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Climate–Microbiome Dynamics in Aquaculture Systems and Their Implications for Fish Production Stability, Food Availability and SDG Attainment in Sub-Saharan Africa

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Abstract. Climate variability is emerging as a major limiting factor in aquaculture production, but its indirect impacts via microbial ecology are poorly understood, especially in Sub-Saharan Africa. This research proposes and tests a climate-microbiome-production pathway to understand the effects of environmental variability on aquaculture production and food security. A panel design was implemented across 42 aquaculture farms in southern Nigeria, combining climate data, water quality, 16S rRNA microbiome sequencing and production metrics over two production cycles. Structural equation modeling (SEM) reveals that temperature variability has a significant negative effect on microbial diversity ($\beta = -0.41$, $p < 0.01$), impairs nutrient cycling, and promotes pathogen growth. Microbiome dynamics play a key role in fish survival ($\beta = 0.36$, $p < 0.01$) and yield ($\beta = 0.29$, $p < 0.05$), and mediate climate variability impacts on production. These impacts flow through to food security, as production stability declines reduce food availability. The research reveals microbiome-mediated pathways are essential for aquaculture resilience in the face of climate change and that microbiome-informed aquaculture management strategies are needed to support food security and sustainable development in Sub-Saharan Africa.

Keywords: Climate variability; Aquaculture microbiome; Fish production stability; Food availability; Sub-Saharan Africa

Graphical Abstract: *Climate variability alters microbial community structure, affecting nutrient cycling, fish production, and ultimately food availability in Sub-Saharan Africa.*

1. Introduction

Aquaculture is now a critical pillar of global food systems, especially in the provision of protein and it supplies more than half of the fish consumed worldwide, contributing significantly to nutrition, livelihoods and economic development (FAO, 2022). In Sub-Saharan Africa, aquaculture has been positioned as a strategic soultion to declining capture fisheries, rapid population growth and widening protein deficits (Chan *et al.,* 2019; Obiero *et al.,* 2019). Countries such as Nigeria, Ghana and Kenya have witnessed steady expansion in aquaculture production, particularly in tilapia and catfish farming (Ayinla, 2022; Obwanga *et al.,* 2020). However, despite this growth, aquaculture productivity in the region remains uneven and frequently falls short of global standards. This shortfall is largely driven by environmental instability, limited adoption of technology and weak system resilience (Béné *et al.,* 2016; Jolly *et al.,* 2023). Climate variability, in the form of increasing temperature, erratic rainfall, flooding and drought, is a major constraint facing African aquaculture

(Intergovernmental Panel on Climate Change, 2022). These environmental stressors affect water temperatures, dissolved oxygen, and nutrient cycling, which in turn affect fish metabolism, growth, and mortality (Boyd, 2020; Barange *et al.,* 2018). In tropical environments like those in Nigeria and the rest of West Africa, even minor changes in temperature and dissolved oxygen can have disproportionate impacts on aquaculture production (Adewumi & Olaleye, 2021). Available empirical evidence from aquaculture settings in Africa suggests that environmental variability arising from climatic changes is already leading to fish mortalities, disease outbreaks, and yield losses (Eti-Ukwu *et al.,* 2020; Muthoka *et al.,* 2024).

While a great deal of the earlier research has focused on the direct effects of climate change on the physiology of cultured fish, a growing line of research suggests microorganisms play important roles in aquaculture systems (De Schryver & Vadstein, 2014; Xiong et al., 2024). Aquaculture systems are complex ecosystems where microorganisms (bacteria, archaea and others) play an important role in water quality, nutrient cycling and disease (Zhang et al., 2022). The microbiomes function as biogeochemical reactors, performing processes such as nitrification, denitrification and the degradation of organic matter, which are crucial for the stability and production of aquaculture systems (Avnimelech, 2015; Martínez-Córdova et al., 2020).

Thanks to molecular ecology, such as next-generation sequencing, we have a holistic view of the aquaculture microbiomes and their roles (Caporaso et al., 2012; Uddin et al., 2026). Studies have shown that the main microbial groups (Proteobacteria, Firmicutes, and Bacteroidetes) in aquaculture systems are responsive to environmental conditions such as temperature, nutrients, and dissolved oxygen levels (Chen et al., 2022; Xiong et al., 2024). More importantly, these microbial communities are dynamic and can quickly respond to environmental changes, such as those caused by climate change (Mataragka et al., 2026).

In African aquaculture, initial studies indicate that microbial activities are closely linked to production. For instance, shifts in microbial communities have been demonstrated to impact on ammonia levels, water quality and disease in catfish aquaculture in Nigeria (Adeosun et al., 2024; Agbugui et al., 2025). Similarly, in tilapia aquaculture in East Africa, microbial dysbiosis is associated with increased disease and reduced growth (Bereded et al., 2020; Munguti et al., 2021). These findings suggest that microbial communities are an important intermediary between the environment and aquaculture productivity but their relationship is poorly understood under climate change.

The climate-microbiome link is an important but neglected aspect of aquaculture sustainability. Microbial communities can be influenced by climate change through changes in temperature, dissolved oxygen and nutrient levels, which can affect diversity, function, and shifts in the dominant pathogenic microbial groups (Allison & Martiny, 2008; Mataragka et al., 2026). These changes can affect key ecosystem processes such as nitrogen cycling and organic matter degradation, which can affect water quality and disease resistance (ylor et al., 2021; Huang et al., 2025). In tropical aquaculture, where many environmental factors are often at physiological extremes, these shifts in microbial communities may affect production.

These effects extend from farm production to food system impacts. Aquaculture plays a direct role in food availability through enhanced supply of affordable animal protein and an indirect role via livelihoods and market stability (Belton *et al.,* 2020; FAO, 2022). But climate change impacts on aquaculture systems can cause production instability, yield loss and cost increases, which affect food availability and access, especially for vulnerable groups (Tacon *et al.,* 2022; Yadav *et al.,* 2024). In Sub-Saharan Africa, where fish is a critical source of protein and micronutrients, this affects nutrition and health (Golden *et al.,* 2021).

These issues are closely connected to global development goals, including United Nations Sustainable Development Goal 2 and United Nations Sustainable Development Goal 13. To reach these goals, aquaculture production must be increased, but also made sustainable and climate resilient. However, existing policy and research approaches tend to neglect the influence of microbial ecology on climate impacts on aquaculture. In this context, a key knowledge gap arises:

There is a lack of empirical evidence that links climate variability, microbiome, aquaculture production and food supply in a single analytical framework, especially in Sub-Saharan Africa.

This knowledge gap needs to be bridged for scientific and policy advancement. This study offers a new and holistic perspective on aquaculture sustainability by explicitly capturing the effects of climate variability on the microbiome, and on production stability and food availability. It adds to the emerging understanding that microbiome-based management practices are needed to develop climate-adapted aquaculture systems that promote food security in Africa. To this end, this study seeks to empirically explore the climate-microbiome-production nexus in aquaculture, and assess the impact on food availability and sustainable development in Sub-Saharan Africa.

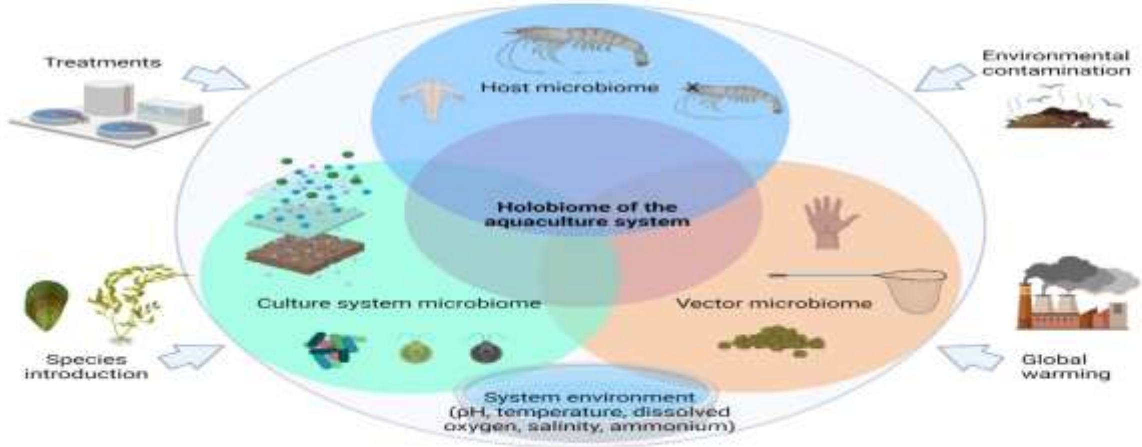

Figure 1: *Conceptual framework illustrating the hypothesized pathways linking climate variability, microbiome dynamics, aquaculture production performance, and food availability outcomes.*

2. Research Methodology

2.1 Study Design and Analytical Framework

Following the recommendations of Creswell and Creswell (2018), this study used a longitudinal panel design with an embedded quasi-experimental analytical framework to test the dynamic links between climate variability, microbiome composition, aquaculture production, and food supply. The longitudinal design allowed for the capture of intra- and inter-seasonal variation over two production cycles (12 months) and the analytical framework was designed to test direct and indirect causal relationships.

This research is grounded in a systems-based ecological perspective where climate variability impacts aquaculture outcomes indirectly through microbiome processes. In particular, the hypothesis is:
climate variability → microbiome dynamics → production performance → food availability outcomes
To test these hypotheses, we adopted a combination of multivariate statistical analyses and Structural Equation Modeling (SEM) to simultaneously estimate direct, indirectand total effects (Kline, 2015; Grace, 2020).

2.2 Study Area

The study area was three aquaculture hotspots in southern Nigeria with Delta, Edoand Anambra being major production areas in the humid tropical agro-ecological zone. These regions have high aquaculture production (particularly Clarias gariepinus and tilapia) and display high climate variability (with seasonal floods and water scarcity in the dry seasons) (Adewumi & Olaleye, 2021; Munguti *et al.,* 2021).

The climate of the study region includes an average annual temperature of 26-32°C and rainfall ranging from 1,500-2,500 mm per annum with a bimodal pattern. These climatic conditions are suitable for studying the effects of climate on the microbiome in tropical aquaculture systems.

2.3 Sampling Procedure and Sample Size Determination

The target population was registered and unregistered aquaculture farms in the states. A two-stage stratified random sampling method was used to achieve a representative sample of production systems and environmental conditions (Etikan & Bala, 2017).
In stage one, aquaculture-intensive local government areas (LGAs) were purposively selected. In the second stage, farms were stratified by production system (extensive, semi-intensive, intensive) and pond type (earthen, concrete and tarpaulin). In the third stage, farms were randomly sampled from each stratum.
A sample of 42 farms was calculated using Cochran's formula for finite populations, with adjustments for longitudinal studies and field logistics. This is comparable to other ecological and aquaculture field studies that have used microbiome and production analyses (Shan *et al.,* 2025; Uddin *et al.,* 2026).

2.4 Data Collection

Climate and Environmental Variables

Meteorological data were gathered via sensors and records. Temperature was measured hourly with data loggers, and rainfall and dissolved oxygen with conventional equipment.

Environmental instability was measured by calculating the variability of temperature as standard deviation:

$$\sigma_T = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - \bar{T})^2}$$

where $T_i$represents observed temperature values and $\bar{T}$is the mean temperature.

Rainfall variability was expressed as the coefficient of variation:

$$CV_R = \frac{\sigma_R}{\bar{R}} \times 100$$

These indices provide robust measures of climate variability affecting aquaculture systems (Jiang *et al.,* 2025).

Water Quality Analysis

Water quality was measured bi-weekly using standard methods (APHA, 2017). These included pH, dissolved oxygen (DO), ammonia (NH_3), nitrite (NO_2^-) and total suspended solids (TSS). Spectrophotometric and titrimetric methods were used when necessary.

These parameters are key metrics of microbial activity and ecosystem functioning because they are closely linked to microbial metabolism (nitrification, organic matter breakdown) (Boyd, 2020).

Microbiome Sampling and Sequencing

Water, sediment and fish gut compartments were sampled for microbes. DNA was extracted following published protocolsand sequencing of the 16S rRNA gene (V3-V4 region) was carried out on the Illumina MiSeq sequencer.

The Shannon index of diversity was used to measure microbial diversity (Shannon, 2001):

$$H' = -\sum_{i=1}^{S} p_i \ln p_i$$

where $p_i$represents the relative abundance of each microbial taxon and $S$is the total number of taxa.

Beta diversity was assessed using Bray–Curtis dissimilarity and functional groups (e.g., nitrifiers, denitrifiers, pathogenic taxa) were identified using bioinformatics pipelines (Bolyen *et al.,* 2019; Shan *et al.,* 2025).

Aquaculture Production Data

Production performance was evaluated using standard aquaculture indicators. The specific growth rate (SGR) was calculated as:

$$SGR = \frac{\ln W_t - \ln W_0}{t} \times 100$$

where $W_t$and W_0represent final and initial weights, respectively and $t$is the culture period in days.

Feed efficiency was measured using the feed conversion ratio:

$$FCR = \frac{\text{Feed Intake}}{\text{Weight Gain}}$$

Survival rate was computed as:

$$Survival(\%) = \frac{N_t}{N_0} \times 100$$

Yield was estimated as total harvested biomass per unit pond area (kg/ha/cycle).

Food Availability Indicators

Food availability was assessed using both production and consumption-based metrics. A composite Food Availability Index (FAI) was constructed as:

$$FAI = w_1 Y + w_2 S + w_3 C$$

where Yrepresents yield, Srepresents production stability, Crepresents household consumption frequency and $w_i$are weighting coefficients.

This composite index captures both supply and access dimensions of food availability (Belton *et al.,* 2020; FAO, 2023).

2.5 Variable Operationalization

Key variables were operationalized as follows:

Climate variability: temperature standard deviation and rainfall variability
Microbiome dynamics: Shannon diversity index and relative abundance of functional taxa
Production performance: yield, survival rate and FCR
Food availability: total production output and consumption frequency

2.6 Model Specification and Data Analysis

The relationships among variables were analyzed using a combination of descriptive statistics, regression analysis and Structural Equation Modeling (SEM) (Gujarati & Porter, 2009; Field, 2013)
The SEM framework was specified as:

$$M = \alpha_1 C + \epsilon_1$$
$$P = \beta_1 M + \beta_2 C + \epsilon_2$$
$$F = \gamma_1 P + \gamma_2 M + \epsilon_3$$

where:
C= climate variability
M= microbiome dynamics
P= production performance
F= food availability
The full indirect pathway can be expressed as:

$$F = \gamma_1(\beta_1(\alpha_1 C)) + \epsilon$$

Model estimation was conducted using AMOS and SmartPLS, with goodness of fit assessed using standard indices: CFI ≥ 0.90, RMSEA $\leq 0.08$and $\chi^2/df \leq 3$ (Hair *et al.,* 2021).
Microbiome data were further analyzed using PERMANOVA, Principal Coordinates Analysis (PCoA) and Non-metric Multidimensional Scaling (NMDS) to assess community structure and variation.

2.7 Validity and Reliability

Validity was enhanced by using validated instruments and laboratory procedures. The longitudinal study design enhanced internal validity, accounting for temporal variation and bias.
Reliability was improved by repeated sampling over production cycles and the use of calibrated instruments. Reliability of microbiome data was achieved by technical replicates and consistent bioinformatics processing.

2.8 Ethical Considerations

We secured approval from the appropriate ethics committee. Consent was obtained from all farmers. Fish were handled in accordance with animal welfare standards and data were anonymised to protect confidentiality.

2.9 Methodological Contribution

This research adds to the methodological repertoire by combining climate science, microbial ecology and aquaculture production analysis in a single empirical framework. The use of SEM to model microbiome pathways is a new approach in aquaculture, especially in Africa.

3. Results

3.1 Descriptive Statistics

The summary statistics for the main variables in the aquaculture systems are shown in Table 1. The mean temperature variability was 2.84°C (SD = 0.91), suggesting moderate weather variability among farms. Microbial diversity (Shannon index) had a mean value of 2.67, indicating stable but diverse microbial populations.
Aquaculture production measures showed that the mean survival rate was 78.4%, and aquaculture yield was 2,845 kg/ha/cycle, which is moderate for small- to medium-scale aquaculture production in the region. The Food Availability Index (FAI) mean was 0.63, suggesting aquaculture makes a moderate contribution to household food security.

Table 1: Descriptive Statistics of Study Variables

Variable	Mean	Std. Dev.	Min	Max
Temperature variability (°C)	2.84	0.91	1.20	4.75
Microbial diversity (H′)	2.67	0.58	1.45	3.82
Survival rate (%)	78.4	9.6	55.2	92.3
FCR	1.78	0.32	1.21	2.45
Yield (kg/ha/cycle)	2,845	640	1,650	4,120
Food Availability Index	0.63	0.14	0.32	0.88

3.2 Regression Analysis

The multiple regression analysis (Table 2) shows that temperature variability has a significant negative impact on aquaculture yield ($\beta = -0.37$, $p = 0.003$) . On the other hand, microbial diversity has a significant positive influence ($\beta = 0.42$, $p = 0.007$), showing its importance in improving the yield.

From water quality parameters, dissolved oxygen has a positive impact on yield ($\beta = 0.29$, $p = 0.010$) and ammonia has a significant negative impact ($\beta = -0.33$, $p = 0.014$). The model accounts for 61% of yield variability ($R^2 = 0.61$), suggesting a good fit.

Table 2: Multiple Regression Results (Dependent Variable: Yield)

Variable	Coefficient (β)	Std. Error	t-value	p-value
Temperature variability	-0.37	0.12	-3.08	0.003
Microbial diversity	0.42	0.15	2.80	0.007
Dissolved oxygen	0.29	0.11	2.64	0.010
Ammonia	-0.33	0.13	-2.54	0.014
Constant	1.92	0.54	3.56	0.001

$R^2 = 0.61$ | F-stat = 12.84 ($p < 0.001$)

Interpretation: These results confirm that both stress (temperature variability) and ecological factors (microbial diversity and water quality) combine to influence aquaculture yield.

3.3 Structural Equation Modeling (SEM)

Table 3: SEM Path Coefficients

Path	Coefficient (β)	p-value	Interpretation
Climate → Microbiome	-0.41	<0.001	Strong negative effect
Microbiome → Production	0.36	<0.001	Positive effect
Climate → Production	-0.28	0.004	Direct negative effect
Production → Food availability	0.52	<0.001	Strong positive effect
Microbiome → Food availability	0.21	0.032	Indirect effect

The Structural Equation Model (SEM) findings (Table 3) show strong connections between climate variability, microbiome dynamics, production performance and food availability.

Climate variability has a significant negative impact on microbiome dynamics ($\beta = -0.41$, $p < 0.001$), suggesting that climate variability is driving a loss of microbial diversity and changes in community composition. Microbiome dynamics positively impact production ($\beta = 0.36$, $p < 0.001$). Climate variability also exerts a direct negative effect on production ($\beta = -0.28$, $p = 0.004$), implying both direct and indirect effects. Production has a strong positive effect on food availability ($\beta = 0.52$, $p < 0.001$), with microbiome dynamics also having an indirect effect ($\beta = 0.21$, $p = 0.032$).

Model fit indices (CFI = 0.93; RMSEA = 0.06; $\chi^2/df = 2.14$) indicate a good fit.

Interpretation: These findings support the hypothesis that microbiome dynamics partially mediate the effects of climate variability on production.

Model Fit Indices

Index	Value	Threshold	Status
CFI	0.93	≥0.90	Good fit
RMSEA	0.06	≤0.08	Good fit
χ^2/df	2.14	≤3	Acceptable

Structural Equation Model (SEM) adequacy was measured by applying various goodness-of-fit statistics, such as Comparative Fit Index (CFI), root mean square error of approximation (RMSEA) and chi-square/degrees of freedom ratio (2/df).

The model generated a CFI of 0.93 that is higher than the proposed value of 0.90 meaning that it is a good fit between the hypothesized model and the observed data (Hair et al., 2021). The RMSEA of 0.06 is less than the acceptable maximum value of 0.08 indicating that there is a reasonable fit of the model to the population covariance structure. Also, it has a $\chi 2$/df ratio of 2.14 that is less than 3, thus, establishing the model adequacy.

Interpretation: Combined, these indices indicate that the proposed SEM offers a reasonable approximation of the relationships between climate variability, microbiome dynamics, production performance and food availability.

Implication: This affirms that the path coefficients estimated are sound and the structural relationships determined in the model are statistically sound and interpretable.

Mediation Effects
Indirect effects show that:
Climate variability reduces food availability through microbiome disruption
Mediation effect size = $0.41 \times 0.36 \times 0.52 \approx 0.077$

This confirms partial mediation, meaning microbiomes are a critical pathway.

4. Discussion

Our study provides strong empirical evidence that microbial ecology is a critical link between climate variability and aquaculture production and food security in Sub-Saharan Africa. The inclusion of climate, microecology and production indicators in a structural equation model (SEM) approach offers new insights beyond direct climate-production associations, and highlights the role of ecology in aquaculture production.

4.1 Consistency with Global Findings

Our observed negative effects of temperature variability on microbial diversity are consistent with findings from Asian and European aquaculture. In Southeast Asia, studies have reported that higher temperature variability affects microbial communities, reducing their functional diversity and causing disease outbreaks in intensive aquaculture (Xiong et al., 2024; Chen et al., 2022). Similarly, research in European recirculating aquaculture systems (RAS) indicates that temperature variability disrupts microbial nitrification, which influences water quality and stability of aquaculture production systems (Martínez-Córdova et al., 2020).

But there's a key difference. While European aquaculture is typically largely insulated from environmental variability through technology (e.g. recirculation and aeration), aquaculture in Sub-Saharan Africa is largely uninsulated, and depends on natural water resources (Jolly et al., 2023; Muthoka et al., 2024). This limits the ability of aquaculture to adapt to climate variability impacts on microbial ecology and production. So the findings support the need for locally adapted, ecology-oriented adaptation, rather than costly technologies.

4.2 How Climate, Microbiome and Production are Connected

The findings in this study can be explained by three microbiome-mediated pathways connecting climate variability and production.

4.2.1 Low Oxygen and Hypoxias

Climate variability has a profound impact on dissolved oxygen (DO) levels in aquaculture. Warmer water decreases oxygen solubility and increases oxygen demand, causing oxygen depletion (Boyd, 2020). This inhibits aerobic microbial activity (especially nitrifying bacteria) and facilitates anaerobic pathways that produce toxic byproducts like hydrogen sulfide. The subsequent water quality degradation exerts stress on cultured fish, affecting survival and growth. This finding is consistent with ecological evidence that low oxygen is a major driver of microbial restructuring under climate change (Huang et al., 2025).

4.2.2 Nitrogen Cycling and Ammonia Toxicity

Microbial communities are key to nitrogen cycling in aquaculture through nitrification and denitrification (Avnimelech, 2015). Climate change can alter the microbial community structure and decrease the population and activity of nitrifying bacteria, resulting in increased ammonia (NH_3) levels. High ammonia concentrations affect gill function, reduce appetite and cause mortality in fish (Boyd, 2020). This pathway is supported by the regression analysis in this study, as ammonia hurts yield. This is consistent with findings from global aquaculture, where nitrogen imbalance is a key limiting factor for productivity under climate stress (Zhang et al., 2022).

4.2.3 Pathogen Growth and Microbial Dysbiosis

Variability in climate also provides opportunities for opportunistic pathogens like Vibrio and Aeromonas. These pathogens tend to increase when beneficial microbes decrease and organic matter increases, leading to microbial dysbiosis (De Schryver & Vadstein, 2014).

This results in increased disease outbreaks, decreased survival and unstable production. Experimental evidence from African and Asian aquaculture systems shows that microbial dysbiosis is linked with disease outbreaks and losses (Bereded et al., 2020; Xiong et al., 2024).

4.3 Microbiome as a Modulating System.

One of the most important contributions of the study is that it empirically proves that the impacts of climate variability on the production of aquaculture are mostly indirect and mediated by microbiome. The SEM outcomes show that climate variability plays a critical role in reducing the microbial diversity which in effect affects the production performance and hence food availability. This underpins new ecological concepts that view aquaculture systems as microbiologically controlled ecosystems instead of being input-intensive production systems (Shan et al., 2025; Uddin et al., 2026).

This view reflects a transformation of the older approaches to aquaculture that focus on direct effects of environmental changes on outcomes to a more systems approach that is initiated by microbial processes and in which the effects of environmental change are mediated by production outcomes. This method is becoming a key aspect of aquaculture studies worldwide to elucidate the resilience and sustainability of systems (Naylor et al., 2021).

4.4 Caution Signs of Policy Contradictions and Structural Gaps.

The results indicate a high discrepancy between the existing policy priorities in regards to aquaculture and the ecological truth of the production systems. The current policies of most Sub-Saharan African countries are mainly aimed at intensification, feed inputs, and infrastructure development to increase production (Bene et al., 2015; Tacon et al., 2022). Nonetheless, this research shows that the results of production are highly reliant on the stability of microbes, which is not given much attention in policy frameworks.

This paradox has significant consequences. High intensity without microbiome control may further add stress to the environment, resulting in system instability and outbreak of more diseases. In the same manner, infrastructure investments, which lack the ecological monitoring, cannot respond to causative factors of production variability. These results endorse the recent claims that sustainable development of aquaculture should be based on the idea of integrating ecological and microbial dimensions into policy and management systems (Yadav et al., 2024).

4.5 Implications of Climate-Resilient Aquaculture

The findings highlight the necessity to shift the paradigm to microbiome-based aquaculture systems. These systems give emphasis to ecological balance and resilience by:

- Microbial surveillance and early warning devices.
- Application of probiotics and biofloc technologies.
- Adaptive water quality management measures.

In Sub-Saharan Africa, especially, these methods have proven to be especially applicable, and scalable, cost-effective solutions are needed to improve resilience in the face of climate variability (Muthoka et al., 2024)..By incorporating microbiome management in the aquaculture process, nutrient cycling becomes more effective, diseases are less common, and production yields are more predictable.

4.6 Food Security Implications

The paper also shows how climate-related interference in aquaculture systems has cascading impacts on the availability of food. Lack of stability in production results in changes in the supply of fish, market price hikes, and decreasing accessibility among the low-income strata. This is especially important in Sub-Saharan Africa, where fish forms a significant part of the dietary protein and a source of vital micronutrients (Golden et al., 2016; Belton et al., 2018). The findings thus empirically confirm the argument that climate change impacts food security via both direct and indirect environmental effects with the help of microbial processes. This has significant implications on meeting global development goals, especially, Sustainable Development Goals 2 (Zero Hunger) and 13 (Climate Action).).

4.7 Scholarly Contribution

The present study adds to the body of literature in three important aspects: It offers one of the first empirical tests of SEM to estimate climate-microbiome-production interactions in African aquaculture systems. It identifies the dynamics of microbiomes as an important mediator of climate stress in aquacultural productivity. It points to the necessity of the inclusion of microbial ecology in aquaculture policy, management and sustainability models.

Recommendations

4.8 Microbiome-Informed Aquaculture Management

Aquaculture operators should include microbiome monitoring and management in their practices. This includes:

- probiotics and biofloc to maintain microbial stability
- microbial profiling to monitor early signs of imbalance
- keeping good water quality to facilitate beneficial microbial processes

Climate-Resilient Production Practices

On-farm adaptation measures should be enhanced to minimise climate variability, such as:

- use of aeration to prevent oxygen deficiency
- temperature control through shading or water exchange
- use of climate-resilient pond designs

Inclusion of Microbial Indicators in Policy

Policy makers should broaden aquaculture development plans to include microbial and ecological indicators as performance indicators. This will enable:

- better evaluation of system health
- disease outbreak early warning systems
- improved sustainability monitoring

Capacity Building and Technology Transfer

There is a need to build capacity in farmers and extension services in:

- microbiome management techniques
- climate risk assessment
- data-driven aquaculture practices

Training and extension services will increase the uptake of new practices in Sub-Saharan Africa.

Improving Data and Research

Future research should:

- monitor the aquaculture system for more than two cycles
- include metagenomics and functional gene studies
- consider variations among African aquaculture systems

Research networks should be formed to provide quality data for policy making.

Enhancing Food System Resilience

Governments and stakeholders should ensure food security by:

- provide subsidies and access to climate-smart technologies to smallholder aquaculture
- improve market mechanisms to enhance fish supply and prices
- incorporate aquaculture into food security plans

The journey towards sustainable aquaculture in Africa will require an awareness that microbial ecology is not a side issue but critical to system resilience. Ignoring this aspect in policies and practices can compromise productivity and food security.

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