable part of life on Earth, exists as electromagnetic (X-rays, gamma rays) or particle radiation (alpha, beta, neutron),

originating from both natural and anthropogenic sources. Naturally Occurring Radioactive Materials (NORM) are found in the Earth's crust, atmosphere, and biosphere, contributing to continuous background exposure (Ajayi et al., 2022; Rafique et al., 2014). Human activities have further increased radiation levels through Technologically Enhanced Naturally Occurring Radioactive Materials (TENORM). In particular, natural radionuclides are released to the environment in mineral processing and uses, such as phosphate fertilizer production and use, and fossil fuel combustion, causing enhanced natural radiation exposures (UNSCEAR,

2000). Combustion of coal, oil, and gas releases harmful emissions that contribute to elevated radiation levels (Omer, 2008).

In Aguata L.G.A., Anambra State, Nigeria, assessing background radiation is vital for public health, environmental safety, and guiding the siting of renewable energy projects. Background radiation data are crucial for environmental impact assessments of solar and wind energy infrastructures (UNSCEAR, 2017). There is a need to determine whether existing radiation levels pose risks or benefits for renewable energy development and to understand how renewable energy adoption may affect local radiation dynamics.

This study, therefore, aims to evaluate the environmental radiation profile of Aguata L.G.A. and its implications for safe and efficient renewable energy development. Such understanding is factor to enhancing radiation safety, reducing risk, and promoting a sustainable green energy transition in Aguata and similar regions in Nigeria.

2.0 METHODOLOGY

2.1 Study Area

The study was conducted in five randomly selected communities; Ekwulobia, Isuofia, Igboukwu, Aguluezechukwu, and Uga, within Aguata Local Government Area (L.G.A.) of Anambra State, Nigeria. Aguata, located in the Anambra South senatorial district, lies between Latitudes: 5.815⁰N to

6.068⁰N and Longitudes: 6.980⁰E to 7.206⁰E. Its headquarters is split between Aguluezechukwu and Ekwulobia. The L.G.A. comprises fourteen autonomous communities and spans a landmass of 19,906.25 km². It is bordered by Orumba South L.G.A. (east), Orumba North (north), Anaocha (west), and Nnewi South and Imo State (south) (Nwangwu et al., 2020). As of 2006, the population was estimated at 434,124, with a projected increase to 527,200 by 2022 (NADPS, 2022). The area experiences two seasons: a rainy season from March to October (with annual rainfall between 180 mm and 270 mm) and a dry season from November to April, characterized by high temperatures. The population is primarily agrarian, with crops cultivated near residences and open areas used for grazing.

2.2 Radiation Survey Method

This study employed in-situ measurements to determine terrestrial outdoor radiation exposure rates using a standardized method. The detector tube was positioned at 1.0 m above ground level, with its window oriented toward the area of interest, to reflect typical human organ exposure and reduce interference from ground emissions (Ugbede, 2018; Ononugbo & Nwokeoji, 2017). Measurements were conducted at five randomly selected sites in each of the five chosen towns, giving a total of 25 sampling locations. Coordinates were recorded using

GPS in decimal degree format, compatible with Geographic Information System (GIS) applications. A Radalert 100X™ nuclear radiation monitor calibrated using a Cesium-137 source by the National Institute of Radiation Protection and Research (NIRPR) on October 12, 2021 (model R100x, Serial No. X02848), and manufactured by Medcom, Inc., USA, was used; with measurements conducted in November 2021. At each sampling position, radiation exposure was recorded three times, and the average value was taken as the final exposure rate. The values initially recorded in micro-Sieverts per hour (μSvh^{-1}) were converted to milli Roentgens per hour (mRh^{-1}) by multiplying by 0.1. These measurements were taken between 10:00 AM and 4:00 PM, when environmental conditions such as solar radiation intensity, ambient temperature, and humidity are relatively stable which enhances the accuracy and consistency of radiation meter readings, as recommended by the National Council on Radiation Protection and Measurements (NCRP, 1993). To account for fluctuations, readings were taken at 4-minute intervals (Agbalagba, 2017). The exposure rate data, including standard deviations, were quantitatively analyzed to assess radiation health risks, and results were compared with international safety standards.

2.3 Dosimetry calculations and Risk Estimation

Absorbed Dose Rate (D). The ADR measures energy deposited by radiation in a unit mass of air and absorbed by the masses. The BIR values gotten for outdoor exposure rate in milli-Roentgen per hour (mRh^{-1}) were transformed into absorbed dose in nGyh^{-1} by applying the conversion factor (Ugbede, 2018).

$$1 \mu\text{R} / \text{h} = 8.7\text{nGy} / \text{h} = \frac{8.7 \times 10}{1/8760\text{y}} \mu\text{Gy} / \text{y} \quad (1)$$

Since the exposure rate is in mRh^{-1} , equation (1) becomes

$$1\mu\text{R} / \text{h} = 0.001\text{mR} / \text{h} = 8.7\text{nGy} / \text{h} \quad (2)$$

Annual Effective Dose Equivalent (AEDE). AEDE indicates the annual radiation dose received by individuals. it was calculated using the computed absorbed dose rates and it is given by Ononugbo and Nte (2017) as

$$\text{AEDE (mSv / y) (outdoor)} = \text{Absorbed dose rate (nGyh}^{-1}) \times 8760\text{h} \times 0.7\text{Sv} / \text{Gy} \times 0.25 \quad (3)$$

Where 8760 is the number of hours in a year, 0.7 SvGy^{-1} is the dosage conversion factor from the absorbed dose in the air to the effective dose and 0.25 (6 out of 24 hours) is the occupancy factor for outdoor exposure (Ugbede, 2018).

Excess Lifetime Cancer Risk (ELCR). The ELCR estimates the probability of developing cancer over a lifetime due to radiation exposure. The ELCR was calculated from the AEDE using the equation

$$\text{ELCR} = \text{AEDE} \times \text{DL} \times \text{RF} \quad (4)$$

DL represent the average life expectancy/duration of life (70 years') and RF denote the fatal cancer Risk Factor (Sv) that is, deadly cancer risk per Sievert (Sv^{-1}) (Agbalagba, and Anekwe, 2021). For probability effects, ICRP 106 and 60 used a figure of $\text{RF} = 0.05$ for the whole masses.

Equivalent Dose Rate (EDR). The EDR tells of the biological effect of the radiation on human tissue. In order to assess the EDR over 1 year period, the recorded exposure rates were transformed to equivalent dose rate using equation (5) below as given by the NCRP for equivalent dose and as used by Ononugbo, Avwiri, & Tutumeni (2015).

$$1\text{mRh}^{-1} = \frac{96 \times 24 \times 365}{100} \text{mSvy}^{-1} = 84.096\text{mSvy}^{-1} \quad (5)$$

Data were analyzed using Microsoft Excel for statistical computations; Surfer-GIS and ArcGIS 10.7 were used for contour and radiometric mapping. Sampling locations were geo-referenced, and point features were used to represent radiation exposure rates on maps. Standard deviations were calculated to assess data variability.

3.0 RESULTS

S/N	Communities by L.G. A	Mean exposure rate (mRh^{-1})	Equivalent dose rate (mSvy^{-1})	Absorbed dose rate (nGyh^{-1})	AEDE (mSvy^{-1})	ELCR $\times 10^{-3}$
1.	Ekwulobia	0.0116 ± 0.0015	0.98 ± 0.13	100.92 ± 13.03	0.124 ± 0.016	0.433 ± 0.056
2.	Igboukwu	0.0122 ± 0.0011	1.03 ± 0.09	106.14 ± 9.75	0.130 ± 0.012	0.456 ± 0.042
3.	Uga	0.0115 ± 0.0009	0.95 ± 0.08	99.76 ± 7.84	0.122 ± 0.010	0.428 ± 0.034
4.	Aguluezechukwu	0.0113 ± 0.0007	0.95 ± 0.06	98.60 ± 5.80	0.121 ± 0.007	0.423 ± 0.025
5.	Isuofia	0.0119 ± 0.0011	1.00 ± 0.10	103.82 ± 9.92	0.127 ± 0.012	0.446 ± 0.043
	Average	0.0117 ± 0.0010	0.98 ± 0.03	101.85 ± 3.09	0.125 ± 0.004	0.437 ± 0.013
	ICRP Recommended limit	0.013	1.00	84.00	1.00	0.29

3.1 Radiation Measurements in Aguata Local Government Area.

Table 3.1: Total outdoor mean exposure rate and the estimated radiation hazard risk parameters as measured in the five different communities in Aguata L.G.A.

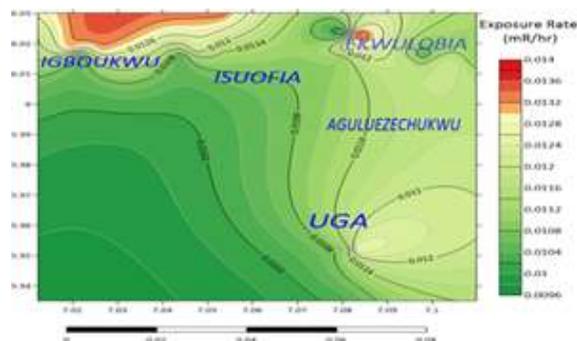


Figure 1: Contour map of outdoor exposure rate in Aguata L.G.A. (Ezemba, et al; 2025)

4.0 DISCUSSION OF RESULTS

Exposure Rate. The exposure rate ranged from 0.0113 mRh^{-1} (Aguluezechukwu) to 0.0122 mRh^{-1} (Igboukwu), with an average of 0.0117 mRh^{-1} . In Figure 1, areas indicated with red color have higher BIR radiation exposure; however, the cumulative average of the study area is lower than the ICRP limit

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of 0.013 mRh⁻¹. This indicates no immediate external radiation risk in the study area.

Equivalent Dose Rate. EDR values ranged from 0.95 mSv y⁻¹ (Uga and Aguluezechukwu) to 1.03 mSv y⁻¹ (Igboukwu), with an average of 0.98 mSv y⁻¹. Most communities fall within or just below the ICRP public dose limit of 1.00 mSv y⁻¹, except Igboukwu, which slightly exceeds it, suggesting a need for continued monitoring.

Absorbed Dose Rate. ADR ranged from 98.60 nGy h⁻¹ (Aguluezechukwu) to 106.14 nGy h⁻¹ (Igboukwu), averaging 101.85 nGy h⁻¹. All values exceed the global outdoor average of 84 nGy h⁻¹, indicating elevated background radiation, though not at dangerous levels.

Annual Effective Dose Equivalent. AEDE values ranged from 0.121 mSvy⁻¹ (Aguluezechukwu) to 0.130 mSv y⁻¹ (Igboukwu), with an average of 0.125 mSv y⁻¹. All are well within the ICRP safety limit of 1.00 mSv y⁻¹, posing no significant health threat under normal environmental conditions.

Excess Lifetime Cancer Risk. ELCR ranged from 0.423×10^{-3} (Aguluezechukwu) to 0.456×10^{-3} (Igboukwu), with an average of 0.437×10^{-3} . All values exceed the ICRP threshold of 0.29×10^{-3} , suggesting a potential long-term cancer risk, though relatively low, and necessitating

precautionary environmental and health surveillance.

4.0 CONCLUSION.

The assessment of environmental radiation levels in the five selected communities of Aguata L.G.A., Anambra State shows that while exposure parameters are generally within or slightly above recommended safety limits, some indicators, especially absorbed dose and excess lifetime cancer risk (ELCR), exceed global averages, warranting ongoing monitoring and public health awareness. Igboukwu consistently recorded the highest radiation levels, likely due to anthropogenic activities, indicating a need for focused attention in that area. Although there is no immediate health threat, the slightly elevated long-term risks call for a proactive environmental management strategy, especially where renewable energy infrastructure like solar farms is planned. The study confirms that, by estimation, the background radiation levels across Aguata are within globally acceptable limits, though above average, reinforcing the need for comprehensive baseline radiation mapping. Incorporating environmental radiation profiling into renewable energy planning is crucial for ensuring site suitability, sustainability, public health protection, and efficient resource use. Hence, A full survey covering all communities in Aguata L.G.A. should be conducted to replace hypothetical

estimates with accurate, location-specific data and a GIS overlay combining radiation data and potential renewable energy sites should be developed and publicly available to guide site selection.

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**GEOPHYSICAL ESTIMATION OF THE ENVIRONMENTAL IMPACT OF
SAND MINING ON THE NWORIE RIVER CHANNEL USING ELECTRICAL
RESISTIVITY TOMOGRAPHY (ERT) AND GROUND PENETRATING RADAR
(GPR) DATA, IMO STATE , NIGERIA**

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Abstract

Sand mining along the Nworie River channel in Imo State, Nigeria, driven by rising demand for construction materials, poses serious environmental threats. The river's ecosystem supports diverse aquatic life through its oxygen-rich water, balanced nutrients, and stable habitat. This study assesses the geophysical impact of excessive sand extraction using electrical resistivity tomography (ERT) and ground-penetrating radar (GPR). Results reveal significant subsurface deformation, including sediment layer collapse and cavity formation, increasing riverbank erosion and destabilization of the riverbed. Water and soil analysis indicate physicochemical changes and contamination, with dissolved oxygen levels varying from 8.5 mg/L at the pristine source to 3.8 mg/L near major sand mining zones. These fluctuations reflect severe habitat disturbance, sediment overload, and pollution, leading to habitat loss and threatening the river's ecological balance. Although oxygen levels show some recovery downstream near the Otamiri River confluence, the overall impact remains alarming. This study emphasizes the urgent need for sustainable mining practices and effective regulatory measures to prevent further environmental degradation. The findings provide critical insights for policymakers and environmental managers to promote responsible resource exploitation and preserve the Nworie River's ecological integrity.

Keywords: *River Channel, Ground-Penetrating radar, Formation, Ecosystem, and Habitat*

1.0 INTRODUCTION

Rivers are vital freshwater ecosystems, providing essential resources for human societies and supporting rich biodiversity. However, these critical environments are increasingly threatened by anthropogenic

activities, among which sand mining stands out as a pervasive and environmentally destructive practice (Koehnken & Rintoul, 2018). The global demand for sand, primarily driven by the booming construction industry, has led to

unprecedented levels of extraction from riverine systems worldwide (Peduzzi, 2014; Bendixen et al., 2022). In Nigeria, a country experiencing rapid urbanization and infrastructural development, the demand for construction materials, particularly sand, has surged, placing immense pressure on its river systems. The Nworie River, a significant freshwater body in Imo State, Southeastern Nigeria, exemplifies a river grappling with the severe consequences of unregulated sand mining. This river is not merely a source of sand; it is an intricate ecosystem providing habitat for diverse aquatic flora and fauna, supporting local livelihoods through fishing, and serving as a source of water for various domestic and economic activities (Amadi et al., 2015; Ejiogu et al., 2019). The escalating scale of sand extraction, often conducted without adherence to environmental guidelines or proper regulatory oversight, poses a grave threat to the Nworie River's ecological integrity and the socio-economic well-being of riparian communities. The environmental impacts of sand mining are multifaceted, encompassing profound geophysical alterations, significant physicochemical changes in water quality, and severe biological degradation (Koehnken & Rintoul, 2018; Bendixen et al., 2022). Geophysical impacts include changes in river morphology, such as bed degradation, channel widening, and increased bank erosion, leading to habitat

loss and instability (Koehnken & Rintoul, 2018). Physicochemical changes often involve increased turbidity, altered dissolved oxygen levels, and changes in nutrient concentrations, which directly affect aquatic life (Koehnken & Rintoul, 2018; Nwankwoala & Ede, 2015). This study aims to comprehensively assess the geophysical and environmental impacts of excessive sand extraction in the Nworie River using advanced geophysical techniques, namely Electrical Resistivity Tomography (ERT) and Ground-Penetrating Radar (GPR). By employing these methods, we seek to provide empirical evidence of subsurface deformation and quantify the extent of environmental degradation caused by sand mining. The findings of this research are critical for informing sustainable mining practices, guiding policy development, and promoting responsible resource management to safeguard the ecological health of the Nworie River and other similar riverine environments in Nigeria.

General Environmental and Geophysical Impacts of Sand Mining

Sand mining, particularly from active river channels, has profound and far-reaching environmental consequences (Koehnken & Rintoul, 2018). Globally, the extraction of aggregates has been identified as a major threat to river ecosystems (Bendixen et al., 2022). The impacts are particularly acute in tropical and sub-Saharan African contexts,

where regulatory frameworks are often weak or unenforced, and communities are highly dependent on river resources (Agyei et al., 2022; Ndimele et al., 2019).

River Bed Degradation and Lowering:

The most direct geophysical impact is the lowering of the riverbed, often by several meters, as large quantities of sand and gravel are removed (Koehnken & Rintoul, 2018). This alters the hydraulic gradient and can lead to increased flow velocity, further exacerbating erosion.

Channel Morphology Changes

Sand mining often causes significant changes in river channel morphology, including widening and deepening of the channel, leading to an over-widened and shallow river that struggles to maintain flow and support aquatic life (Koehnken & Rintoul, 2018; Ayanlade & Ojedeji, 2020).

River Bank Erosion and Instability

The removal of bed material undermines the stability of riverbanks, leading to increased erosion, bank collapse, and loss of riparian vegetation (Koehnken & Rintoul, 2018; Ayanlade & Ojedeji, 2020; Alabi et al., 2024). This not only reduces land available for agriculture and infrastructure Figure 1: Map of Study Location Showing Nworie River Outlines Typical aquatic life in similar Nigerian freshwater ecosystems, including the Otamiri River, encompasses a variety of fish species, belonging to families such as Cichlidae (e.g., *Tilapia* species), Clariidae

(catfishes), Bagridae, and Mormyridae (Ejiogu et al., 2019; Amadi et al., 2015). Benthic macro-invertebrates are also present and are often used as bio-indicators of water quality. Examples include Mollusca (Gastropods like *Melanoides tuberculata* and *Gabiella africana*) and Arthropoda (Insecta, such as *Chironomus* larvae and *Tubifex* larvae) (Amadi et al., 2015). The river also supports various aquatic macrophytes and riparian vegetation, including *Panicum* species, ferns, *Pistia stratiotes*, *Azolla africana*, *Lemna Polvrrhiza*, *Nymphaea* spp, *Valisneria* spp, and *Typha* (Ejiogu et al., 2015; DOPA Explorer, n.d.). These diverse life forms rely on stable habitats, oxygen-rich water, and balanced nutrient levels, all of which are directly threatened by unregulated sand mining.

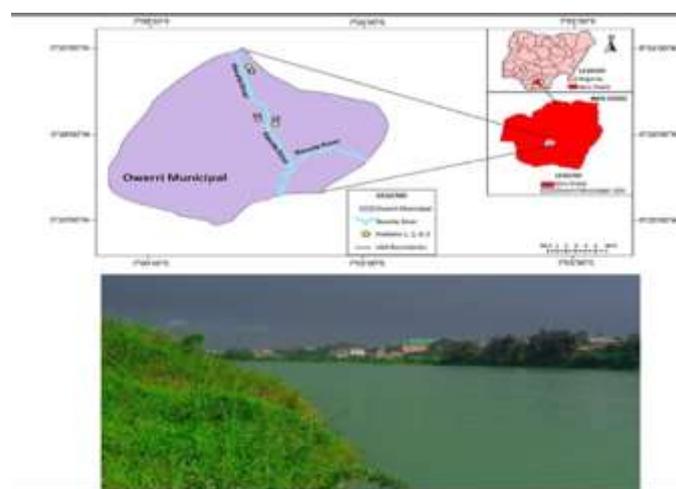


Figure 1: Map of Study Area Indicating Location points (flowing) and lentic (stagnant) habitats, with some areas becoming wider and deeper, almost static, demonstrating the profound morphological changes (Nwankwoala & Ede, 2015).

Previous studies have highlighted the unsupervised commercial sand mining in the Nworie River, leading to significant degradation of its physical characteristics and worsening indicators of organic pollution, including low dissolved oxygen and high carbon dioxide levels (Nwankwoala & Ede, 2015). These activities have led to the creation of alternating lotic

2.0 MATERIALS AND METHODS

This study employed Electrical Resistivity Tomography (ERT) and Ground-Penetrating Radar (GPR) to assess the geophysical impact of excessive sand extraction in the Nworie River channel. Identification of multiple transects across the Nworie River, encompassing areas of intense sand mining activity, less disturbed zones (upstream or downstream from mining), and a relatively pristine source area for comparative analysis were selected.

Electrical Resistivity Tomography (ERT) and Ground Penetrating Radar (GPR)

Deployment of ABEM Terrameter 1000 SAS, a multi-electrode resistivity system was transected along Emmanuel College Owerri, Federal Polytechnic Nekede, Imo State University, Alvan Ikoku Federal University, and Nworie River (Near River bank) using Schlumberger configuration to achieve desired depth of investigation and resolution. Collection of resistivity data points and subsequent 2D inversion modeling to generate subsurface resistivity

tomograms. Interpretation of resistivity anomalies to identify areas of sediment layer collapse, cavity formation, and changes in subsurface lithology or water saturation indicative of sand extraction impacts were carried out (Fig 2:a-e).

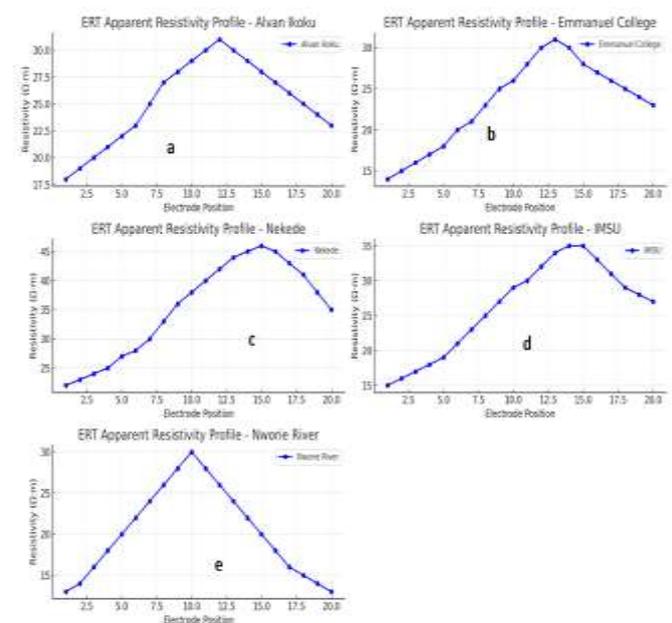


Fig 2:a-e Nworie river channel Electrical Resistivity Tomography (ERT) Survey Line Tomograms

GPR systems with appropriate antenna frequencies (e.g., 50 MHz to 250,) with good penetration depth and resolution was also run along the same or parallel transects as the ERT. Collection of GPR profiles (radargrams) and subsequent processing (e.g., filtering, migration) to enhance subsurface features were done. Interpretation for reflection patterns, hyperbolic anomalies, and chaotic zones to identify subsurface voids, disturbed sediment layers, and the extent of riverbed and bank destabilization was carried out (Fig 3: A-E).

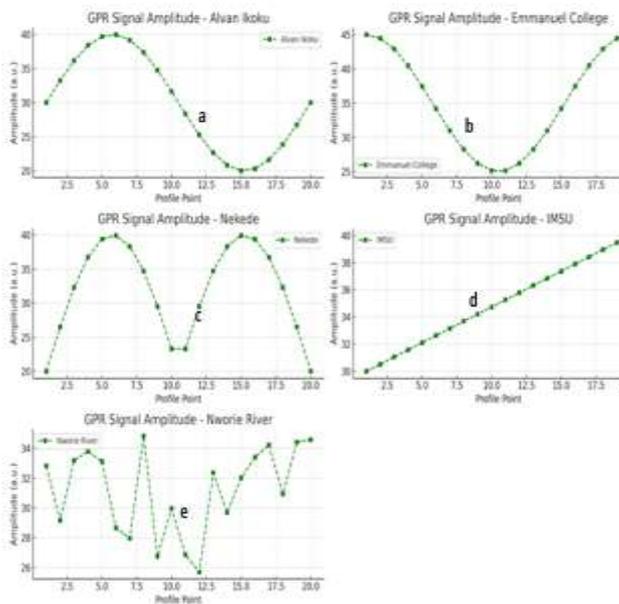


Figure 3:a-e Nworie River Channel Ground-Penetrating Radar (GPR) Survey Line Radargrams Water and Soil Analysis

Water samples from various points along the river, including the pristine source, major sand mining zones, and downstream near the Otamiri River confluence were collected.

Analysis of key physicochemical parameters, including Dissolved Oxygen (DO), pH, Electrical Conductivity (EC), Temperature, Turbidity, and potentially nutrient levels (e.g., nitrates, phosphates). Collection of soil/sediment samples from the riverbed and banks in affected and unaffected areas for textural analysis and potential contaminant screening was done.

Data Integration and Interpretation

Gradual increase in resistivity up to the middle, then decrease is observed at Alvan Ikoku Federal University site. This suggests

a partially compacted fill or topsoil over saprolite. In the case of Emmanuel College, Owerri, there seems to be a steady rise with a peak at point 13, then gradual drop. This shows a higher resistivity due to dry, coarse material or buried rubble surrounded by more moist silt or clay. At Nekede site is a steep rise to a peak at points 14-15, then decline. This is typical of anthropogenic fill or coarse gravels, likely used in site development. It is a well-drained material with good subsurface porosity. In the IMSU flank, a gradual rise to a plateau at points 14-15, then slightly dropped. Uniform sandy-clayey layer over bedrock is probably the case here. The moderately high resistivity suggests dry sediments or infill of construction materials. The Nworie River points indicate a bell-shaped alluvial deposit, where the resistivity increases with distance from saturated riverbed materials. The central highs may correspond to dry, loose sand, while edges are more water-logged. From GPR, depth variation with sinusoidal pattern between 0.5-0.7m indicating layering likely due to controlled fill or consistent sediment deposition implied a stable subsurface with insignificant disturbances. At Emmanuel College outlay of 0.3-0.5m indicates soil with mixed lithologies and topsoil over silt. This indicates low amplitude variability. Nekede has moderate wave in depth variation of 0.55-0.7m. This indicates a high rate of

changes in construction debris of sand and gravel. IMSU depth points of 0.4-0.5m are fairly uniform. This shows a feature of compacted soils or uniform fill materials. River Nworie depth points of 0.2-0.3m are fluctuating. This reflects water table or riverbank sediment zones. Here marks regions of erosion, deposition and sand mining.

Correlation of geophysical data (ERT tomograms and GPR radargrams) with observed surface features (e.g., bank erosion, visible cavities) and results from water and soil analysis shows

Results and 3.0 DISCUSSION

The application of ERT and GPR techniques in the Nworie River revealed compelling evidence of significant geophysical and environmental degradation directly attributable to excessive sand extraction.

Geophysical Impacts: Subsurface Deformation and Instability

The geophysical surveys provided clear insights into the subsurface consequences of sand mining:

Sediment Layer Collapse and Cavity Formation

ERT tomograms showed distinct high-resistivity anomalies often corresponding to subsurface voids or air-filled cavities where sand had been removed. These anomalies were particularly prevalent in areas of active mining. Complementary GPR radargrams provided high-resolution images revealing

disrupted reflection patterns, indicating the collapse of overlying sediment layers into excavated areas (Jol, 2009). The presence of parabolic reflections or "no-data" zones within otherwise continuous stratigraphy strongly suggested the formation of significant cavities and areas of localized subsidence, consistent with observations in other mined rivers (SandStories.org, 2023). This subsurface instability directly undermines the structural integrity of the riverbed.

Increased Riverbank Erosion

Both ERT and GPR data indicated compromised riverbank integrity. ERT profiles perpendicular to the river flow showed anomalous resistivity distributions near the banks, suggesting areas of preferential water infiltration or loss of cohesive sediment due to undermining. GPR profiles along the banks revealed evidence of slumping and detachment of bank material, indicative of active erosion (Alabi et al., 2024). These geophysical findings corroborate surface observations of severe riverbank erosion and provide a subsurface understanding of the destabilization mechanisms.

Riverbed Destabilization

The overall geophysical signature in heavily mined zones pointed to extensive riverbed destabilization. ERT data showed inconsistent and highly variable resistivity patterns across the riverbed, reflecting

heterogeneous material distribution due to repeated excavation and infilling by less consolidated sediments. GPR radargrams displayed chaotic and discontinuous reflections within the riverbed, indicative of widespread disturbance and loss of the natural stratified sediment layers. This pervasive destabilization contributes to continuous remobilization of sediments and an altered hydraulic regime within the river (Koehnken & Rintoul, 2018; IRJMETS, 2025).

Physicochemical Changes and Contamination

Water and soil analysis confirmed significant physicochemical changes and signs of contamination in the Nworie River, particularly in areas impacted by sand mining:

Dissolved Oxygen (DO) Fluctuations

The study reported dissolved oxygen levels, ranging from 8.5 mg/L at the pristine source to 3.8 mg/L near major sand mining zones, represent a critical decline in environmental quality. This substantial reduction (over 50%) is indicative of severe habitat disturbance, sediment overload, and pollution. Such low DO levels (3.8 mg/L) are detrimental to most aquatic organisms, leading to physiological stress, reduced biodiversity, and, in severe cases, fish kills (Koehnken & Rintoul, 2018). While this study's figures are specific, they are consistent with the *trend* of DO reduction

observed in other sand-mined rivers in Nigeria. For example, some studies on the Nworie River have reported DO values as low as 5.35 ± 0.68 mg/L in downstream sections affected by anthropogenic activities, compared to 6.6 ± 0.73 mg/L upstream (Amadi et al., 2015), both falling below recommended standards. The slight recovery in oxygen levels observed downstream near the Otamiri River confluence suggests some degree of natural re-aeration or dilution, possibly due to the less disturbed nature of the Otamiri River and its designated protected status (DOPA Explorer, n.d.). However, this partial recovery does not negate the severe impacts upstream.

Other Physicochemical Parameters

While the abstract specifically highlights DO, similar studies on sand-mined rivers consistently report increases in turbidity, suspended solids, and often changes in pH and electrical conductivity (Nweze et al., 2018; Osuocha et al., 2022). High turbidity, caused by suspended sediments from mining, reduces light penetration, directly impacting primary productivity and further exacerbating DO depletion (UBC Wiki, 2023). The destabilization of the riverbed also leads to the release of fine sediments and potentially adsorbed pollutants, contributing to overall water quality degradation (IRJMETS, 2025).

Ecological Consequences

The observed geophysical and physicochemical changes have profound ecological consequences for the Nworie River:

Habitat Loss and Fragmentation

The physical alteration of the riverbed, bank erosion, and the formation of unstable, often deeper or shallower, segments directly destroy critical habitats for fish, benthic macro-invertebrates, and aquatic plants (Ndimele et al., 2019). The creation of alternating lotic and lentic habitats, with some areas becoming almost static, further fragments existing habitats and restricts the movement and survival of aquatic species (Nwankwoala & Ede, 2015).

Threat to Aquatic Life

The severe fluctuations and reduction in dissolved oxygen, coupled with increased turbidity, directly threaten the diverse aquatic life known to inhabit the Nworie and Otamiri Rivers, including various fish families (Cichlidae, Clariidae) and benthic invertebrates (Mollusca, Arthropoda) (Amadi et al., 2015; Ejiogu et al., 2019). Sensitive species are particularly vulnerable to these changes, potentially leading to shifts in community structure and a reduction in overall biodiversity. The disruption of nutrient balance and the introduction of potential contaminants further stress the ecosystem.

Ecosystem Imbalance

The cumulative impacts lead to a significant disruption of the river's ecological balance. The loss of primary producers due to turbidity, the stress on higher trophic levels due to low oxygen, and the destruction of physical habitats compromise the river's ability to provide essential ecosystem services, including water purification, nutrient cycling, and support for fisheries. The alarming overall impact underscores the urgent need for intervention, as the Nworie River's ecological integrity continues to be compromised by current sand mining practices.

Sustainable Mining Practices and Regulatory Measures

The findings of this study underscore the urgent need for a paradigm shift from current unsustainable sand mining practices to responsible resource exploitation in the Nworie River and similar environments. Effective solutions require a multi-pronged approach encompassing sustainable practices, robust regulatory frameworks, and community engagement.

Sustainable Mining Practices

Adopting sustainable sand mining practices involves integrating environmental considerations throughout the entire extraction process:

Hydrodynamic and Sediment Transport Modeling

Utilizing advanced modeling techniques (e.g., HEC-RAS models) to assess river morphology, sediment dynamics, and replenishment rates before granting extraction permits (UNEP, 2019; Vietnam MoNRE, 2023). This helps identify areas where mining can occur with minimal impact and ensures extraction rates do not exceed natural replenishment.

Dynamic Sand Reserve Mapping

Regularly mapping sand reserves and identifying sustainable extraction zones based on scientific assessment of river equilibrium and sediment budgets (UNEP, 2019; Vietnam MoNRE, 2023).

Extraction from Depositional Zones

Prioritizing sand extraction from natural depositional areas (e.g., point bars, floodplains) rather than active river channels (Agyei et al., 2022; UNEP, 2019). This minimizes direct disturbance to the riverbed and reduces scour.

Controlled Extraction Depths and Volumes

Implementing strict limits on the depth and volume of sand extracted from any given area to prevent excessive bed degradation and undermining of riverbanks (Agyei et al., 2022).

Phased Mining and Rehabilitation

Designing mining operations with clear phases for extraction and immediate,

progressive rehabilitation of mined-out areas, including re-vegetation of riverbanks and restoration of habitat features (UNEP, 2019).

Minimizing Turbidity and Pollution

Employing techniques that minimize sediment suspension during extraction (e.g., using hydraulic dredges with enclosed systems) and preventing spills of fuel and lubricants from machinery (IRJMETS, 2025).

Promoting Circularity and Alternatives

Encouraging the use of recycled construction materials, promoting sand alternatives (e.g., manufactured sand from quarry dust, fly ash), and responsible procurement practices to reduce the overall demand for virgin river sand (UNEP, 2019).

Effective Regulatory Measures and Policy Frameworks

Robust regulatory and policy frameworks are essential to enforce sustainable practices and prevent illicit mining:

Integrated Policy Frameworks

Developing comprehensive national and state-level policies specifically for sand mining that integrate environmental protection, resource management, and socio-economic considerations (UNEP, 2019). Such frameworks should clearly define permissible mining zones, extraction limits, and environmental performance standards (Muzerengi & Dube, 2022).

Strong Enforcement and Monitoring

Establishing dedicated regulatory bodies with adequate resources and authority to monitor mining activities, conduct regular inspections, and enforce compliance (Muzerengi & Dube, 2022). This includes penalties for illegal mining and non-compliance. Satellite imagery and remote sensing can aid in large-scale monitoring (Alabi et al., 2024).

Licensing and Permitting Systems

Implementing transparent and stringent licensing and permitting processes that require detailed environmental impact assessments (EIAs) prior to granting permits. These permits should specify conditions related to extraction methods, volumes, rehabilitation plans, and monitoring requirements (Agyei et al., 2022).

Inter-Agency Collaboration:

Fostering collaboration among various government agencies (e.g., environmental protection agencies, water resource ministries, mining departments, local governments) to ensure coordinated oversight and avoid conflicting regulations (Muzerengi & Dube, 2022).

Community Engagement and Participation

Involving local communities in decision-making processes, environmental monitoring, and the development of sustainable mining plans. Empowering

communities to report illegal activities can significantly improve enforcement (Muzerengi & Dube, 2022).

Market-Based Instruments

Exploring the implementation of economic incentives and disincentives such as sand output taxes, export taxes, or even a "Sand Extraction Allowances Trading Scheme" (SEATS) to internalize the environmental costs of extraction and promote responsible practices (Oberhuber & Schandl, 2023).

Ecosystem Restoration Fund

Establishing funds, possibly through taxes or levies on sand extraction, to finance large-scale ecosystem restoration projects in degraded riverine areas (UNEP, 2019). In Nigeria, while environmental laws exist, the challenge often lies in their enforcement and the prevalence of illegal mining operations (Alabi et al., 2024; Nwankwoala & Ede, 2015). The findings of this study on the Nworie River provide critical, localized evidence that can inform and strengthen existing regulatory efforts, promoting a more responsible and sustainable approach to sand resource management.

5.0 CONCLUSION AND RECOMMENDATIONS

The present study, utilizing Electrical Resistivity Tomography (ERT) and Ground-Penetrating Radar (GPR), provides compelling evidence of the profound geophysical and environmental impacts of excessive sand mining in the Nworie River, Imo State, Nigeria. The findings reveal

significant subsurface deformation, including widespread sediment layer collapse and cavity formation, directly contributing to increased riverbank erosion and destabilization of the riverbed. These geophysical alterations are accompanied by critical physicochemical changes in the water, most notably a severe reduction in dissolved oxygen levels from a relatively pristine 8.5 mg/L to an alarming 3.8 mg/L in major sand mining zones. Such fluctuations reflect severe habitat disturbance, sediment overload, and pollution, leading to substantial habitat loss and threatening the overall ecological balance and biodiversity of the Nworie River ecosystem. While some recovery in oxygen levels was noted downstream near the Otamiri River confluence, the cumulative impact of upstream mining remains a grave concern. This research underscores the urgent and undeniable need for immediate intervention and a fundamental shift towards sustainable sand mining practices in the Nworie River basin. The current unregulated and extensive extraction activities are systematically degrading a vital natural resource, jeopardizing both its ecological integrity and the socio-economic well-being of riparian communities.

Recommendations

Based on the findings of this study, the following recommendations are put forth to

policy makers, environmental managers, and stakeholders:

1. Enforcement of Strict Regulatory Frameworks

The Imo State government and relevant federal agencies must establish and rigorously enforce clear, comprehensive, and explicit regulatory frameworks specifically addressing river sand mining. This includes stringent permitting processes, adherence to environmental impact assessments, and strict penalties for illegal operations.

2. Implementation of Geophysical Monitoring

Regular geophysical surveys (ERT and GPR) should be mandated for areas earmarked for or subjected to sand mining. This will allow for proactive identification of subsurface instability, monitoring of impacts, and adaptive management.

3. Promotion of Sustainable Extraction Methods

Encourage and incentivize the adoption of sustainable sand extraction methods, such as limiting extraction to natural depositional zones, controlling extraction depths and volumes, and employing methods that minimize turbidity and pollution.

4. Investment into Alternative Materials and Recycling

Promote research into and the use of alternative construction materials (e.g., manufactured sand, recycled aggregates) and encourage circular economy principles

within the construction sector to reduce reliance on virgin river sand.

5. River Restoration and Rehabilitation

Develop and implement comprehensive river restoration and rehabilitation plans for already degraded sections of the Nworie River, including bank stabilization, habitat restoration, and re-vegetation. Funds for such initiatives could be generated from levies on sand extraction.

6. Public Awareness and Community Engagement

Launch robust public awareness campaigns to educate local communities and sand miners on the environmental consequences of unsustainable practices. Foster community involvement in monitoring and reporting illegal mining activities.

7. Inter-Agency Collaboration

Enhance collaboration and coordination among all relevant government agencies (e.g., Ministry of Environment, Ministry of Mines and Steel Development, Water Resources Ministry, local governments) to ensure a harmonized approach to sand resource management.

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IMPACTS OF SUGARCANE BAGASSE ASH ON THE STRENGTH CHARACTERISTICS AND DURABILITY OF CONCRETE

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Abstract

Sugarcane bagasse ash is a by-product generated from the cogeneration boilers utilized in sugar production, arising after the economical sugar has been extracted from the sugarcane. The disposal of this agricultural by-product leads to environmental issues surrounding the sugar manufacturing sector. Similarly, the cement industry contributes to environmental concerns by releasing carbon dioxide during cement production and utilizing substantial raw materials. This research focuses on repurposing agricultural waste ash (specifically sugarcane bagasse ash) as a partial substitute for cement in the creation of sustainable and eco-friendly concrete. The study examined the synergistic effects of sugarcane bagasse ash (SCBA) on concrete, with additions of 0, 5, 10, 15, 20, and 25% by weight of the cement. We investigated the compressive and splitting tensile strengths, as well as the workability of concrete containing various percentages of SCBA. Both 100 mm cubes and 100 mm x 200 mm prisms of SCBA-concrete were subjected to tests for compressive and splitting strengths at curing periods of 7, 14, 28, and 56 days. The slump test results indicated that incorporating SCBA enhances the workability of the fresh concrete. Nonetheless, it was observed that the strengths of SCBA-concrete increase with longer curing times while decreasing with higher SCBA content. The analysis revealed that concrete with 5% SCBA content surpassed the targeted strength of 20 N/mm² after 28 days of curing. Additionally, it was found that water absorption rises with increasing SCBA content. Ultimately, the conclusion drawn is that the maximum allowable SCBA replacement in concrete production should not exceed 5%.

Keywords: *Cement, Concrete, Compressive Strength, Sugarcane Bagasse Ash*

1.0 INTRODUCTION

Concrete stands out as one of the most extensively utilized building materials globally, while cement serves as a key binding agent in concrete production. The manufacturing of cement necessitates raw materials and energy, resulting in heightened CO₂ emissions. The cement production process produces significant quantities of

solid and liquid waste, which requires considerable energy and raw material usage (Althaqafi *et al.*, 2024). Additionally, cement manufacturing not only escalates costs but also negatively impacts the environment. The cement sector accounts for approximately 5 to 8% of the total global carbon dioxide emissions. It is crucial to

diminish carbon dioxide (CO₂) emissions during cement production and thereby lower energy expenses, while also promoting safety and sustainability (Mohamad *et al.*, 2022). The agricultural sector has seen considerable growth, leading to the generation of large amounts of waste materials. Effective waste disposal management is a crucial issue, considering that a significant portion of waste ends up in landfills, which reduces available land and contributes to environmental pollution (Althaqafi *et al.*, 2024). Various by-products from the agricultural industry, such as rice husk ash (RHA), groundnut husk ash (GHA), maize corn ash (MCA), wheat husk ash (WHA), and rice straw ash (RSA), have been used as cementitious materials, resulting in improved concrete performance. Sugarcane is the leading global crop cultivated for sugar production. Sugarcane bagasse (SCBA), primarily used as a fuel source in sugar production, is also a key resource in the paper-making industry. Sugarcane [bagasse ash](#) (SCBA) is the final waste material in the sugar production chain. Due to the pozzolanic characteristic and the abundance, SCBA has been tried to utilize in construction materials Wu *et al.*, (2022). A study by Shaban *et al.*, (2024) demonstrates the technical feasibility of using Sugarcane Bagasse Ash (SCBA) as cement substitutes alone or in combination with SLA or SCBA for UHPC production and its potential for

wider applications in the construction industry. Research conducted by Wu *et al.*, (2022) verified the technical feasibility of SCBA application as a cement replacement in UHPC and may further promote the utilization of agricultural by-products in cementitious materials. Yaseen (2024) highlighted the potential of using energy-efficient SCBA as a sustainable supplementary cementitious material to improve mortar mix performance and contribute to the development of environmentally friendly cementitious materials. As reported by Kumar and Sindhu (2020), sugarcane bagasse ash, by-product of sugar production is considered to be an active pozzolan. However, the effective use of bagasse ash in mortar and concrete needs the controlled process of grinding to achieve the required fineness and uniformity to meet the standards of industry. It possesses notable pozzolanic activity and enhances strength when utilized as a hydraulic binder due to its high carbon content exceeding 15% and fine particle size (Payá *et al.*, 2002). Ahmed *et al.*, (2024) pointed out that the chemical composition of SBA contains 62.43% silica due to absorption of silicic acid by sugar cane crops from the soil which is very high percentage. It is noticed that the total amount of SiO₂, CaO, Al₂O₃, and Fe₂O₃ is higher than 50% which makes SBA as pozzolanic material. A study by Abdalla *et al.*, (2022) revealed that incorporating 10% SCBA

enhances the mechanical properties of concrete, diminishes its workability, and increases its water absorption capacity as the bagasse ash content rises. Yaseen (2024) The incorporation of minimally processed SCBA up to 15 wt% improved compressive strength, exceeding ASTM C270-14 specifications, and achieved higher values for ultrasonic pulse velocity with improved density results, indicating enhanced material properties, durability, and structural integrity. Research by Sulaiman *et al.*, (2020) showed that adding sugarcane bagasse ash blended with metakaolin reduced the workability and elevated the water absorption of mortar. Nonetheless, the compressive strength of the mortar escalated up to a 10% SCBA-MK blend before declining. The results show that the behavior of cement pastes and mortars changed significantly up to 10% replacement level of treated bagasse ash Kumar *et al.*, (2020). As reported by Sobuz *et al.*, (2024) the hardened test results revealed that a mixture having SCBA up to 10 % content SCBA resulted in nearly 10 % to 30 % better performance to satisfy the requirement of LWC. Regarding the sustainability assessment, the less embodied CO₂ (eCO₂) is produced in SCBA mixes, whereas it is also economically beneficial to produce SCBA mixes. Yaseen (2024) reported that the water absorption increased with SCBA content, but the water absorption values of mortars with up to

15 wt% SCBA replacement remained within acceptable limits for medium and severe weathered conditions, as per ASTM C62-17. A study by Ahmed *et al.*, (2024) indicated that the compressive strength of specimen with 3% SBA is 27.79 MPa for curing period of 28 days, which satisfy the standard requirements. Higher the percentages of SBA decrease the compressive strength which does not satisfy the standard requirements.

This research focuses on repurposing agricultural waste ash (specifically sugarcane bagasse ash) as a partial substitute for cement in the creation of sustainable and eco-friendly concrete.

2.0 MATERIALS AND METHODS

2.1 Materials

The Portland limestone cement (PLC) utilized was Dangote BlocMaster, which has a specific gravity of 3.16. The composition of the cement oxides is shown in Table 1. The fine aggregate was obtained from the Zaria Local Government Area in Kaduna State, Nigeria, and it contains 2% silt with a specific gravity of 2.65. The coarse aggregate has a specific gravity of 2.74. The sugarcane bagasse ash (SCBA) was collected from Samaru Zaria, Kaduna State, Nigeria, and has a specific gravity of 2.84. The water used was potable and was sourced from the Civil Engineering Laboratory at ABU in Zaria, Kaduna State, Nigeria.

2.2 Methods

2.2.1 Slump of Fresh Concrete

The workability test was performed on fresh concrete in line with BS EN 12390, Part 2, (2009 (1983)).

2.2.2 Compressive Strength of SCBA-Concrete

The strength test on SCBA- concrete was conducted in accordance with BS EN 12390, Part 3, (2009). Concrete samples were cast and cured in potable water, and a total of 3 cubes were considered for an average for each curing age 7, 14, 28, and 56 days.

2.2.3 Splitting Tensile Strength of SCBA-Concrete

The splitting tensile strength test on SCBA-concrete prisms was conducted according to BS 1881-117: (1983). Prisms were cast and three specimens were tested for a mean for each curing span 7, 14, 28, and 56 days

2.2.4 Water Absorption of SCBA-Concrete

The water absorption test was performed on SCBA-concrete specimens in accordance with BS 812, Part 2, (1995). Concrete samples were cast and three samples were tested for a mean for each curing time 7, 14, 28, and 56 days.

3.0 RESULTS AND DISCUSSIONS

3.1 Chemical Properties of Cement and SCBA

The findings from the XRF analysis carried out on cement and SCBA are shown in Table 1. The oxide makeup of SCBA reveals that the combined percentage of aluminium oxide (Al_2O_3), silicon oxide (SiO_2) and iron oxide (Fe_2O_3) is 71.65%, which exceeds the minimum threshold of 70% set by ASTM C 618 for pozzolanic materials. Additionally, the CaO content in SCBA is 18.91%, indicating its potential cementing properties. Consequently, SCBA qualifies as a pozzolana and can be utilized as a partial replacement for cement in concrete production.

Table 1: Oxide Composition of Cement and SCBA

Oxides	Na_2O	MgO	Al_2O_3	SiO_2	SO_3	BaO	K_2O	CaO	Fe_2O_3	ZnO
Cement (%)	0.18	1.05	2.83	21.43	1.42	0.01	0.62	68.02	2.77	0.39
SCBA (%)	0.21	0.50	3.92	65.19	1.83	0.08	15.93	18.91	2.54	0.08

3.2 Workability of Fresh Concrete

The outcomes of the workability test conducted on fresh concrete are illustrated in Figure 1. It was noted that the inclusion of SCBA content led to a reduction in the workability of the concrete. This reduction

was measured at 10.87 %, 13.33 %, 20 %, 27.5 %, and 61.9 % at 5 %, 10 %, 15 %, 20 %, and 25 % SCBA content, respectively, when compared to the control sample (0 %). The decrease in slump may be attributed to the SCBA content, which absorbed more

water than the cement. It could also be that it retained more water than cement.

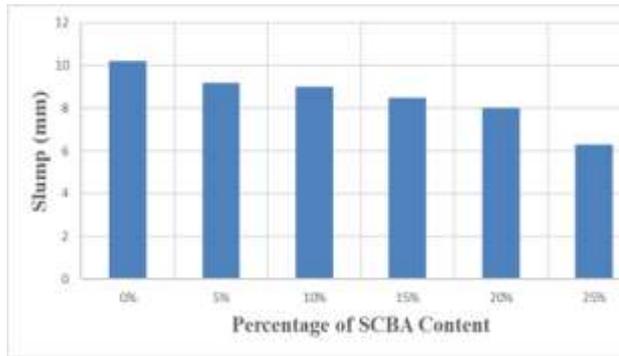


Figure 1: Slump against Percentage of SCBA content

3.3 Compressive Strength of Concrete

The findings on the compressive strength of concrete containing SCBA are illustrated in Figure 2. It was noted that the inclusion of SCBA reduced the compressive strength of the concrete. Specifically, this reduction was by 17.04 %, 29.03 %, 54.89 %, 77.78 %, and 166.67 % for SCBA contents of 5 %, 10 %, 15 %, 20 %, and 25 %, respectively, after 3 days of curing. Furthermore, after 28 days of curing, the compressive strength of concrete showed a decrease of 11.51 %, 17.28 %, 88.9 %, 100 %, and 142.98 % at the same respective SCBA levels. The reduction in compressive strength may be attributed to the SCBA addition, which reduces the available cement for hydration (Sulaiman *et al.*, 2020a). Conversely, the compressive strength of concrete improved with the increase in curing duration. This enhancement in concrete strength can be attributed to the hydration process involving both cement and SCBA (Ogork and Ayuba, 2014; Sulaiman *et al.*, 2022b).

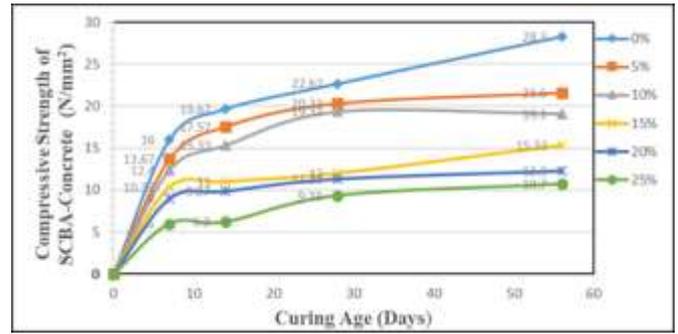


Figure 2: Compressive Strength of SCBA-Concrete against Curing Age (Days)

3.4 Splitting Tensile Strength of Concrete

The findings related to the splitting tensile strength of SCBA-concrete are illustrated in Figure 3.

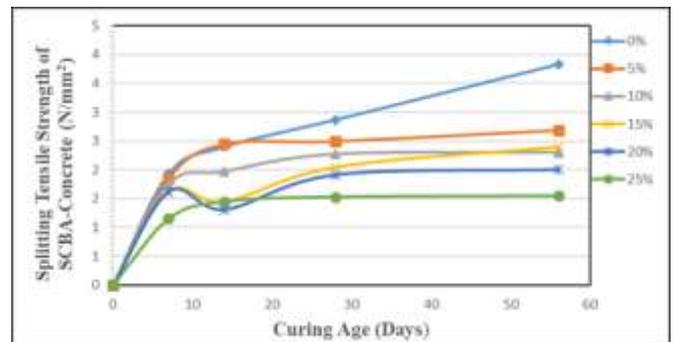


Figure 3: Splitting Tensile Strength of Concrete against Curing Age (Days)

It has been noted that the splitting tensile strength of concrete rises with an increase in curing age, with this strength increase likely attributed to cement hydration. Furthermore, it was observed that the strength decreased as the SCBA content increased, which could be due to the dilution effect caused by both the cement and SCBA materials. This decrease in strength might also result from the heightened pozzolanic chemical reaction involving silica from SCBA and the calcium hydroxide released as a by-product during cement hydration, leading to an excess of calcium-silicate-hydrate where the

efficiency of the binder improved, in alignment with the findings of (Ettu *et al.*, 2021; Sulaiman *et al.*, 2022b).

3.5 Water Absorption

Figure 4 displays the findings regarding the water absorption of concrete mixed with varying amounts of SCBA. It was observed that as the SCBA content increased, the water absorption by the concrete also rose by 1.92 %, 5.03 %, 15.14 %, and 36.25 % for 5 %, 10 %, 15 %, 20 %, and 25 % SCBA content, respectively. The rise in water absorption might be attributed to the addition of SCBA.

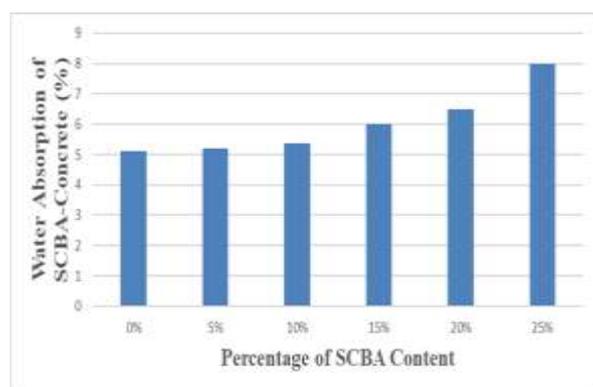


Figure 4: Water Absorption against Percentage of SCBA Content

4.0 CONCLUSIONS

The following deductions were made in light of the findings

- i. Sugarcane Bagasse Ash (SCBA) has a sum total of aluminium oxide (Al_2O_3), silicon oxide (SiO_2) and iron oxide (Fe_2O_3) as 71.65%, which is higher than the lower limit of 70 % highlighted by ASTM C 618 for pozzolana and concluded to be a very reactive pozzolana.

- ii. Incorporating SCBA contents decreased the workability of fresh SCBA concrete
- iii. The compressive and splitting tensile strength of SCBA-concrete increase as the curing age increases and decrease as the percentage of SCBA content increases.

It was concluded that up to 5 % SCBA content is recommended for the production of concrete.

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SUITABILITY OF LOCUST BEAN HUSK ASH AS A PARTIAL FILLER REPLACEMENT IN HOT MIX ASPHALT DESIGN

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Abstract

This study investigates the feasibility of using locust bean husk ash (LBHA) as a partial replacement for mineral filler in hot asphalt mix design. The experiment replaced mineral filler with LBHA at varying proportions (10%, 20%, 30%, 40%, and 50%) while maintaining a constant bitumen content of 6.05%. A total of 15 Marshall mix samples were prepared, with three specimens for each LBHA proportion. The samples were tested for stability and flow using the Marshall Stability test. Results demonstrated that a 50% replacement of mineral filler with LBHA, combined with 6.05% bitumen content, yielded the highest stability and flow values. This suggests that LBHA can be effectively utilized as a sustainable alternative in asphalt mix design for highway construction, offering both environmental and performance benefits.

Keywords: *Locust beans husk Ash (LBHA), Partial replacement, Mineral filler, Hot mix asphalt, Marshall stability test*

1.0 INTRODUCTION

Locust bean husks are waste by-products of agricultural processing of the African locust bean fruit. Substantial quantities can be found across northern Nigeria during the harvest season. Across the globe, much research efforts in recent times are geared towards possible ways of recycling these wastes for reuse to keep the environment clean and safe (Adama and Jimoh, 2011; Murana *et al.* 2024). The transportation, construction, and environmental industries have the greatest potential for reuse because they use large quantities of earthen materials

annually (Adrian, 2015; Murana *et al.* 2023). Locust bean pod, which is a Waste Agricultural Biomass (WAB) obtained from the fruit of the African locust bean tree (*ParkiaBiglobosa*), is the material resource required for the production of locust bean pod ash (Adama and Jimoh, 2011). The harvested fruits are ripped open while the yellowish pulp and seeds are removed from the pods. The empty pods are the needed raw material. The pods make up 39% of the weight of the fruits while the meal yellowish pulp and seeds make up 61% (Adama, 2010).

Pozzolana have the characteristics of combining with the free lime liberated during the hydration process of Ordinary Portland Cement (OPC) to produce stable, insoluble calcium silicates thus reducing the process of mortar and concrete attacks from sulphate, salts and chlorides. By-products mineral admixtures such as fly ash, rice husk ash and ground granulated blast furnace slag contribute to improvement of concrete performance (for example, high strength, high durability and reduction of heat of hydration) as well as reduction of energy and carbon dioxide generated in the production of cement (Ogundipe and Jimoh, 2009).

2.0 MATERIAL AND METHODS

2.1 Materials

The material used in this study work are as follow;

1. Locust Bean Husk
2. Bitumen
3. Aggregate (Fine and Coarse)
4. Cement (Filler)

Methods

1. Aggregate Impact Value (AIV)
2. Aggregate Crushing Value (ACV)
3. Specific Gravity
4. Water Absorption
5. Flakiness and Elongation
6. Particle Size Distribution
7. Bitumen Test

3.0 RESULT AND DISCUSSION

The Preliminary tests results for the aggregates are presented in Table 1. The

result obtained satisfied all the relevant codes requirements, Hence the aggregate are suitable for used as Asphaltic concrete materials.

Test Conducted	Code Used	Test Result	Code Limit
Aggregate Crushing Value (%)	BS 812 Part 112	21.23	Max. 25
Aggregate Impact Value (%)	BS 812 Part 111	22.12	Max. 25
Specific Gravity Of Coarse Aggregate	ASTM C127	2.77	2.55 – 2.75
Specific Gravity Of Fine Aggregates	ASTM C128	2.50	2.55-2.75
Water Absorption For Coarse Aggregate (%)	BS 812 Part 2	0.46	< 2
Water Absorption For Fine Aggregate (%)	BS 812 Part 3	8.62	< 15
Flakiness	ASTM-D4791 (2019)	27%	< 30%
Elongation	ASTM-D4791 (2019)	26%	-

Table 1 Result of preliminary result on Test Coarse and Fine Aggregates Materials

Optimum Bitumen Content (OBC)

The optimum bitumen content was found equal to 6.05% by weight of the total mix which is calculated as the average of bitumen content values that corresponds to the maximum stability, maximum density and median of the air voids are utilized to find the three values.

- Bitumen content at the maximum stability = 6.15 %
- Bitumen content at the maximum value of bulk density = 5.96%
- Bitumen content at the median percent of air voids = 6.04%

Optimum Bitumen Content (OBC) = 6.05 implies that the design bitumen content (DBC) is equal to the optimum bitumen content (OBC)

Preliminary Test on Bitumen

The Preliminary tests results for bitumen are presented in Table 2. The result obtained satisfied all the relevant codes requirements; hence the bitumen is suitable for use as Asphaltic material.

Test	Test Method	Specification by code s for penetration
		60/70
Penetration 25 ⁰ C	at ASTM D5	60 – 70
Specific gravity	ASTM D70	0.97-1.02
Ductility at 25 ⁰ C min	ASTM D113	50-100

Table 2: Preliminary tests results for bitumen

Marshall Test

Marshall Test results of mixture with binder content are shown in Table 3. The relationship between binder content and the properties of mixtures such as stability, flow, bulk density, air void (VIM), VMA, and VFB are shown in Tables 4 and 5. a number of 15 samples weighing 1200g each was prepared using 6.05% of optimum bitumen contents.

LBHA% (Filler)	Samples	Weight In Air In Water	Volume Ave Density	Air Voids	Thickness	Diameter	VFB	VMA	Stability	Flow	MQ
0%	A	1273.8 718.8	555		70.51	101.53	77.72				
	B	1260.9 715.3	545.6	2.303	3.881	67.51	101.77	17.42	6.10	2.10	2.90
	C	1263.4 726.8	536.6			67.87	101.87				
10%	A	1268.1 719.4	548.7			66.52	101.56				
	B	1267.5 720.1	547.4	2.313	3.464	64.36	101.84	79.31	16.74	6.03	4.25 1.42
	C	1267.2 720.5	549.5			65.20	101.67				
20%	A	1260.1 716.4	544.8			66.12	101.98				
	B	1260.5 716.8	543.7	2.317	3.314	62.98	104.36	79.25	15.97	5.50	3.50 1.57
	C	1259.3 716.6	542.5			64.30	103.33				
30%	A	1247.5 715.6	531.9			62.37	101.84				
	B	1234.5 645.3	589.2	2.318	3.255	65.81	101.48	78.67	15.26	6.11	2.70 2.26
	C	1246.5 702.2	544.3			67.98	101.71				
40%	A	1241.4 703.5	537.9			65.41	101.33				
	B	1211.1 693.5	517.6	2.323	3.048	63.70	101.68	79.34	14.75	5.11	3.80 1.34
	C	1222.5 670.4	527.8			64.10	101.44				
50%	A	1224.4 692.4	532.0			66.18	101.58				
	B	1223.5 696.6	526.9	2.312	3.505	65.63	101.58	75.79	14.48	6.70	2.10 3.19
	C	1223.6 695.8	536.0			66.10	101.67				

Table 3: Marshall Test result on locust bean husk ash.

Compiled version of Marshall test results after replacement with Locust Beans Husk Ash

LBHA% (Filler)	Density	Air voids	VFB	VMA	Stability	Flow	MQ
0%	2.30	3.88	77.72	17.42	6.10	2.10	2.90
10%	2.31	3.46	79.31	16.74	6.03	4.25	1.42
20%	2.32	3.31	79.25	15.97	5.50	3.50	1.57
30%	2.32	3.26	78.67	15.26	6.11	2.70	2.26
40%	2.32	3.05	79.34	14.75	5.11	3.80	1.34
50%	2.31	3.51	75.75	14.48	6.70	2.10	3.19

Table 4: Compiled version of Marshall test results after replacement with Locust Beans Husk Ash

The Stability against Percentage of Locust Beans husk Ash

Stability serves as a gauge of the compacted material's strength. According to figure 1, it's evident that the highest stability recorded is 6.70kN, observed at a 50% locust beans husk ash content. This surpasses the stability of 3.5kN at a 5% cement content, noted at an optimal bitumen content of 6.05%.

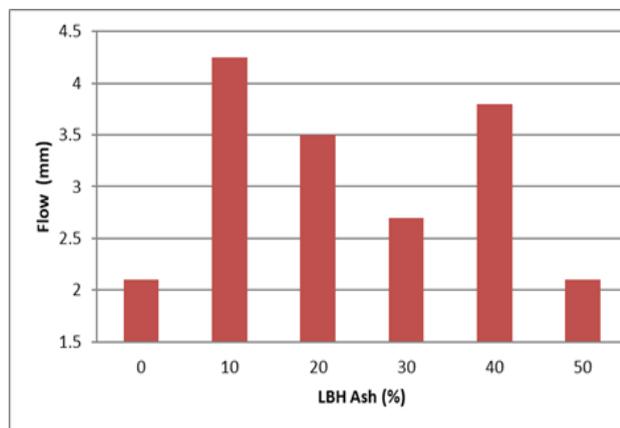


Figure 1; The Flow against the Percentage of Locust Beans Husks Ash content

The Flow against the Percentage of Locust Beans Husks Ash content

The flow exhibited a consistent rise with the increment in locust beans husk ash content percentage, followed by a subsequent

decrease in content. At the optimal bitumen content, this suggests that the flow falls within the satisfactory range of 2mm to 4mm, meeting the criteria outlined in the Asphalt Institute Marshall Design.

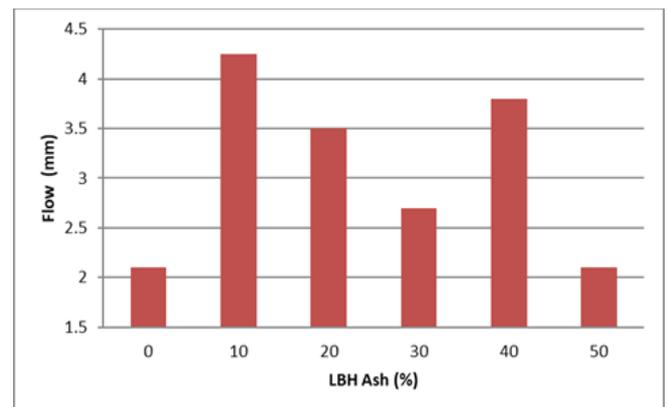


Figure 2: The Flow against the Percentage of Locust Beans Husks Ash content

The Density against the Percentage of Locust Beans Husk Ash

The figure illustrates that a 40% increase in the locust beans husk ash percentage yields the highest density, while 0% marks the lowest density. However, at the optimum bitumen content, the density does not exhibit consistency with an increase in locust bean husk ash content, as it can lead to either an increase or reduction in density.

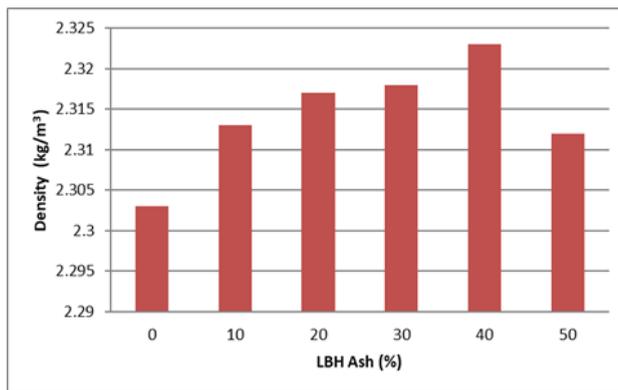


Figure 3: The Density against the Percentage of Locust Beans Husk Ash.

Relating the percentage of air void in mix (VIM) to LBHA% content

The graph indicates a consistent decline in the percentage of air void in the mix (VIM) as the Locust beans husk ash content increases, specifically at the optimal binder content. As per the design criteria outlined in the Asphalt Institute Marshall Design, the majority of these values fall within the range of 3 to 5, emphasizing adherence to the specified criteria.

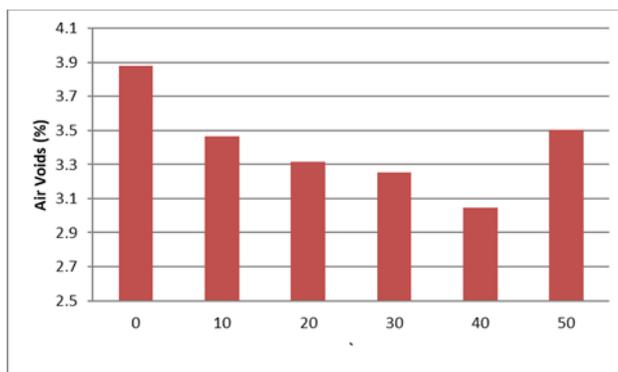


Figure 4: Relating the percentage of air void in mix (VIM) to LBHA% content.

The Void in Mineral Aggregate against Locust Beans Husk Ash content.

The figure illustrates that the minimum void in the mineral aggregate measures 50%, while the maximum void stands at 0%,

attributed to the use of a maximum particle size of 12.5mm in this study. The VMA values depicted in the graph fall within the expected range. However, an increase in VMA allows for more room to accommodate additional air voids.

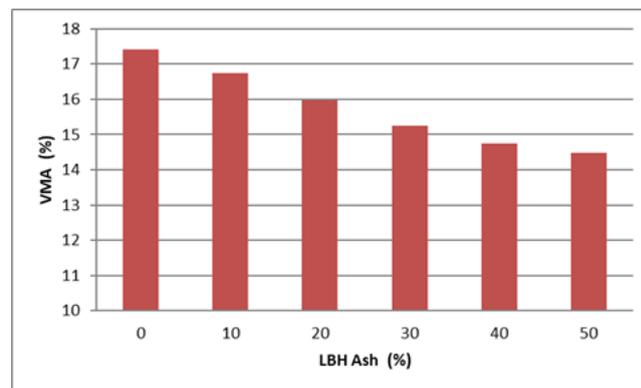


Figure 5: The Void in Mineral Aggregate against Locust Beans Husk Ash content.

The Graph of Void Filled with Bitumen (VFB) against Locust Beans Husk Ash content

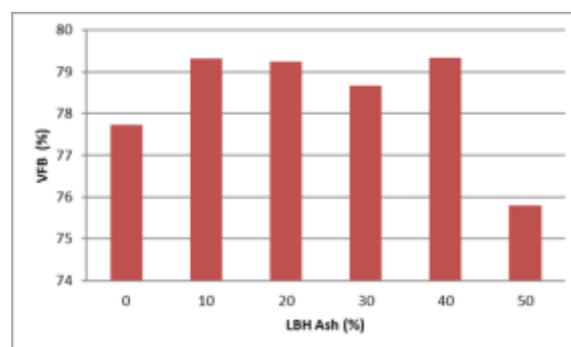


Figure 6: The Graph of Void Filled with Bitumen (VFB) against Locust Beans Husk Ash content.

The percentage of voids filled with bitumen displays a consistent pattern of both increase and decrease corresponding to the rising locust beans husk ash contents, particularly at the optimal bitumen content. It indicates 40% as the highest VFB and 50% as the

lowest. Consequently, the VFB falls within the satisfactory range of 75 to 79, meeting the criteria outlined in the Asphalt Institute Marshall Design.

Graph of MQ (Marshall Quotient) against LBHA content

Comparing asphalt using the Marshall Quotient (MQ) involves evaluating the ratio between stability and flow values, aiding in the determination of a suitable concrete asphalt mixture. The characteristic of the Marshall Quotient graph differs from other graphs as it doesn't exhibit a specific discernible pattern due to its reliance on the stability-to-flow ratio for analysis.

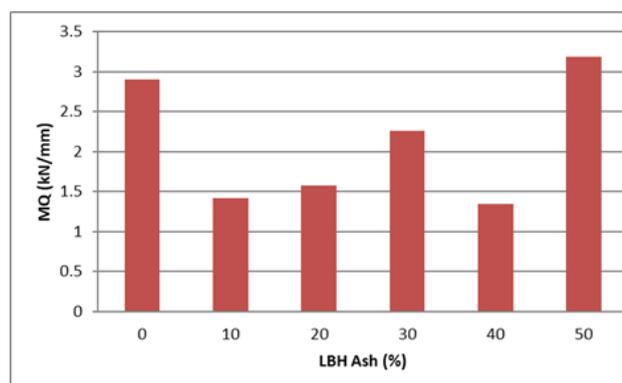


Figure 7; Graph of MQ (Marshall Quotient) against LBHA content.

CONCLUSION

At the end of the research work, the following conclusions were drawn;

1. Locust bean husk ash is suitable to be used as partial replacement of filler in asphaltic concrete design at 50% replacement. Because 6.70 kN of stability was obtained, and 4.25 flow at 10%, which is within the range of ASTM specification.

2. The bitumen successfully passed all initial tests outlined in the ASTM code. Additionally, the optimal bitumen content crucial for achieving stability in the mix design was identified as 6.05 percent.

3. The aggregate crushing value for coarse aggregate is 21.23 percent, meeting the recommendations of BS 812 part 112. Similarly, the aggregate impact value for coarse aggregate stands at 22.12 percent, fulfilling the requirements of BS 812 part 111. Additionally, the specific gravity of the coarse and fine aggregates is 2.77g/cm³ and 2.50g/cm³, respectively.

4. The optimum bitumen content for the stability of mix design was ascertained to be 6.05 percent.

5. Stability, indicative of the compacted material's strength, reached a peak of 6.70 kN at a 50% locust beans husk ash content. This exceeded the stability recorded at 5% cement content, which was 3.5 kN at an optimal bitumen content of 6.05%. Additionally, the flow consistently increased with rising locust beans husk ash content but decreased thereafter at the optimal bitumen content.

RECOMMENDATION

Based on the outcome of the study, the maximum stability and lowest flow were obtained at 50%. It has been concluded that locust bean husk ash can serve as a partial substitute for mineral filler in hot asphaltic

mix design. The optimal replacement value was identified as 50%, demonstrating optimal stability at an optimum bitumen content of 6.05%.

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HARNESSING FOOD AND NON-FOOD PLANTS AS ALTERNATIVE SOURCES OF RENEWABLE ENERGY

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Abstract

The growing global population, projected to reach nearly 10 billion by 2050, has intensified the need for sustainable resources to support both food and energy demands. As societies strive for economic growth and urban expansion, the pressure on natural resources escalates, driving a parallel need for solutions that ensure food security while addressing energy needs in an environmentally responsible way. Plants, as versatile biological resources, offer a unique dual-functionality as sources of both food and renewable energy, positioning them at the core of sustainable development strategies. In recent decades, bioenergy—particularly biofuels derived from plant biomass—has gained prominence as a sustainable alternative to fossil fuels. Plant-based bioenergy has the potential to reduce greenhouse gas emissions and reliance on non-renewable resources, providing energy solutions that align with global climate targets. However, as more agricultural land is devoted to energy crops, concerns arise regarding competition between food and fuel production, often referred to as the “food vs. fuel” dilemma. This issue highlights the importance of identifying plant species that can fulfill both roles without compromising food security or ecosystem stability. This paper aims to highlight various plant categories based on their potential to serve as both food and energy sources. By examining food crops, oilseed plants, and non-food bioenergy crops, as well as aquatic species, this paper will assess each category's nutritional and energy yield, environmental impact, and socioeconomic implications. Through this analysis, we seek to clarify the trade-offs and synergies in using plants for dual purposes and identify pathways toward sustainable and integrated food-energy systems.

Keywords: *Bioenergy, Food Security, Sustainable Resources, Food vs. Fuel, Plant Biomass*

1.0 INTRODUCTION

As the global population steadily rises, projected to reach nearly 10 billion by 2050, the demand for food and energy resources has reached unprecedented levels. According to the Food and Agriculture Organization of the United Nations (FAO), approximately 828 million people currently

face hunger worldwide, a stark reminder of the challenges to food security in both developed and developing nations (Tze et al 2022). FAO data reveals that agricultural production will need to increase by approximately 50% by 2050 to meet projected food needs, which require sustainable intensification of agriculture

without compromising ecological stability (World of Corn 2017).

Simultaneously, the International Energy Agency (IEA) reports a comparable surge in energy demands driven by economic growth and urbanization, with global energy consumption expected to grow by 25% by 2040 under current policies (Fueling the Future 2015). This heightened energy demand, coupled with the urgent need to reduce carbon emissions, has placed bioenergy from plant sources in the spotlight as a renewable solution (Twidell and Weir 2015). Biofuels, such as bioethanol and biodiesel derived from crops like corn, sugarcane, and oilseeds, offer potential reductions in greenhouse gas emissions and decreased reliance on fossil fuels (de Souza et al 2010). However, as agricultural land is increasingly allocated to bioenergy crops, concerns arise regarding potential competition between food and fuel resources—a dilemma often referred to as the “food vs. fuel” debate. Balancing these dual demands is crucial, as food security and sustainable energy production are both essential to achieving the United Nations Sustainable Development Goals (SDGs).

The Potential of Plants as a Renewable Bioenergy Resource

Plants are one of the most promising renewable resources for bioenergy, offering diverse applications through biofuels, biomass, and bioproducts that can substitute fossil fuels and reduce greenhouse gas

emissions (Rajaeifar et al 2013). As photosynthetic organisms, plants convert solar energy into chemical energy, which can be harnessed directly as biomass or transformed into various bioenergy products, such as bioethanol, biodiesel, and biogas. These bioenergy sources are seen as pivotal to achieving energy security, reducing reliance on fossil fuels, and addressing climate change by lowering carbon footprints (Raheem et al 2016).

Biofuels: Bioethanol and Biodiesel

Biofuels, derived directly from plant material, are among the most widely researched and implemented forms of bioenergy. Bioethanol, typically produced from starch or sugar-rich crops like corn, sugarcane, and wheat, is commonly blended with gasoline to power vehicles (Bio-fuel-news 2009). Brazil, one of the world leaders in bioethanol production, derives significant energy from sugarcane, a highly efficient crop for biofuel due to its high sugar content and favorable growth cycle. Studies have shown that bioethanol can reduce carbon emissions by approximately 34-52% compared to gasoline, contributing to a significant reduction in air pollution (Xavier 2007).

Biodiesel, another major form of biofuel, is produced from oil-rich crops like soybean, rapeseed, and oil palm (Amanda et al 2023). Used as a substitute for diesel fuel, biodiesel is renewable, biodegradable, and generates

lower levels of sulfur and particulate emissions than conventional diesel (Alavijeh et al 2013). According to research, biodiesel can reduce life-cycle greenhouse gas emissions by up to 86% compared to petroleum-based diesel, making it a critical component of cleaner transport energy (Huang et al 2012).

Biomass for Heat and Electricity

Biomass, or plant-derived organic material, can be used directly for heat and electricity production (Hassan and Kalam 2013). Plant residues, wood chips, and agricultural by-products are burned or gasified to produce energy, particularly in rural and agricultural regions (Akia et al 2014, Mustafa et al 2024). Biomass energy production leverages residual waste, making it a cost-effective and environmentally friendly solution that can reduce agricultural waste disposal issues while contributing to local energy grids (Easterly and Burnham 1996). For instance, forestry residues and agricultural wastes in the United States alone could generate enough biomass energy to supply around 10% of the nation's energy needs (Kumar et al 2020).

Biogas and Other Bio-based Energy Sources

Biogas, typically produced from anaerobic digestion of plant residues and other organic materials, is a versatile bioenergy source that generates methane-rich gas for electricity, heating, and even vehicle fuel (Ciotola et al 2011). Biogas from crops like maize and

from agricultural waste has gained popularity in Europe, particularly in Germany, where biogas plants contribute significantly to renewable energy supplies (Kolesarova, et al 2011). This process also recycles nutrients back into the soil, supporting sustainable agricultural practices and reducing the need for chemical fertilizers.

Benefits and Challenges

The versatility of plants as bioenergy resources is evident across these applications, offering numerous environmental and economic benefits. However, challenges such as land-use changes, water demand, and the food-energy balance need to be managed carefully (Pishvae et al 2021). As technology advances, improvements in crop yields, genetic engineering, and more efficient processing methods may address some of these constraints, enhancing the overall sustainability of plant-based bioenergy.

Food Crops with Energy Potential

Corn

Corn (*Zea mays*) is one of the world's most versatile crops, serving as a dietary staple, animal feed, and a key biofuel source (Dutton, 2017). In the United States, corn-based bioethanol production is central to the nation's renewable fuel strategy, accounting for roughly 40% of the country's corn harvest. This bioethanol is blended with gasoline to create E10 and E85 fuel, which helps lower greenhouse gas emissions and

reduce reliance on imported oil (Aamri et al 2018). The bioethanol produced from corn has an energy balance that, while lower than sugarcane, still offers a reduction of about 34% in carbon emissions compared to gasoline. The dual role of corn, however, brings complexities (Mohlala et al 2016). As corn demand grows for biofuel, it drives up prices, affecting food supplies and costs, particularly in regions where corn is a dietary staple. For example, increased demand for corn bioethanol has been linked to price hikes in food products like cornmeal and livestock feed, illustrating the challenge of balancing food and energy needs in a sustainable way.

Sugarcane

Sugarcane (*Saccharum officinarum*) is another high-potential crop for bioethanol production, with an even more favorable energy yield than corn (Zuurbier and Van de Vooren 2008). Sugarcane's high sucrose content enables a highly efficient conversion to ethanol. Brazil, the global leader in sugarcane bioethanol production, has implemented one of the most successful ethanol programs worldwide. Since the 1970s, Brazil's Proálcool (National Alcohol Program) has promoted sugarcane-based ethanol as an alternative fuel, enabling the country to power nearly 40% of its automotive fleet with ethanol-only engines or flex-fuel engines that run on either ethanol or gasoline (Xavier 2007).

The environmental impact of sugarcane bioethanol is notably positive, as it produces about 90% fewer greenhouse gas emissions than gasoline on a life-cycle basis (Timmons, 2010). Furthermore, the energy return on investment (EROI) for sugarcane ethanol is approximately 8:1, meaning it yields eight units of energy for every one unit used in its production—a significantly higher yield than corn-based ethanol. Brazil's ethanol program has demonstrated the potential for sugarcane to meet both food and energy needs in a sustainable way, as by-products from sugarcane, like bagasse, can also be used as biomass for electricity generation (Raju and Raju 2005). This integration not only provides clean energy but also minimizes waste, making sugarcane one of the most efficient crops for bioethanol (Moses et al 2013). However, scaling sugarcane production to meet growing energy demands poses sustainability challenges, as it requires vast land and water resources and can lead to deforestation if not managed carefully.

Wheat

Wheat (*Triticum spp.*), a key global food crop, also serves as a source for bioethanol, especially in regions like Europe where wheat-based biofuel is produced alongside food. Wheat's starch can be converted into ethanol through similar processes used with corn, although it is generally less efficient due to lower starch content and higher cultivation costs (Prado and Rial 2025).

Wheat-based bioethanol production is less common than corn and sugarcane but remains a viable option, especially when surplus production is available (Prado and Rial 2025). However, like corn, using wheat for energy can contribute to food security issues, particularly when production competes with food supply in regions reliant on wheat as a dietary staple.

Both corn and sugarcane exemplify the dual potential of food-energy crops in contributing to sustainable fuel alternatives while supporting food security. However, realizing their full potential requires careful management to mitigate environmental impacts and ensure that increasing biofuel production does not adversely affect global food systems.

Non-food Energy Crops

Non-food energy crops like jatropha, switchgrass, and miscanthus are cultivated exclusively for bioenergy, enabling sustainable fuel production without competing directly with food resources. These crops are particularly valued for their low maintenance requirements and adaptability to marginal lands, where traditional food crops may not thrive. Their high energy yield and resilience make them strategic options for expanding renewable energy sources sustainably.

Jatropha

Jatropha (*Jatropha curcas*) is a hardy, drought-resistant shrub that thrives in arid

and semi-arid regions with low soil fertility. Its seeds contain up to 40% oil, which can be converted into biodiesel. Unlike traditional biofuel crops, jatropha requires minimal water, fertilizers, and land management, making it a sustainable option for energy production in areas unsuitable for food agriculture (Pandey et al 2012). Jatropha biodiesel can reduce greenhouse gas emissions by up to 60% compared to conventional diesel (Kandpal et al 1995). However, challenges such as labor-intensive harvesting and yield variability highlight the need for improved breeding and management practices to unlock its full potential.

Switchgrass

Switchgrass (*Panicum virgatum*), a native North American prairie grass, is a perennial crop renowned for its high biomass yield and cellulose content, ideal for producing cellulosic ethanol. Its resilience allows it to grow on marginal lands with minimal input, and as a C4 plant, it demonstrates efficient photosynthesis, leading to robust growth (Perrin et al 2018). The ecological benefits of switchgrass include soil erosion control, habitat support, and carbon sequestration. Studies indicate that switchgrass-derived bioethanol can reduce greenhouse gas emissions by up to 94% compared to gasoline (Mitchel et al 2008). Its low maintenance and high energy yield make it a leading non-food crop for biofuel production (Patzek and Pimentel 2005).

Miscanthus

Miscanthus (*Miscanthus x giganteus*) is a tall, fast-growing grass capable of producing high biomass with minimal water and nutrient inputs. It can yield up to 30 metric tons of dry matter per hectare annually, significantly higher than most biofuel crops (INCD – ECOIND 2015). *Miscanthus* has deep roots that improve soil structure, enhance water retention, and sequester carbon, making it an environmentally beneficial crop. Studies have shown that miscanthus-derived bioethanol offers over 100% life-cycle greenhouse gas emission reductions compared to fossil fuels (Baxter et al 2014, Daraban et al 2015a, 2015b). The crop's low maintenance needs, along with its high yield potential, make it one of the most sustainable options for bioenergy.

Jatropha, switchgrass, and miscanthus illustrate the potential of non-food energy crops to supply sustainable bioenergy with minimal environmental impact. Their adaptability to marginal land, low maintenance, and high energy yields position them as promising solutions in renewable energy systems. Addressing challenges like yield consistency and harvesting efficiency through research and policy support could enhance their contributions to global energy security.

Implications of Redirecting Food Crops to Biofuel Production

The shift of food crops like corn, wheat, and soybeans from food supply chains to biofuel production has complex economic, environmental, and social implications. While biofuels from these crops help reduce reliance on fossil fuels and support renewable energy goals, their increased demand can exacerbate food scarcity, elevate food prices, and impact ecosystem stability. Recognizing these trade-offs is essential to creating policies that balance food security with sustainable energy production.

1. Food Security and Price Increases

Redirecting food crops to biofuel production can intensify competition for agricultural resources, driving up food prices and impacting food access, especially in low-income regions. For example, bioethanol production in the United States consumes around 40% of the nation's corn supply. This allocation contributes to higher prices for corn-based foods like cornmeal and animal feed, increasing the costs of poultry, beef, and dairy (Ajanovic 2011). In developing countries, where corn is a dietary staple, these price increases can significantly affect food security (Hassan and Kalam 2013). The FAO reports that biofuel demand has contributed to increased food price volatility, which disproportionately affects vulnerable populations.

2. Land and Resource Competition

The cultivation of food crops for biofuel requires substantial land, water, and inputs, often leading to land-use changes that can disrupt food production (Ben Fradj et al 2016). Expanding biofuel crop acreage may involve converting forests, grasslands, or marginal lands into agricultural zones, resulting in habitat loss and biodiversity decline (Vera et al 2020). For instance, large-scale soybean and palm oil plantations for biodiesel production have led to significant deforestation in regions like Southeast Asia and South America. Such conversions reduce available arable land for food production, creating a trade-off where increased energy crop production undermines both food availability and environmental health (Muscat et al 2020).

3. Environmental Impacts

Biofuel production from food crops can contribute to greenhouse gas (GHG) emissions, undermining the climate benefits often associated with renewable energy (Macedo et al 2008). Land-use changes, such as deforestation and soil tillage, release large amounts of stored carbon, creating a “carbon debt” that takes years, or even decades, to offset through biofuel use (Berndes et al 2013). Corn-based ethanol, for example, is estimated to reduce GHG emissions by only 34% compared to gasoline, a relatively modest reduction when factoring in emissions from fertilizer use, transportation,

and land conversion ([Creutzig et al 2015](#)). The environmental trade-offs are more pronounced in cases where food crop biofuels require intensive inputs, leading to soil degradation, water pollution, and increased nutrient runoff (Beringer et al, 2011, Brandão et al 2011).

4. Economic Impacts on Farmers and Rural Communities

For farmers, redirecting crops to biofuel markets can increase profits and support local economies, especially when biofuel prices are favorable (Demirbas 2008). For instance, the biofuel industry in Brazil has provided significant income opportunities for sugarcane farmers, contributing to rural development and job creation (Larson 2008, Perrin et al 2008). However, these economic benefits are often unevenly distributed and may lead to land concentration, where larger agribusinesses dominate biofuel crop production, limiting smallholder farmers’ participation and potentially displacing traditional farming practices (Demirbas 2009). This economic shift can reshape rural landscapes and increase dependency on biofuel markets, which may not be as stable as food markets (Arndt et al 2012).

5. Technological and Policy Solutions

Addressing the trade-offs of food crops in biofuel production requires a combination of technological innovation and policy intervention (Venkatesh et al 2012).

Advancements in second-generation biofuels, which use non-food biomass such as agricultural residues, forestry by-products, and dedicated energy crops like switchgrass, offer an alternative pathway that reduces competition with food resources (Prado and Rial 2025). Additionally, policy measures such as subsidies, incentives for non-food energy crops, and biofuel blending mandates can help balance energy production with food security goals (Przybylski 2011, Gabrielle et al 2014). For example, policies that prioritize non-food biofuels and promote sustainable agricultural practices can mitigate some of the adverse impacts on food systems.

The redirection of food crops to biofuel production presents a complex trade-off between the benefits of renewable energy and the critical need for food security. While food-based biofuels offer a renewable alternative to fossil fuels, their environmental and economic impacts raise questions about long-term sustainability. A balanced approach, integrating technological advancements in biofuels with supportive policies, is essential to ensure that bioenergy growth does not come at the expense of food availability, affordability, and environmental health.

Case Studies Illustrating Food vs. Fuel Conflicts

The allocation of food crops like corn, sugarcane, and palm oil to biofuel

production has led to significant “food vs. fuel” conflicts globally. These cases demonstrate how biofuel policies and practices can drive up food prices, affect food security, and strain natural resources, highlighting the need for balanced approaches to bioenergy.

U.S. Corn Ethanol Debate

The United States has been a leading producer of corn ethanol since the early 2000s, with federal policies such as the Renewable Fuel Standard (RFS) mandating biofuel blending to reduce greenhouse gas emissions and support renewable energy goals. Approximately 40% of the U.S. corn crop now goes toward ethanol production, positioning corn ethanol as an essential component of U.S. renewable energy strategies. While corn ethanol offers some reductions in greenhouse gas emissions compared to gasoline, the diversion of corn to fuel has sparked debates over its impact on food prices and availability.

The U.S. corn ethanol mandate has significantly influenced food prices domestically and internationally. For instance, during the 2007-2008 global food crisis, rising corn prices—driven partly by biofuel demand—contributed to increased costs for corn-based products and livestock feed. This price spike had ripple effects in countries reliant on corn imports, leading to food inflation and unrest in some regions. Researchers estimate that ethanol production

has contributed to a 20-40% increase in corn prices over the past decade, illustrating the trade-off between supporting renewable energy and maintaining affordable food supplies. Producing corn ethanol requires substantial water, fertilizer, and land resources. Studies have shown that intensive corn cultivation can lead to soil erosion, nutrient runoff, and water pollution, particularly in the Midwestern U.S. Corn Belt. The environmental costs raise questions about the sustainability of corn ethanol, with critics arguing that the ecological impacts outweigh the biofuel's modest carbon reduction benefits. This case has prompted calls for more research and investment in second-generation biofuels that don't compete with food crops.

Brazil's Sugarcane Ethanol Program

Brazil is a global leader in sugarcane ethanol, with nearly 20% of its transport fuel derived from ethanol. The country's National Alcohol Program (Proálcool), launched in the 1970s, encouraged sugarcane-based ethanol production to reduce dependence on oil imports. While Brazil's ethanol program is often cited as a model of sustainable biofuel production, it has raised concerns over land use and food prices.

Sugarcane used for ethanol competes with sugar used in food production, affecting global sugar markets. When global sugar prices rise, Brazilian producers often shift to

ethanol production, which can drive up sugar prices for consumers. This dynamic became particularly apparent in 2010-2011 when a spike in sugar prices led to higher food costs, illustrating how biofuel demand can affect global commodity markets and food affordability.

Despite sugarcane ethanol's high energy yield and relatively low carbon footprint, its expansion requires large tracts of land, which has driven deforestation and habitat loss in certain regions. While Brazil has implemented zoning policies to protect critical ecosystems, the indirect effects of expanding sugarcane acreage for fuel remain a concern. This case illustrates how a successful biofuel program can still have unintended environmental and economic consequences, especially as demand for land increases.

Palm Oil Biodiesel in Southeast Asia

Palm oil biodiesel production in Indonesia and Malaysia has become a major source of biofuel in Asia. Palm oil is used not only in biodiesel but also in food products, cosmetics, and industrial goods, making it a highly versatile and valuable commodity (Abdullah and Sulaiman, 2013). However, the rapid expansion of palm oil plantations has sparked food vs. fuel conflicts due to its impacts on food prices, food security, and the environment.

As demand for palm oil biodiesel grows, food-grade palm oil prices have increased,

impacting countries reliant on imports for cooking oil (Amin et al 2007) In regions where palm oil is a staple food item, such as parts of Southeast Asia and Sub-Saharan Africa, rising prices have affected food affordability. The competition between food and fuel demand for palm oil exacerbates food insecurity for low-income populations, who rely on it as a low-cost dietary fat. Palm oil biodiesel production is a leading driver of deforestation, particularly in Indonesia and Malaysia, where rainforests and peatlands have been cleared to establish plantations (Al-Widyan and Al-Shyoukh, 2002). This deforestation not only releases stored carbon, worsening climate change, but also threatens biodiversity, including endangered species like orangutans. Additionally, the expansion of palm oil plantations has led to social conflicts over land rights and displacement of indigenous communities. These environmental and social impacts illustrate how the pursuit of biofuel from food crops can compromise ecosystem health and social stability.

European Rapeseed Biodiesel

In Europe, rapeseed (canola) is a primary source for biodiesel, supported by the EU's Renewable Energy Directive, which mandates biofuel usage to achieve climate goals. While rapeseed biodiesel provides a renewable alternative to fossil fuels, its production has created food vs. fuel tensions within Europe (Przybylski, 2011).

Redirecting rapeseed oil for biodiesel has driven up prices for rapeseed products, affecting costs for food-grade oils and animal feed, both of which are derived from rapeseed (Amanda et al 2023). As demand for biodiesel grows, so does competition for limited rapeseed oil supplies, raising prices for consumers and livestock producers (Kusdiana and Saka 2001). This situation has led to greater reliance on imported oils, such as palm and soybean oil, adding to global food price volatility. Rapeseed cultivation requires significant pesticide and fertilizer inputs, leading to concerns over soil health and water quality. Moreover, increased demand for rapeseed biodiesel has led to land-use changes across Europe, raising questions about sustainable agricultural practices (Rajaeifar et al 2013). This case highlights how biofuel mandates can influence agricultural resource allocation, sometimes with unintended consequences for food systems and environmental health. These case studies reveal the complex dynamics of food vs. fuel conflicts, illustrating how biofuel production from food crops can elevate food prices, strain resources, and impact environmental sustainability. Solutions such as adopting second-generation biofuels, implementing sustainable agricultural practices, and creating policies that balance food and fuel needs are essential to mitigate these conflicts. These examples underscore the need for a

multifaceted approach to bioenergy that considers both the benefits and costs to global food systems.

Bioethanol Production Efficiency: Corn vs. Sugarcane

Corn and sugarcane are the two leading feedstocks for bioethanol production worldwide, with corn being dominant in the United States and sugarcane primarily used in Brazil (Demirbaş, 2005). While both crops produce bioethanol through fermentation, their efficiency, yield, and environmental impact vary considerably, making each suited to different production contexts and climate goals (Table 1).

Energy Yield and Conversion Efficiency

Corn produces about 400-450 liters of ethanol per ton of corn. The energy balance for corn ethanol—measured as the ratio of energy output to input—is around 1.3 to 1.6, meaning it yields 1.3 to 1.6 units of energy for every unit of fossil fuel energy used in its production. The relatively low energy return on energy invested (EROI) is due to the significant energy required for farming, fertilizers, and conversion. As a result, corn ethanol has limited greenhouse gas reduction potential compared to other biofuels, offering about 34% reduction in greenhouse gas emissions compared to gasoline.

Sugarcane is more efficient, producing approximately 650-700 liters of ethanol per ton of sugarcane. Brazil's sugarcane ethanol has an energy balance ranging from 8:1 to

10:1, a considerably higher yield than corn ethanol. The high EROI is largely due to sugarcane's efficiency in converting solar energy through photosynthesis, as well as the crop's lower reliance on fertilizers and water. Sugarcane ethanol offers a 90% reduction in greenhouse gas emissions compared to gasoline, making it one of the most sustainable biofuel options.

Land and Resource Efficiency:

Corn requires relatively high levels of fertilizer, water, and other inputs to achieve optimal yields. In the U.S., average corn yields for ethanol production are around 10-12 metric tons per hectare (about 2,500-3,000 gallons of ethanol per hectare). However, because corn is typically grown on high-quality agricultural land, it competes directly with food crops and animal feed, raising concerns over its impact on food prices and availability.:

Sugarcane, particularly in Brazil, can produce up to 90 metric tons per hectare with suitable climate conditions, yielding around 6,500 liters of ethanol per hectare. This is nearly twice the yield of corn ethanol per hectare, making sugarcane ethanol more land-efficient. Sugarcane also requires fewer inputs after establishment, particularly due to its perennial nature, meaning it does not need to be replanted each year. Additionally, the by-product bagasse (sugarcane fiber residue) can be used as a renewable energy source for

electricity, further increasing the energy efficiency of sugarcane ethanol production.

Environmental Impact and Sustainability

The environmental impact of corn ethanol production is considerable due to intensive farming practices, which often lead to soil degradation, water pollution from fertilizer runoff, and high greenhouse gas emissions from fertilizer use. The need for annual replanting further disturbs soil structure and increases erosion risks. Additionally, corn ethanol production’s dependence on arable land and water resources raises questions about sustainability, especially in areas where corn serves as a dietary staple.

Sugarcane ethanol is more sustainable, particularly when grown in tropical climates like Brazil, where it is harvested multiple times over its lifespan. Sugarcane cultivation also promotes carbon sequestration through its extensive root system and soil conservation from reduced tillage. However, large-scale sugarcane farming can drive deforestation if poorly managed. Brazil’s policies on agricultural zoning for sugarcane have helped mitigate this issue by restricting sugarcane expansion into critical ecosystems.

Economic Viability and Market Considerations

Corn ethanol benefits from strong policy support in the U.S., where subsidies and mandates have incentivized production. However, without these subsidies, corn ethanol’s economic viability may be lower

due to its relatively high production costs and moderate energy returns. The reliance on corn for both biofuel and food/feed markets also leads to price volatility, as biofuel demand affects food prices.

In Brazil, sugarcane ethanol has proven economically competitive, thanks to the high energy return and favorable climate conditions. Brazilian ethanol production benefits from lower production costs and government support, making it resilient even without subsidies. Sugarcane ethanol’s economic viability is enhanced by its use of bagasse for energy, reducing reliance on external power sources and further lowering production costs.

Table 1. Summary Table of Yield and Efficiency

Factor	Corn Ethanol	Sugarcane Ethanol
Yield (liters per ton)	400-450	650-700
Energy Return (EROI)	1.3-1.6	8-10
GHG Reduction	34%	90%
Yield per Hectare (liters)	2,500-3,000	6,500
Environmental Impact	Higher soil and water impact, moderate GHG reduction	Lower soil impact, high GHG reduction

While both corn and sugarcane are valuable biofuel sources, sugarcane ethanol is notably more efficient and environmentally sustainable. Its high energy yield, minimal input requirements, and significant greenhouse gas reduction potential make it

one of the most promising biofuel sources, particularly in tropical regions suited to sugarcane cultivation. Corn ethanol, though beneficial in supporting renewable fuel mandates, requires greater resources and produces fewer environmental benefits. Moving forward, a balanced approach that supports both food security and sustainable energy production is crucial to addressing the food vs. fuel challenges inherent to each crop.

Biodiesel Production from Oilseed Crops: Soybeans and Rapeseed

Oilseed crops, particularly soybeans and rapeseed (canola), are widely cultivated for biodiesel production due to their high oil content and suitability as renewable energy sources. These crops produce vegetable oils that can be processed into biodiesel through transesterification, yielding a cleaner-burning fuel alternative with lower greenhouse gas emissions than traditional diesel (Table 2). Biodiesel from oilseeds has become a central component in renewable energy strategies, especially in countries seeking to reduce dependency on fossil fuels while managing agricultural resources sustainably.

Soybeans for Biodiesel Production

Soybeans (*Glycine max*) are one of the most versatile and widely grown oilseed crops, particularly in North and South America, where they are a key biodiesel feedstock. Known for their high protein and oil content,

soybeans are valuable as both food and energy resources.

Soybeans contain approximately 18-20% oil, making them suitable for large-scale biodiesel production. A hectare of soybeans can yield around 450-600 liters of biodiesel depending on regional farming practices and soybean varieties. This yield is relatively lower compared to other oilseed crops, but soybeans' adaptability and dual-use potential make them a critical component in biofuel strategies. Soybean-based biodiesel reduces greenhouse gas emissions by around 57% compared to fossil diesel, mainly due to the lower carbon intensity of soy farming and the renewable nature of the fuel. However, soybeans require significant land and water resources, and expanding soybean acreage can lead to deforestation and biodiversity loss, especially in regions like the Amazon. Initiatives promoting sustainable soybean farming practices, such as the Round Table on Responsible Soy, aim to mitigate these environmental impacts.

Soybeans' popularity as a biodiesel feedstock is partially driven by the economic benefits of their by-products, including protein-rich meal for animal feed, which enhances the crop's economic viability. Nevertheless, the use of soybeans for biodiesel can affect food prices, as increased demand for fuel competes with food and feed markets.

Rapeseed (Canola) for Biodiesel Production

Rapeseed (*Brassica napus*), commonly processed as canola in North America, is another leading biodiesel crop, particularly in Europe. Rapeseed’s high oil content and favorable fatty acid composition make it especially efficient for biodiesel production. Rapeseed has one of the highest oil yields among oilseed crops, containing about 40-45% oil by weight. This high oil content allows for biodiesel yields of around 1,200-1,600 liters per hectare, significantly higher than soybean-based biodiesel. The higher yield per hectare makes rapeseed a preferred biodiesel source, particularly in regions with limited arable land. Rapeseed biodiesel offers up to 83% greenhouse gas emission reduction compared to fossil diesel, largely due to its high energy yield and efficient conversion process. Rapeseed’s lower input requirements for nitrogen fertilizers and pesticides, combined with its suitability for cooler climates, enhance its environmental benefits. However, rapeseed cultivation can still lead to nutrient runoff and soil degradation if not managed sustainably. In Europe, rapeseed biodiesel has been heavily incentivized through policies such as the EU’s Renewable Energy Directive, which has led to widespread cultivation across the continent.

The high yield and favorable environmental profile of rapeseed biodiesel make it a

critical biofuel feedstock, particularly in European renewable energy programs. Rapeseed biodiesel’s fatty acid profile also enhances its fuel stability, making it a more viable and efficient option for commercial biodiesel production.

Table 2. Comparative Analysis of Soybeans and Rapeseed for Biodiesel

Factor	Soybeans	Rapeseed
Oil Content (%)	18-20%	40-45%
Biodiesel Yield (L/ha)	450-600	1,200-1,600
GHG Emission Reduction	57%	83%
Environmental Impact	Moderate (high land use)	Lower impact, higher efficiency
Regional Suitability	North/South America	Europe, Canada

Soybeans and rapeseed are integral to biodiesel production, each with unique advantages in terms of energy output, sustainability, and regional adaptability. Rapeseed’s higher oil yield and lower environmental impact per liter of biodiesel make it more efficient, particularly in Europe, while soybeans’ dual-purpose value contributes to its prominence in North America. As biodiesel demand grows, policies supporting sustainable farming practices for these crops will be essential to balance renewable energy production with food security and environmental health.

Comparison of Biogas Production from Food Crop Residues and Non-food Biomass

Biogas production from both food crop residues and non-food biomass presents valuable renewable energy solutions with unique advantages. Food crop residues like corn stover and wheat straw offer high energy yields and repurpose agricultural waste, though they require more intensive processing. Non-food biomass, particularly animal manure and energy crops like switchgrass, provides a simpler, more sustainable option, as it requires minimal processing, prevents methane emissions, and can grow on marginal lands (Table 3).

Together, these sources contribute to a diversified and scalable biogas system that supports both renewable energy goals and sustainable agriculture.

consideration in biofuel production, as the cultivation of biofuel crops requires substantial acreage, which can compete with land needed for food production. The spatial demands of biofuel crops vary widely based on crop type, yield per hectare, and regional agricultural practices. Balancing land use for biofuels and food is essential to prevent negative impacts on food security, biodiversity, and environmental sustainability.

Sugarcane and Rapeseed (Bioethanol and Biodiesel):

Sugarcane is one of the most land-efficient crops for bioethanol, with yields of

approximately 6,500 liters of ethanol per hectare in regions like Brazil.

Table 3. Summary of Comparison

Factor	Food Crop Residues	Non-food Biomass
Pretreatment Needs	High (especially lignocellulosic)	Moderate to Low (varies by type)
Energy Output	350-500 m ³ biogas/ton (corn stover, wheat straw)	25-400 m ³ biogas/ton (animal manure, switchgrass)
Resource Use	Moderate (minimal land use, but high pretreatment)	Low (minimal inputs for non-food crops and manure)
Environmental Impact	Reduces waste and emissions from crop residue burning	Reduces methane emissions (manure) and preserves arable land (switchgrass)
Scalability	High in agricultural regions	High in rural and marginal land regions

Its high yield per hectare reduces the total land needed for bioethanol production, making it more sustainable in terms of land use. However, large-scale sugarcane farming can still compete with food crops in regions where arable land is limited. Brazil's success with sugarcane bioethanol, largely attributed to the favorable climate, has minimized its competition with food crops, though careful land management is essential to avoid encroachment on native ecosystems. Rapeseed, extensively grown in Europe, is a

high-yield biodiesel crop that produces about 1,200-1,600 liters per hectare. Although rapeseed biodiesel is land-efficient, its cultivation is resource-intensive, requiring high levels of water and fertilizer. Rapeseed's increased demand for biodiesel has led to land-use competition in Europe, where it competes with food-grade vegetable oils and animal feed crops, impacting food prices.

Palm Oil and Non-food Energy Crops (Biodiesel and Biogas):

Palm oil has one of the highest oil yields, producing up to 5,000 liters of biodiesel per hectare, making it highly land-efficient for biodiesel production (Yusoff, 2006). However, the expansion of palm oil plantations, particularly in Southeast Asia, has resulted in extensive deforestation, biodiversity loss, and carbon emissions, leading to significant environmental and social concerns. Palm oil production's impacts on land-use competition are primarily due to its overlap with food and industrial markets, where it is a common ingredient in processed foods and personal care products (Husain et al 2002, Geng, 2013, Kurnia et al 2016)

Perennial grasses like switchgrass and miscanthus, cultivated for bioethanol or biogas, are more sustainable options in terms of land-use efficiency because they can grow on marginal lands unsuitable for food crops. These crops do not compete directly with

food production and provide high biomass yields per hectare (e.g., switchgrass can yield around 400 cubic meters of biogas per ton). Their cultivation on degraded or marginal lands supports biodiversity and soil health, making them a promising option for biofuel production without compromising food security.

Socioeconomic Impact of Dual-purpose Food and Energy Crops

The cultivation of crops that serve both food and bioenergy needs, such as corn, soybeans, and sugarcane, has profound socioeconomic effects on rural farmers and local markets. On one hand, these dual-purpose crops provide income opportunities and market stability, particularly in regions with strong biofuel demand. On the other hand, they can create challenges such as increased land and input costs, price volatility, and potential shifts away from traditional agricultural practices. Balancing these effects is critical for ensuring that biofuel production supports rural development without compromising local food security.

1. Income Opportunities for Rural Farmers

Increased Crop Demand and Price Incentives:

The growing demand for biofuels has created additional markets for crops like corn, soybeans, and sugarcane, providing farmers with new revenue streams. By selling crops for both food and energy purposes, farmers can benefit from price incentives linked to

biofuel policies, such as subsidies, biofuel blending mandates, and tax credits.

For instance, Brazil's sugarcane farmers have gained significant economic benefits from the country's bioethanol program, which has driven up demand for sugarcane and offered stable prices. Similarly, U.S. corn farmers benefit from the Renewable Fuel Standard (RFS), which guarantees a consistent market for corn ethanol, reducing income fluctuations associated with global food markets.

Diversified Income and Risk Reduction:

For farmers, having the option to sell crops for either food or biofuel adds a layer of financial security. When food market prices are low, biofuel demand can stabilize income by providing an alternative revenue source. This diversification reduces farmers' reliance on a single market, helping them better manage economic risk and seasonal price volatility.

Additionally, biofuel crops like soybeans, which also produce high-protein meal for animal feed, create dual-income opportunities. After oil extraction for biodiesel, the soybean meal can be sold as feed, generating extra income and enhancing the overall economic viability of soybean farming.

2. Impacts on Land and Input Costs

Rising Land Prices:

The increased demand for land to grow biofuel crops can drive up land prices,

making it difficult for smallholder farmers to acquire or lease land. As larger agribusinesses expand to meet biofuel demand, they often buy up farmland, leading to land concentration and displacement of smallholders. In countries like Indonesia and Brazil, where biofuel production has grown rapidly, land prices have surged, impacting local farmers and indigenous communities who may struggle to compete for access. This trend often forces smallholders to lease land at higher costs, affecting profitability and potentially leading to land tenure conflicts.

Increased Cost of Agricultural Inputs:

Dual-purpose crop cultivation often requires more inputs, such as fertilizers, pesticides, and water, to maximize yields and meet the needs of both food and energy markets. These input costs can strain smallholder farmers, particularly if biofuel prices are volatile or if there is no financial assistance to offset these expenses. In some cases, government incentives and subsidies for biofuel crops have driven up prices for fertilizers and seeds. For example, corn farmers in the U.S. faced higher input costs as corn demand for ethanol increased, impacting profit margins, especially for those not directly benefiting from biofuel subsidies.

3. Local Food Markets and Price Volatility

Impact on Food Prices:

The redirection of crops to biofuel production can reduce the supply available for food, leading to higher food prices in local markets. This price increase affects both rural and urban populations, particularly in developing countries where staple crops like corn, soybeans, and sugarcane play a crucial role in local diets. For example, as corn prices rose due to ethanol demand in the U.S., food prices for corn-based products and animal feed increased. The resulting price hikes in meat and dairy products, due to higher feed costs, impacted consumers and created food security concerns. In developing regions, such price increases can exacerbate poverty and limit food access, disproportionately affecting low-income communities.

Food Security Challenges for Smallholder Farmers:

While biofuel markets offer income potential, smallholder farmers in regions with limited food supply may face food security risks if they prioritize energy crops over subsistence or food crops. In countries where farmers rely on their crops to meet household food needs, growing biofuel crops for commercial markets can lead to local shortages and increased dependence on food imports. This shift from food to biofuel crops can also erode traditional agricultural practices, as farmers move away from diverse, subsistence-based cropping systems to monocultures focused on high-demand

biofuel crops. Such changes in farming practices can reduce dietary diversity, resilience to market fluctuations, and the ability of farmers to meet their own food needs.

4. Employment and Rural Development

Job Creation and Rural Infrastructure:

Expanding biofuel industries often leads to job creation in both agricultural and processing sectors, supporting rural employment. For example, Brazil's sugarcane ethanol industry has created millions of jobs in planting, harvesting, and ethanol processing, contributing to regional development. Biofuel programs also drive infrastructure improvements, such as transportation, storage, and processing facilities, which can have positive spillover effects on rural communities. Improved infrastructure can increase market access for farmers, reduce transport costs, and enhance local economic development.

Labor Intensity and Working Conditions:

While biofuel crop expansion creates jobs, it also raises concerns about labor conditions, particularly in large-scale operations. Labor-intensive crops like sugarcane require significant manual work, often leading to exploitation and poor working conditions for seasonal laborers. In countries with inadequate labor protections, the expansion of biofuel crops can exacerbate issues of low wages, inadequate health and safety standards, and insecure employment. These

factors highlight the importance of implementing fair labor practices and supporting smallholder inclusion in biofuel value chains.

The socioeconomic impacts of dual-purpose food and energy crops on rural farmers and local markets are complex, offering both opportunities and challenges. While biofuel production creates new income streams, diversifies markets, and generates rural employment, it also risks increasing land and input costs, creating food security challenges, and impacting local food prices. Ensuring that biofuel expansion benefits rural communities requires policies that balance food and fuel needs, protect smallholder land rights, and promote sustainable farming practices. With the right support, dual-purpose biofuel crops can contribute positively to rural development and local economies without compromising food security.

Challenges and Future Perspectives

1. Genetic Engineering and Hybridization to Improve Crop Yields

The need for high-yield, resource-efficient crops has driven significant advances in genetic engineering and hybridization, especially for dual-purpose crops like corn, soybeans, and sugarcane that serve both food and biofuel markets. These technologies enhance crop performance by improving resilience to environmental stresses,

increasing biomass production, and optimizing nutrient use efficiency. As a result, genetically modified (GM) and hybrid crops can yield more biofuel per hectare while minimizing the impact on food supplies and environmental resources.

i. Genetic Engineering in Biofuel Crops

Increased Yield and Biomass Production:

Genetic engineering (GE) can increase the photosynthetic efficiency of crops, leading to higher biomass production—a key factor for bioethanol and biodiesel yields. For example, genetically engineered corn varieties designed to improve starch content and enhance overall biomass are better suited for ethanol production, yielding more fermentable sugars per unit of land. In sugarcane, GE technology has been applied to develop varieties with increased sucrose content and faster growth rates, significantly boosting ethanol yields per hectare (Larson2008). Such high-sugar varieties of sugarcane are being developed in Brazil, where they help maximize energy output from the same land area, reducing the need to expand cultivation into natural habitats.

Improved Environmental Resilience:

Genetic modifications for drought tolerance and water-use efficiency allow biofuel crops to thrive in regions with limited water availability. For instance, drought-resistant GM corn varieties enable farmers to achieve stable yields in arid and semi-arid regions, reducing the need to divert water from food

crops and enhancing sustainability in water-scarce areas. Resistance to pests and diseases, such as the development of Bt (*Bacillus thuringiensis*) corn and soybeans, decreases the reliance on chemical pesticides, reducing environmental impact and input costs. Pest-resistant varieties allow for higher crop yields without intensive pesticide use, benefiting both food security and biofuel production.

Enhanced Nutrient Use Efficiency:

Genetic engineering has also improved nutrient use efficiency, particularly nitrogen uptake, which is essential for crop growth. For example, nitrogen-efficient GM crops like corn and soybeans require less fertilizer, decreasing both production costs and nutrient runoff into waterways. This improved nutrient efficiency is especially beneficial in biofuel production, as it reduces the environmental footprint of biofuel crops by minimizing pollution and resource use, while still achieving high yields.

ii. Hybridization in Biofuel Crops

Hybridization, a traditional plant breeding method that involves crossbreeding two genetically distinct plants to produce offspring with superior traits, is widely used to enhance yield, vigor, and resilience. Hybrid crops often exhibit heterosis, or hybrid vigor, which results in increased productivity and adaptability.

Hybrid Corn and Sugarcane:

Hybrid corn varieties have become the standard in many regions, particularly in the United States, where hybrid corn is predominantly grown for bioethanol. These hybrids are bred for traits such as increased starch content, pest resistance, and resilience to varying climate conditions, enhancing yields for both food and energy production. High-yield hybrid corn varieties enable farmers to produce more ethanol per hectare, reducing the land required for biofuel without impacting food supplies. In Brazil, hybrid sugarcane varieties have been developed to boost sugar content and enhance resistance to diseases like sugarcane smut and mosaic virus. Hybrid sugarcane also grows more rapidly and has higher biomass accumulation, supporting efficient ethanol production. Improved hybrids can achieve yields up to 40% higher than traditional varieties, maximizing biofuel output while using less land.

Non-food biofuel crops like switchgrass and miscanthus, widely used for cellulosic ethanol, have also benefited from hybridization. Hybrid varieties of these perennial grasses are selected for traits such as higher cellulose content and faster growth rates, which directly impact biogas and bioethanol yields. For instance, hybrids of miscanthus can yield up to 30 metric tons of biomass per hectare, compared to around 20 metric tons for wild-type varieties. Hybrid switchgrass, developed for resilience to

drought and cold, can grow in diverse climates and on marginal lands, ensuring high yields in non-arable regions and minimizing competition with food crops.

iii. Socioeconomic and Environmental Implications

Economic Benefits for Farmers:

Higher-yielding genetically modified and hybrid crops can increase farm income by enabling farmers to produce more biofuel feedstock per hectare. These innovations offer potential economic resilience, as farmers benefit from stable yields even under challenging conditions such as drought or pest outbreaks. Reduced input costs associated with pest-resistant or nutrient-efficient crops also enhance profitability. With lower pesticide and fertilizer requirements, farmers can achieve high yields at a lower production cost, making dual-purpose crop cultivation more economically viable.

Environmental Sustainability:

By reducing the need for chemical inputs and water resources, genetic engineering and hybrid crops contribute to more sustainable agriculture, with fewer environmental impacts. Pest-resistant varieties reduce pesticide use, benefiting biodiversity and soil health, while drought-tolerant varieties allow biofuel crops to grow with less water. Improved land-use efficiency helps prevent land expansion into natural ecosystems, such as forests and grasslands, preserving

biodiversity. Crops that yield more biofuel per hectare reduce the need to increase cultivation area, aligning biofuel production with conservation efforts.

Biofuel from Marine Species-Algae

Algae are diverse group of photosynthetic eukaryotic organisms that are found in various aquatic and most terrestrial environments. They grow in exponential rate. Like plants, algae contain chlorophyll and other pigments that allow them to convert sunlight into energy via photosynthesis. They concentrate solar energy into liquid fuel. They are non-foodplants and grow in non-arable farm land. Algae have amazing potentials as biofuel with remarkably high yield/acre. Algae biofuel is 2nd generation biofuel (Milano et al 2016, Ok and Eun, 2016, Adeniyi et al 2018).

Future Research Directions for Dual-purpose Food and Energy Crops

As the demand for both renewable energy and food resources grows, the development of dual-purpose crops that can meet these needs sustainably has become a critical research area. Current literature has explored various aspects of crop yield, biofuel efficiency, and environmental impact, but several gaps remain. Future research is needed to address these gaps, focusing on enhancing crop resilience, improving processing technologies, and creating sustainable biofuel systems that minimize competition with food production.

1. Development of Drought-resistant and Climate-resilient Crop Varieties

Developing drought- and heat-tolerant varieties of dual-purpose crops like corn, sugarcane, and soybeans should be prioritized. These crops would support food and biofuel production in regions prone to water scarcity and extreme temperatures, helping to stabilize yields and reduce irrigation needs. Research should explore genetic engineering and marker-assisted selection to improve both water-use efficiency and biomass production. For example, improving root structure to enhance water absorption in arid soils could increase resilience without compromising yield.

2. Improved Processing Technologies for Higher Efficiency and Lower Environmental Impact

Development of advanced bioprocessing methods, such as enzyme-based hydrolysis and microbial fermentation, can increase the conversion efficiency of biomass into biofuel. These methods could allow dual-purpose crops to produce more energy per hectare, improving land-use efficiency. Research on integrated biorefineries that co-produce biofuels, bio-products (e.g., bio-based chemicals), and fertilizers from agricultural residues can enhance economic viability. Using multi-output processing systems would reduce waste, maximize resource utilization, and lower production

costs. Exploring renewable energy sources, such as solar or wind, to power biofuel processing facilities can reduce the environmental footprint of biofuel production. Energy-efficient processing technologies would also allow regions with limited fossil fuel resources to develop sustainable biofuel industries.

3. Enhancing Nutrient Use Efficiency to Reduce Input Costs and Environmental Impact

Developing nitrogen- and phosphorus-efficient crop varieties that maintain high yields for food and biofuel production is essential. Genetic engineering and genome editing tools like CRISPR can be used to improve nutrient absorption and utilization in crops. Research on microbial soil amendments, such as nitrogen-fixing bacteria and mycorrhizal fungi, could reduce the need for synthetic fertilizers. These natural soil enhancers can improve nutrient uptake and crop resilience, supporting sustainable farming practices for dual-purpose crops. Testing intercropping systems that combine nutrient-efficient biofuel crops with legumes or cover crops could also enhance soil fertility naturally. By increasing soil nitrogen levels, these systems could reduce the overall need for fertilizers, lowering input costs and environmental impact.

4. Developing Economically Viable Non-food Biofuel Crops

Conducting cost-benefit analyses of non-food biofuel crops on marginal or degraded lands could provide valuable insights for policymakers and farmers. Research should address yield optimization, soil restoration, and scalability to make these crops a viable alternative to food-based biofuels. Developing new varieties of non-food energy crops with enhanced adaptability to diverse climates and minimal input requirements can improve their feasibility in different regions. This research would expand the range of crops available for biofuel production, reducing reliance on food crops and increasing biofuel diversity. Exploring integrated crop-livestock-biofuel systems could also enhance economic and ecological sustainability. For instance, cultivating non-food biofuel crops alongside livestock grazing areas could support both energy and food systems while preserving biodiversity and soil health.

5. Socioeconomic Impact Studies and Policy Development

Conducting longitudinal studies on the socioeconomic impacts of dual-purpose biofuel crops in rural areas would provide insights into the effects of biofuel policies on local economies and food security. Research should examine how biofuel markets affect crop prices, land ownership, and employment in biofuel-producing regions.

Developing policy recommendations for balancing biofuel and food production is critical. Studies evaluating the effectiveness of policy incentives, such as biofuel blending mandates and subsidies, on dual-purpose crop sustainability can inform future regulatory frameworks. Research should also explore “smart subsidies” that prioritize sustainable farming practices and protect vulnerable communities from food price volatility. Investigating community-based biofuel models, such as farmer cooperatives and small-scale biorefineries, could enhance the economic feasibility of biofuel production for smallholders. These models can increase community ownership, reduce costs, and generate local employment while aligning with food security goals.

CONCLUSION

Future research in dual-purpose crops should focus on improving resilience, processing efficiency, and economic viability, addressing both environmental and socioeconomic challenges. Developing drought-resistant and nutrient-efficient varieties, advancing bioprocessing technologies, and exploring sustainable non-food biofuel crops are essential to achieving a balanced biofuel-food system. Additionally, research on socioeconomic impacts and policy frameworks is critical for supporting rural communities and ensuring that biofuel production contributes positively to global sustainability goals. A

comprehensive research agenda addressing these areas will pave the way for a more sustainable and resilient biofuel industry.

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COMMUNIQUE OF RENEWABLE AND ALTERNATIVE ENERGY SOCIETY OF NIGERIA (RAESON)

The 13th Annual and International Hybrid Conference of Renewable and Alternative Energy Society of Nigeria (RAESON) was held at Kingsley Ozumba Mbadiwe University (KOMU), Ideato Imo State from 26th - 29th March 2025 with the theme “*Clean Energy Transition for National Security and Industrial Growth*”. In attendance were many dignitaries including the Vice-Chancellor (KOMU), Professor Ikechukwu N S Dozie, several other Vice-Chancellors were present in person or sent in their Representatives namely; Imo State University, Owerri and University of Agriculture and Environmental Sciences, Umuagwo, Others include Professor A C Onyeka, Acting Vice-Chancellor Alvan Ikoku Federal University of Education, Owerri who also doubled as the LOC Chairman. The Conference President was Professor Bashir Garba, FRAES, the Vice-Chancellor of Usmanu Danfodiyo University, Sokoto. The keynote presentation was delivered by Dr Izuchukwu Okafor, FRAES, Dir. Energy Centre UNN. The special guests of honour were Professor Alex D W Acholonu, FAS, OON and the President of the Nigerian Academy of Sciences, Professor A S Sambo, FAS. The highlight of the conference was the presentation of the first award winners of Emeritus Professor Acholonu- RAESON Prize for the best paper presentation during the 2024 conference by High Chief Emeritus AD W Acholonu who further made a donation in order to ensure the sustainability of the prize.

At the end of the conference the following resolutions were reached:

1. The Conference observes that even though every person depends on energy, the over dependence on fossil fuel is not sustainable. The need to invest more in renewable energy technologies was advocated in order to accelerate efforts to enhance national security and economic growth and to minimize Green House Gas Emissions.
2. RAESON calls on the Government and most especially the State Governments to take advantage on the liberalization of the generation and distribution of power in the Country to carry out massive investments in renewable energy. This should be followed with enlightenment campaign to educate the populace about renewable energy.
3. RAESON notes that Nigeria as a Nation has only made little progress on transitioning to clean energy usage compared to other countries due mainly to poor funding and lack of appropriate and inconsistent policy implementations. More responsive and effective policies are needed in order to promote clean energy transition for national security and industrial growth.
4. RAESON notes that the high initial investment of transitioning to clean energy is a major constraint. Nevertheless, we call on the Government to make efforts to promote policy issues on private sector participation in the generation, transmission and distribution of clean energy.
5. RAESON once again reiterates the need to encourage and involve professional bodies like RAESON in policy implementation of clean energy programmes and projects. Furthermore, Industry and Academia collaboration was recognized as crucial to elevate renewables in the energy mix plans,
6. It is of major concern the frequent collapse of the national grid due to inadequate maintenance and overloading. Consequently, we call on the government to invest heavily in maintenance, research and development. In addition, energy-saving practices across industries, households and transportation systems should be encouraged.
7. The Renewable and Alternative Energy Society of Nigeria (RAESON) hereby offers to partner with the Government to solve the lingering energy crises.

We appreciate the support of the Vice-Chancellor of Kingsley Ozumba Mbadiwe University, Ideato Professor Ikechukwu N S Dozie, the Staff and Students of KOMU, the LOC Chairman who is the Ag Vice-Chancellor of Alvan Ikoku Federal University of Education Owerri, Professor A C Onyeka and his incredible team for a job well done. Finally, we thank all the numerous organizations and individuals that made this year's conference a success.

Professor Oamen E Abumere, FNIP, FRAES
Communiqué Committee Chairman

Prof. Chidi E. Akujor, FAS, FRAES
President RAESON