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ENVIRONMENTAL STRESS AND SMART AGRICULTURE

POLLUTION, AI EXTENSION AND PLANT HEALTH

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PREFACE

Agriculture remains the backbone of many economies and communities across the globe, yet it faces mounting challenges from environmental degradation, technological gaps, and biological complexities. This book brings together three critical explorations that illuminate the evolving landscape of agricultural science and practice.

The first chapter examines the profound impact of environmental pollution on agricultural productivity in Nigeria's Niger-Delta region, revealing how industrial activities and ecological disruption threaten food security and rural livelihoods. The second chapter shifts focus to innovation, showcasing how artificial intelligence can revolutionize smallholder farming in Sub-Saharan Africa by enhancing agricultural extension services and empowering farmers with data-driven decision-making. The final chapter delves into plant physiology, investigating the role of rootstocks in mediating heavy metal transfer and bioaccumulation in apple trees—an inquiry that bridges environmental science with horticultural resilience.

Together, these chapters offer a compelling narrative of challenge and transformation, underscoring the urgent need for sustainable, intelligent, and adaptive agricultural systems in the face of global change.

Editoral Team
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Türkiye

CHAPTER 1
EFFECTS OF ENVIRONMENTAL POLLUTION ON AGRICULTURAL PRODUCTION ACTIVITIES IN THE NIGER-DELTA REGION OF NIGERIA

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INTRODUCTION

Agriculture plays a critical role in achieving the Sustainable Development Goals (SDGs) by promoting food security, boosting income generation, and creating employment, thereby fostering economic growth and development (Ayinde et al., 2021). In Africa, especially Nigeria, agriculture is a cornerstone of the economy, with 70% of Africans, including 80% of the continent's poor, residing in rural areas and relying heavily on agriculture for their livelihoods. In Nigeria, agriculture was historically the most important economic sector, vital for rural employment, food, fibre sufficiency, and export earnings before the discovery of oil. However, the rise of the oil industry has significantly overshadowed agriculture's role, contributing substantially to Nigeria's GDP, government revenue, and foreign exchange earnings since the 1970s (Eleke et al., 2019). This shift has led to environmental consequences, including agricultural pollution, as efforts to meet human needs have disrupted natural balances, rendering many areas unsuitable for cultivation and habitation (Okojie et al., 2019).

Environmental pollution, a critical global issue, is exacerbated by human activities and technological manipulation of ecosystems. Common pollutants include chemicals, garbage, and wastewater, which negatively impact both human health and agricultural productivity, leading to significant welfare losses (Godson-Ibeji and Chikaire, 2016; Wel and Wang, 2021). Intensive oil production has led to severe environmental pollution, affecting water bodies, terrestrial ecosystems, and farmlands, which are critical for the livelihood of many Nigerians (Ejiba et al., 2016). Oil spills alone have caused Nigeria to lose over 30% of its habitable environment, leading to the destruction of crops and aquaculture and increased soil infertility, which impoverishes farmers further (Otunkor and Ohwovorione, 2015; Godson-Ibeji and Chikaire, 2016). The resultant environmental pollution presents significant challenges, including air and water pollution, chemical application, solid waste management, deforestation, desertification, wind erosion, and flooding, particularly in highly industrialized cities (Akpokodje and Salau, 2015).

Despite the critical economic role of agriculture and the severe impacts of environmental pollution, the Nigerian government and oil companies often downplay these issues.

Addressing the environmental damage caused by oil production is essential to revitalize agricultural productivity and ensure the well-being of the population (Godson-Ibeji and Chikaire, 2016).

1. STATEMENT OF THE PROBLEM

The Niger Delta, comprising the states of Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo, and Rivers, is richly endowed with natural resources. Oil and gas account for over 85% of Nigeria's National Gross Domestic Product (GDP), over 95% of the national budget, and over 80% of national wealth (Ekanem and Nwachukwu, 2015). Despite its abundance, the Niger Delta region faces a development incongruity characterized by endemic poverty amidst vast natural and financial resources. The region's ecosystem is considered one of the most endangered globally (Anejionu et al., 2015).

Before crude oil exploitation, the host communities had a thriving economy, with about 90% of the population engaged in agriculture and fishing. The locals relied on land, water, and forest resources, being farmers, fishermen, and hunters who valued their environment for their sustenance and future generations. The discovery of oil raised their hopes for development, but they soon realized that the Nigerian state and oil companies prioritized profit and capital accumulation over their welfare and development (Ani et al., 2015).

Crude oil exploitation has disrupted the economic activities of the people and destabilized the ecosystem. The economic activities, particularly agriculture and fishing, are now vulnerable to these shocks, resulting in significant decreases in outputs and increasing poverty. Pollution and continuous gas flaring from oil production have created health hazards and rendered fishing and farming nearly impossible. Large oil spills occasionally kill fish, destroy crops, and pollute water sources, severely impacting families and communities. The primary occupations of farming and fishing have been decimated, and the region lacks basic infrastructure and amenities such as electricity, roads, schools, hospitals, and potable water (Bassey, 2013). Given this backdrop, this study aims to investigate the effects of environmental pollution on agricultural production activities in the Niger-Delta region of Nigeria.

1.1 Objectives of the Study

Specifically, the study:

- Describe the socioeconomic characteristics of respondents in the study area;
- Identify the agricultural production activities of the respondents in the study area;
- Highlight the causes of environmental pollution in the study area;
- Examine the perceived effect of environmental pollution on agricultural production activities in the study area:
- Determine the factors predisposing the farmers to environmental pollution in the study area;
- Assess the adaptation strategies adopted to cope with the environmental pollution effects in the study area.

2. LITERATURE REVIEW

Environmental Pollution in Nigeria

According to Godson-Ibeji and Chikaire (2016), environmental pollution is the introduction of different harmful pollutants in a certain environment that make the environment unhealthy for survival of man, flora and fauna. Some of the most common pollutants are garbage, waste water and chemicals. In Nigeria, environmental pollution is a significant concern, particularly in the Niger Delta region. Oil spills, gas flaring, and industrial discharges have severely impacted the environment and local communities. Agricultural activities are also affected, leading to reduced productivity and economic challenges for farmers. Studies (Nriagu et al., 2016; Okojie et al., 2019) have shown that environmental pollution in Nigeria has led to health problems, loss of biodiversity, and socio-economic challenges for affected communities.

The Niger Delta region is the oil producing area of Nigeria, which consists of highly diverse ecosystems that are supportive of numerous species of terrestrial and aquatic fauna and flora (Osuagwu and Olaifa, 2018). The key environmental issues in the Niger Delta of Nigeria relate to its petroleum industry (Albert et al.,2018).

Sadly, the advent of oil production has also negatively impacted the Niger Delta region due to unprecedented oil spillage which has been on-going for the past 5 decades making the region one of the most polluted in the world. It is estimated that while European Union experienced 10 incidence of oil spills in 40 years, Nigeria recorded 9,343 cases within 10 years (Albert et al., 2018) The carelessness of the oil industry has also precipitated this situation, which can perhaps be best encapsulated by a 1983 report issued by the NNPC, long before popular unrest surfaced. The resultant environmental degradation from gas flaring, dredging of larger rivers, oil spillage and reclamation of land due to oil and gas extraction across the Niger Delta region costs about US$758 million every year (Ayanlade and Ulrike, 2015).

Environmental pollution also constitutes industrial waste disposal, seismic operations, hazardous substance, gaseous emission/flare and oil spill. However, gas flare and oil spill constitute the major source of environmental pollution in the region. These pollutants diminish property value and health of the people of the oil bearing communities. In some cases, firms including international oil companies (IOCs) released pollution (e.g. flare and spill) into the environment which degrade environmental resources of water bodies, farmland and mangrove ecosystem. The toxicity of oil spill disrupts ecosystem stability, causes severe damage to marine fish and fisheries, and threatens as well as destroys biodiversity habitat (Kornom-Gbaraba, et al., 2022).

Sources of Environmental Pollution in Agricultural Settings

Agricultural production activities in the Niger-Delta region are affected by various sources of environmental pollution. These include:

- **Agricultural Runoff:** The use of pesticides, herbicides, and chemical fertilizers in farming practices contributes to runoff that contaminates water bodies and affects soil health (Maton et al., 2016).
- **Industrial Emissions:** Industries located near agricultural areas emit pollutants such as particulate matter and toxic chemicals, which can degrade air quality and impact crop growth and human health (Wei and Wang, 2021).
- **Oil Exploration Activities:** Oil exploration and production activities generate environmental pollutants such as oil spills, drilling fluids, and

gas flaring, which can contaminate soil, water, and air, affecting agricultural lands and livestock (Ndu-Ogbuji and Kenigua, 2022).

- **Waste Disposal Practices:** Improper disposal of agricultural and industrial waste can lead to soil contamination and groundwater pollution, posing risks to agricultural sustainability (Aminu et al., 2020).

Impacts of Environmental Pollution on Agricultural Production

Previous research has documented several impacts of environmental pollution on agricultural production to include:

- **Soil Degradation:** Pollutants from agricultural runoff and industrial activities can degrade soil fertility, reducing crop yields and compromising agricultural sustainability (Eleke et al., 2019).
- **Water Contamination:** Pollution from various sources contaminates water used for irrigation and domestic use (Kornom-Gbaraba, et al., 2022).
- **Crop and Livestock Health:** Exposure to pollutants such as pesticides and heavy metals can adversely affect crop growth and livestock health, especially seafoods, leading to reduced productivity and economic losses for farmers (Osuagwu and Olaifa, 2018).

Consequences of Environmental Pollution in the Niger Delta

Environmental pollution in the Niger Delta has wide-ranging consequences for health, natural resources, and livelihoods. Women's reproductive health is particularly affected, with exposure to pollutants linked to irregular menstrual cycles, infertility, pregnancy loss, low birth weight, premature birth, and congenital abnormalities, corroborating Schwartz et al., (2016). Access to safe water sources is also severely compromised. Petroleum hydrocarbons from oil spills and industrial discharges contaminate rivers, streams, and wells, making drinking water unsafe. Raji and Abejide (2013) reported hydrocarbon concentrations in Ogoni community water sources far above EU safety limits, while Balogun and Kareem (2013) estimated that over 68% of water in Ilaje community has been contaminated, complicating access to potable water.

Biodiversity loss is another critical impact. The Niger Delta's diverse ecosystems of mangroves, wildlife, and aquatic species are increasingly threatened by oil exploration activities. UNEP (2011) noted the destruction of mangrove forests, while Mogborukor (2014) reported habitat distortion and disrupted reproductive cycles of both terrestrial and aquatic species. Eshagberi and Ofotokun (2019) stressed that such biodiversity loss diminishes ecosystem stability and productivity. Pollution also undermines livelihoods, especially farming and fishing, which remain the backbone of rural subsistence. Oil spills damage farmlands, reduce soil fertility, and contaminate water, thereby threatening food security and income generation (Ejiba et al., 2016; Osuagwu and Olaifa (2018).

2.1 Theoretical Review

The theoretical framework for understanding the effects of environmental pollution on agricultural production activities is anchored in several theories that explain the relationship between the environment and agricultural productivity. Key theories include the Environmental Kuznets Curve (EKC), the Theory of Externalities, and the Sustainable Livelihoods Framework. These theories provide a basis for examining how pollution impacts agricultural practices, yields, and the overall socio-economic well-being of farmers in Nigeria.

The Environmental Kuznets Curve (EKC) suggests that pollution may rise with early stages of development but decline with technological advancement and stricter regulations (Grossman and Krueger, 1995). The Theory of Externalities (Pigou, 1920) explains pollution as a negative externality where industries impose costs on farmers through soil degradation and water contamination. The Sustainable Livelihoods Framework highlights how environmental quality directly shapes household resilience and agricultural productivity (Chambers and Conway, 1992). In this context, balancing economic growth with environmental sustainability becomes a central concern of development policies. Effective environmental regulations and innovative technologies can enhance productivity while reducing ecological degradation.

2.2 Empirical Review

Empirical studies confirm that environmental pollution reduces soil fertility (Ani et al., 2015; Eshagberi and Ofotokun, 2019), contaminates water sources (Kornom-Gbaraba, et al., 2022; Adeniran et al., 2023), and lowers crop yields (Godson-Ibeji and Chikaire, 2016; Osuagwu and Olaifa, 2018). These impacts lead to declining incomes, poverty, and food insecurity among farming households (Ejiba et al., 2016; Eleke et al., 2019).

3. METHODOLOGY

The study was conducted in the Niger Delta Region of Nigeria, a vast wetland in the country's south where the River Niger flows into the Atlantic Ocean through creeks, rivers, and mangroves. Covering nine states: Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo, and Rivers, and about 70,000 km^2, the region is characterized by low-lying coastal terrain, heavy rainfall (2,000-4,000 mm), and a humid tropical climate that supports crops such as cassava, yam, maize, rice, plantain, oil palm, and vegetables, alongside fishing as a major livelihood. Although richly endowed with crude oil and natural gas, which contribute over 80% of Nigeria's foreign exchange, decades of exploitation have led to severe environmental pollution such as oil spills, gas flaring, deforestation, soil and water degradation undermining agricultural productivity and rural livelihoods. With over 31 million people, the region is densely populated yet suffers from poverty, unemployment, and poor infrastructure, reflecting the paradox of resource wealth and socio-economic deprivation. These conditions make the Niger Delta a relevant case for assessing the impacts of environmental pollution on agriculture and rural welfare. Over the years, numerous studies have highlighted the complex interactions between environmental degradation, resource management, and community livelihoods in the region.The persistent environmental challenges have also intensified migration, social unrest, and conflicts over access to land and natural resources. Consequently, understanding the dynamics of pollution and its effects on agricultural systems is essential for formulating sustainable development and policy interventions in the Niger Delta.

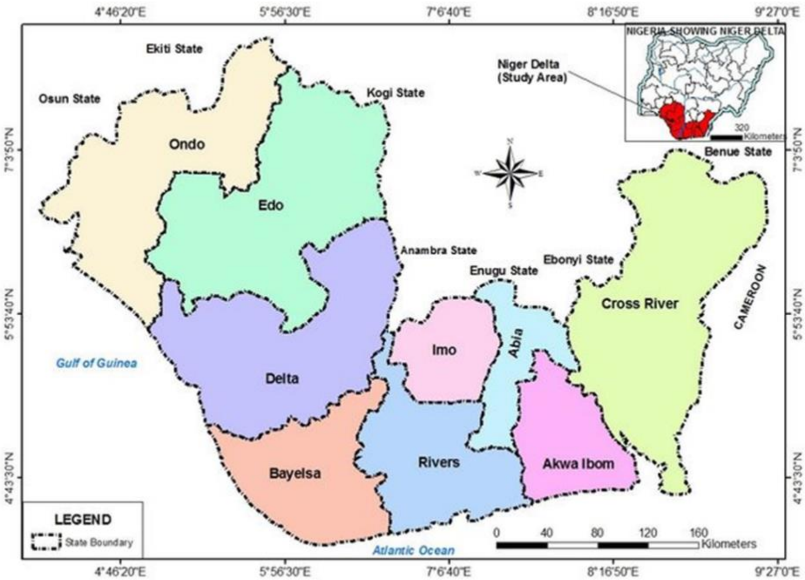

Figure 1. Map of the Niger Delta region (Udotong et al., 2017)

3.1 Sample and Sampling Technique

The study employed a multistage sampling technique to select 240 respondents. In the first stage, two states were purposively selected from the Niger Delta region for ease of data collection. The second stage involved the purposive selection of two Local Government Areas (LGAs) from each selected state due to the significant prevalence of environmental pollution. In the third stage, two farming communities were randomly selected from each of the chosen LGAs, resulting in a total of eight communities. At the final stage, 30 farmers were randomly selected from each of the selected communities. Community leaders assisted in identifying notable farmers within their respective communities to participate in the study. The sample size was 240 respondents.

3.2 Data Collection

Data for the study were collected from both primary and secondary sources. The primary sources of data included questionnaires, oral interviews, and personal observation.

Questionnaires allowed for structured data collection, oral interviews provided qualitative insights, and personal observation helped in understanding contextual factors. The secondary data sources included books, journals, and Internet searches. These sources provided background information and supported the findings from primary data.

Likert Scale Rating Technique

The study used a 5-point Likert scale to assess the perceived effects of environmental pollution on agricultural production activities. The scale ranged from Strongly Agreed (SA) = 5 to Strongly Disagreed (SD) = 1. The weighted mean (x) was calculated for each statement. The mean score cut-off point was set at 3. Statements with a mean score of 3 and above indicated agreement with the statement, while statements with a mean score below 3 indicated disagreements.

3.3 Analytical Techniques

The following techniques were employed to analyse data collected for the study:

3.3.1 Descriptive Analysis

This was used to describe demographic variables of the respondents, identify the agricultural practices prevalent among the respondents, describe the sources of pollution, calculate means to assess the perceived impact of pollution and document the strategies adopted by farmers to mitigate the effects of pollution in the region.

3.3.2 Multiple Regression Analysis

This was used to determine factors predisposing the farmers to environmental pollution in the study area. The model is specified as:

$$Qi = f(\beta 1X1+\beta 2X2 + \beta 3X3 +\beta 4X4 +\beta 5X5 + \beta 6X6 +\ldots + \beta nXn + ei \quad (1)$$

The dependent variable (Qi) is an index of the degree of environmental pollution experienced.

The X's are the explanatory variables expressed as:

X1 = Sex of farmers (1 if male; 0 otherwise), X2 = Age (years), X3 = Education level (years), X4 = Household size (number), X5 = Farm size (hectares), X6 = Farming/Fishing experience (years), X7 = Frequency of extension contact, X8 = Major occupation (1 if agricultural activities; 0 otherwise), X9 = Off-farm engagement (1 if yes; 0 otherwise), X10 = Membership of cooperative association (1 if yes; 0 otherwise), X11 = Access to credit/loan (1 if yes; 0 otherwise), X12 = Proximity of farm to industrial activities/pollution sites, X13 = Monthly income (₦). β's = parameters to be estimated, ε = error term.

Four functional form of the models - Linear, Exponential, Double Log, Semi-log were tested, and the best model was selected based on the following criteria: economic criteria, in terms of a-priori expected signs of coefficient; and statistical criteria considering the values of the coefficient of multiple determination (R2) and F-test statistics.

4. RESULTS AND DISCUSSION

4.1 Socio-Economic Characteristics of the Respondents

The results on socio-economic characteristics revealed that farming in the study area was male-dominated (56.7%), supporting the findings of Ani et al., (2015) that men are more engaged in agricultural production due to their roles as household heads. The majority of farmers were above 50 years with a mean age of approximately 57 years, indicating an aging farming population, which may reduce efficiency and slow adoption of pollution mitigation measures. Education levels showed that most respondents had some form of formal education, aligning with Edet et al., (2019), who emphasized that education enhances innovation adoption and improves farm management. Marital status results indicated that nearly half (46.7%) were married, corroborating Osarenren and Emakoro (2015), who observed that married farmers are often more mature and better positioned for collaborative decision-making. Household size was relatively large (mean = 9 persons), with 40% having between 6-10 members. This suggests potential labour availability, consistent with Ogunleye et al., (2021), who linked larger households to higher technology adoption. However, as noted by Godson-Ibeji and Chikaire (2016), large families can deepen poverty when pollution reduces farm output.

Table 1. Summary of Selected Socio-economic Characteristics of the Respondents

Variable	Frequency	Percentage (%)	Mean
Sex			
Male	104	43.3	
Female	136	56.7	
Age (years)			
41-50	88	36.7	57.28±15.425
>50	152	63.3	
Educational Qualification No formal Education	24	10.0	
Primary	32	13.3	
Secondary	96	40.0	
Tertiary	88	36.7	
Marital Status Single	8	3.3	
Married	112	46.7	
Divorced	56	23.3	
Widowed	64	26.7	
Household Size			
≤5	64	26.7	
6-10	96	40.0	9±2.755
>10	80	33.3	
Farming Experience			
≤10	16	6.7	
11-30 >30	164 60	68.3 25.0	28.76±15.047
Farm Size			
≤1	98	40.8	
1.1-3	46	19.2	2.07±1.907
>3	96	40.0	
Extension Contact			
No	144	60.0	
Yes	96	40.0	
Farm's Proximity to Pollution Site No Yes	 88 152	 36.7 63.3	

Nevertheless, respondents had long years of farming experience (average ≈ 29 years), in line with Ani et al., (2015), who noted that experienced farmers often witness and manage long-term environmental changes affecting production. Furthermore, majority of respondents (60%) had no contact with extension agents, while 40% had some level of interaction with them. This suggests that most farmers lacked access to vital information on innovative strategies for mitigating the effects of environmental pollution on their agricultural activities. Majority (63.3%) of respondents' farms were located near pollution sites. Exposure to pollutants such as heavy metals, industrial waste, and toxic chemicals can degrade soil quality, deplete fertility, and ultimately reduce crop yields.

4.2 Agricultural Activities of the Respondents

Figure 1 presents the results on the general agricultural production activities of the respondents in the study area. The results show that majority of the respondents were involved in mixed farming, combining both crop and livestock production, 59.2% were solely involved in crop production and 46.7% were involved in producing livestock only. This emphasizes the need to curb the effects on environmental pollution on agricultural activities, a major means of livelihood of the respondents in the study area.

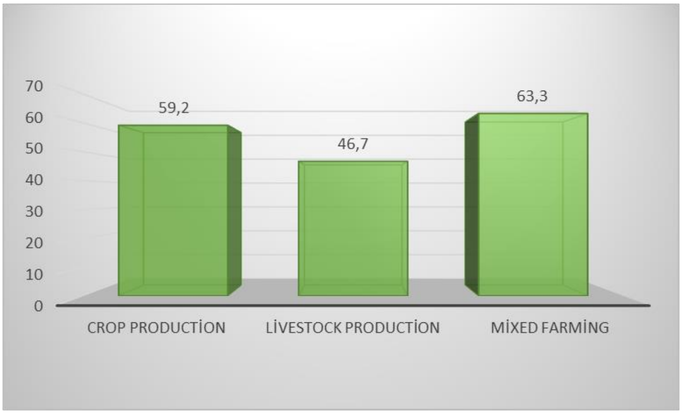

Figure 2. Agricultural Activities of the Respondents

4.3 Major Sources of Environmental Pollution in the Study Area

Table 2 presents the major sources of environmental pollution affecting agricultural activities in the study area. The findings indicate that oil exploration activities were the predominant source, as reported by 93.3% of respondents. These activities contribute to land degradation, water contamination, and air pollution through oil spills, gas flaring, and chemical discharges, adversely affecting agriculture, biodiversity, and human health. Additionally, oil exploration exacerbates climate change, displaces communities, and creates socio-economic instability in the Niger Delta region. This finding agrees with the reports of Otunkor and Ohwovorione (2015) and Godson-Ibeji and Chikaire (2016), which highlight that oil spills alone have led to the loss of over 30% of Nigeria's habitable environment, resulting in the destruction of crops and aquaculture, increased soil infertility, and worsening poverty among farmers. The study also corroborates the findings of Osuagwu and Olaifa (2018), who noted that the long-term effects of oil spills often include reduced crop yields and fish mortality.

Water pollution from agricultural runoff or waste disposal was identified as a source of environmental pollution by 70% of respondents. This form of pollution leads to chemical contamination, eutrophication, and oxygen depletion in aquatic ecosystems, endangering marine life and reducing water quality for human consumption. Additionally, the build-up of pesticides, fertilizers, and organic waste in water bodies increases the risk of toxic algal blooms, waterborne diseases, and long-term ecosystem degradation. This underscores the need for stricter regulations and sustainable farming practices. These findings align with Jibir et al., (2016), who reported that excessive agrochemical use has led to severe environmental issues, including pollution, land degradation, and the loss of both wildlife and beneficial organisms.

Soil erosion and land degradation were identified as sources of environmental pollution by 63.3% of respondents, leading to the loss of fertile topsoil, reduced agricultural productivity, and increased sedimentation in water bodies. These processes disrupt aquatic ecosystems and degrade water quality.

Additionally, land degradation contributes to desertification, carbon release into the atmosphere, and reduced vegetation cover, further exacerbating climate change and biodiversity loss. This finding corroborates the report by Godson-Ibeji and Chikaire (2016), which highlights that land degradation, as a cumulative decline in the productive potential of the land, negatively impacts agricultural productivity in Nigeria.

The majority (53.3%) of respondents identified emissions from livestock production as a source of environmental pollution in the study area. Livestock emissions, primarily methane (CH_4) from enteric fermentation and nitrous oxide (N_2O) from manure, significantly contribute to greenhouse.

Table 2. Major Sources of Environmental Pollution in the Study Area

Sources (Multiple responses)	Frequency	Percentage
Oil exploration activities	78	93.3
Emission from livestock production	64	53.3
Water pollution from run off or waste disposal	84	70.0
Soil erosion and land degradation	76	63.3
Excessive irrigation	36	30.0
Air pollution from agricultural activities	46	36.3

Gas accumulation, global warming, and climate change. Additionally, ammonia (NH_3) emissions degrade air and water quality, leading to acid rain, biodiversity loss, and health risks for both humans and animals. This finding is in tandem with the study by Harisfina and Zornitsa (2018), which reported that methane, ammonia, and carbon dioxide are the leading pollutants from the agricultural sector. They also noted that ammonia emissions from agricultural activities accounted for 83% of total agricultural air pollution in 2015. Furthermore, the anaerobic decomposition of manure releases methane (CH_4) and nitrous oxide (N_2O), both of which contribute significantly to global warming. A minority (36.3%) of respondents identified air pollution from agricultural activities as a source of environmental pollution in the study area. Agricultural air pollution, resulting from practices such as bush burning, crop residue burning, pesticide spraying, and livestock emissions, releases greenhouse gases and particulate matter that contribute to climate change, respiratory diseases, and reduced air quality. Additionally, ammonia from fertilizers and manure reacts with atmospheric compounds to form fine particulate pollution, leading to acid rain and ecosystem degradation. This finding is consistent with the report by Wei and Wang (2021), which highlights that air pollutants disrupt plants' biochemical and physiological processes, while acid rain caused by air pollution degrades soil quality and reduces the concentration of essential nutrients needed for crop growth.

Excessive irrigation was identified as a major source of environmental pollution by 30% of respondents. Over-irrigation leads to waterlogging, soil salinization, and depletion of groundwater resources, which reduce soil fertility and crop productivity. Additionally, it contributes to chemical runoff and the contamination of water bodies, negatively impacting aquatic ecosystems and increasing the risk of waterborne diseases. This finding aligns with the study by Makone et al., (2021), which reported that poorly managed irrigation can cause irreversible damage to soil properties, both in the short and long term. Long-term effects include soil erosion, groundwater pollution, and increased salinity, all of which threaten sustainable agricultural production.

4.4 Perceived Effect of Environmental Pollution on Agricultural Production Activities

The results of the Likert scale on respondents' perceived effects of environmental pollution on agricultural production activities, as presented in Table 3, indicate strong agreement among the majority of respondents on several key issues. Specifically, 80% strongly agreed that polluted water sources have caused diseases in livestock, while 73.3% believed environmental pollution has increased pest resistance due to pesticide use. Additionally, 71.7% reported a decline in livestock production due to contaminated feed, and 70% stated that livestock health has deteriorated due to pollution. Furthermore, 70% of respondents agreed that environmental pollution has reduced the variety of crops they can grow, while 66.7% indicated that pollution has led to increased agricultural production costs. Moreover, 65% of respondents acknowledged that agricultural activities in their locality are vulnerable to environmental pollution, and 59.2% agreed that pollution has affected their ability to store and preserve agricultural products.

In the same vein, 90% agreed that polluted water sources have negatively impacted irrigation practices, 73.3% reported adverse health effects, 70% noted that soil contamination has reduced soil fertility, and 52.5% observed changes in soil texture and colour due to pollution.

However, 58.3% of respondents disagreed with the statement that "Environmental pollution has forced farmers to abandon their farms," explaining that despite its negative impact on their livelihoods, they have continued farming, as it remains their primary source of income

Table 3. Perceived effects of environmental pollution on agricultural activities

Statements	SA	A	U	D	SD	Mean
Pollution impacts local farming	65%	26.7%	8.3%	0%	0%	4.57
Pollution reduces crop yield	51.7%	28.3%	3.3%	16.7%	0%	4.15
Polluted water affects irrigation	10%	90%	0%	0%	0%	4.10
Pollution reduces soil fertility	30%	70%	0%	0%	0%	4.30
Pollution alters soil texture and color	33.3%	52.5%	14.2%	0%	0%	4.47
Pollution reduces availability of clean water for farming	50%	43.3%	6.7%	0%	0%	4.50
Polluted water causes crop diseases	56.7%	43.3%	0%	0%	0%	4.57
Pollution has reduced crop variety	70%	30%	0%	0%	0%	4.70
Pollution affects storage of agricultural products	59.2%	36.7%	4.2%	0%	0%	4.63
Pollution increases pest resistance	73.3%	26.7%	0%	0%	0%	4.73
Pollution harms livestock health	70%	30%	0%	0%	0%	4.70
Polluted water causes livestock diseases	80%	20%	0%	0%	0%	4.80
Contaminated feed reduces livestock production	71.7%	25.8%	2.5%	0%	0%	4.73
Pollution raises agricultural production costs	66.7%	33.3%	0%	0%	0%	4.67
Reduced agricultural productivity lowers household income	56.7%	43.3%	0%	0%	0%	4.57
Pollution forces farmers to abandon farms	9.2%	10%	0%	58.3%	22.5%	2.25
Pollution increases my reliance on external support	56.7%	43.3%	0%	0%	0%	4.57
Pollution harms my health	22.5%	73.3%	4.2%	0%	0%	4.20

4.5 Factors Predisposing Farmers to Environmental Pollution in the Study Area

The multiple regression model results presented in Table 4 indicate that several socio-economic and farm-related factors significantly predispose farmers to environmental pollution in the study area. The linear regression model was selected as the best fit based on its high coefficient of determination ($R^2 = 0.783$), indicating that approximately 78% of the variation in farmers' exposure to environmental pollution was explained by the included variables. The model's F-statistic was significant at the 1% level, confirming the overall significance of the explanatory variables in determining environmental pollution exposure.

The results show that sex of respondents, age, education, household size, farm size, frequency of extension visits, agricultural activities as major occupation, off-farm engagement, cooperative membership, access to loan, farm located close to pollution site and income were the significant factors predisposing farmers to environmental pollution in the study area. The coefficient of sex was negative and significant at 1% level of probability. This implies that the level of environment pollution experienced by the farmers' decreases with sex, indicating that female farmers were more prone to experiencing environmental pollution than male farmers in the study area. This agrees with the findings of Ndu-Ogbuji and Kenigua (2022) that pollution significantly affected the social, economic, and health conditions of the women in Rivers State, Nigeria and that proximity to polluted areas and lack of ownership of land were the major causes of vulnerabilities for women.

Educational level of the farmers was also negative and significant at 1% alpha level. This implies that the degree of experiencing environmental pollution decreases with education in the study area. This is because education enhances awareness and adoption of sustainable practices, enabling the farmers to mitigate environmental pollution through informed decision-making and responsible resource management. This is in line with the reports of Famuyiwa and Akinola (2018) that educated farmers are better knowledgeable about the appropriate decisions to make in order to mitigate the impact of risks on their farms.

Household size ($p<0.01$) and frequency of extension agents' visits ($p<0.01$) also had negative significant relationship with the level of environmental pollution experienced in the study area. This implies that experience of environmental pollution decreases with household size and regular visits by extension agents in the study area. A smaller household size reduces resource consumption and waste generation, minimising environmental pollution and promoting sustainable living practices.

Table 4. Factors Predisposing Farmers to Environmental Pollution in the Study Area

Variable	Coefficient	T-ratio	Sig
(Constant)	2.639	7.601	0.001
Sex	-0.405***	-3.626	0.001
Age	0.013*	1.968	0.052
Education	-0.249***	-4.798	0.001
Household size	-0.051***	-4.656	0.001
Farm size	0.040**	2.019	0.046
Farming experience	-0.004	-0.915	0.362
Frequency of visit	-0.175***	-2.582	0.011
Agric. activities as major occupation	0.979***	6.766	0.001
Off-farm engagement	0.131**	2.440	0.016
Cooperative association membership	-0.241**	-2.036	0.044
Access to loan	-0.928***	-7.942	0.001
Farm located close to pollution site	0.401***	3.556	0.001
Income	-0.000**	-2.085	0.039
R	0.863		
R^2	0.783		
Adj. R^2	0.727		
F	10.472		

Also, regular visits from extension agents promote the adoption of eco-friendly farming practices, enhancing environmental awareness and reducing pollution from agricultural activities.

Additionally, coefficients of cooperative association membership, access to loan and income were negative and significant at 5% alpha levels, respectively. This indicates that these variables reduce the level of environmental pollution experienced in the study area.

Membership in cooperatives facilitates knowledge sharing and access to sustainable farming technologies; access to loan and higher income levels enables farmers to invest in modern eco-friendly equipment and practices, adopt cleaner technologies and implement better waste management practices, minimizing and promoting sustainable agriculture. This corroborates the findings of Aminu et al., (2021) that high income earners are better equipped to device coping mechanisms and undertake investments that quickly lessen the impact of risks.

Conversely, age of the respondents was found to have a direct relationship with the levels of environmental pollution experienced at 10% alpha levels. This suggest that the level of experiencing environmental pollution increases with the age of the farmers. Older farmers may experience environmental pollution due to prolonged exposure to unsustainable farming practices and resistance to modern eco-friendly methods. Engaging in agricultural activities as the major occupation also had a positive significant relationship with the levels of experiencing environmental pollution in the study area. This implies that the level of experiencing environmental pollution increases with agricultural activities as the major occupation. This could be due to intensified land use, chemical application, and waste generation, leading to soil, water, and air pollution.

In the same vein, farm size of the respondents was found to be positive and significant at 5% alpha levels implying that experience of environmental pollution increases with farm size. Larger farms generate more agricultural waste, require higher chemical inputs, and contribute more to deforestation leading to greater environmental pollution. Off-farm engagement also had positive significant relationship with the level of experiencing environmental pollution in the study area. This implies that, the more the farmers engage in off-farm engagements, the more they experience environmental pollution. This could be because farmers with off-farm jobs may have less time to implement sustainable practices, increasing reliance on conventional methods that contribute to pollution. Furthermore, having farms located close to pollution site increases the level of experiencing environmental pollution at 5% level of probability.

Proximity to pollution sites exposes farms to contaminated soil, water, and air, worsening environmental degradation and reducing agricultural productivity.

4.6 Adaptation Strategies Adopted to Cope with the Environmental Pollution Effects

Farmers in the study area employed various strategies to cope with the adverse effects of environmental pollution on their agricultural activities. The results presented in Table 5 indicate that, the most commonly adopted strategies include use of agrochemicals, adopted by 76.7% of the respondents. This was followed by crop diversification (74.3%). Soil conservation measures was adopted by 63.3% of the respondents and changing crop selection or rotation pattern was adopted by 61.7% of the respondents. Other adaptation strategies adopted in the study area included efficient water and nutrient management (40%), use of organic or bio-pesticides (36.7%), participation in agricultural extension programs on pollution management (30%), use of alternative pest control methods (26.7%), organic farming methods (23.3%), among others. Adopting these various strategies to mitigate environmental pollution enhances ecosystem resilience, improves agricultural sustainability and reduces health risks for farmers and communities. It also promotes efficient resource use, minimizes economic losses and ensures long-term environmental protection for future generations. The choice of adaptation strategies often depended on farmers' access to knowledge, resources, and technical support, highlighting the importance of targeted training and extension services. Farmers combining multiple approaches tended to achieve better crop performance and lower contamination risks, demonstrating the benefits of integrated management practices. Overall, these adaptive measures underscore the critical role of proactive responses in sustaining agricultural productivity in areas affected by environmental pollution.

Table 5. Strategies Adopted to Mitigate the Effects of Environmental Pollution

Strategies	Frequency	Percentage
Changed crop selection or rotation pattern	74	61.7
Use of agrochemicals	92	76.7
Implemented soil conservation measures	76	63.3
Efficient water and nutrient management	48	40.0
Adopted organic farming methods	28	23.3
Use of alternative pest control methods	32	26.7
Use precision agricultural technologies	4	3.3
Use of organic or bio-pesticides	44	36.7
Participation in agricultural extension programs on pollution management	36	30.0
Implementation of crop diversification	89	74.3
Installation of water purification systems	20	16.7

4.7 Initiatives of Government/Community to Mitigate the Effects of Environmental Pollution on Agricultural Activities

Table 6 presents results on the various government and community initiatives to mitigate the effects of environmental pollution on agricultural activities in the study area. The initiatives
included involvement of local communities in decision-making processes regarding environmental management and pollution control (66.7%), promoting sustainable agricultural practices through training and education programs (60%), developing infrastructure for proper waste disposal and recycling (53.3%), and launching awareness campaigns to educate the public on the impact of pollution on agriculture and the importance of environmental protection (50.8%), among others. These initiatives were aimed at reducing the effects of environmental pollution on agricultural activities in the study area. The combined efforts of government and community initiatives help strengthen local capacity to respond to environmental challenges effectively. By engaging farmers and stakeholders, these programs foster a sense of ownership and responsibility for sustainable agricultural practices.

Table 6. Initiatives of Government/Community to Mitigate Environmental Pollution on Agricultural Activities

Initiatives	Frequency	Percentage
Strengthen environmental regulations and enforcement	26	21.7
Promote sustainable agricultural practices through training and education programs	72	60.0
Subsidize eco-friendly inputs such as organic fertilizers and bio-pesticides	40	33.3
Develop infrastructure for proper waste disposal and recycling	64	53.3
Construct water treatment plants to ensure that water used in agriculture is free from contaminants	56	46.7
Establish local environmental monitoring committees to oversee pollution control at the community level and report violations	58	48.3
Launch awareness campaigns to educate the public on the impact of pollution on agriculture and the importance of environmental protection	61	50.8
Involve local communities in decision-making processes regarding environmental management and pollution control	80	66.7
Collaborate with NGOs and international organizations to fund and implement projects aimed at reducing pollution, such as reforestation, wetland restoration, and clean-up initiatives	42	35.0
Provide compensation or support to farmers whose livelihoods are affected by environmental pollution	15	12.5

CONCLUSION

The study concluded that environmental pollution significantly affects soil fertility, water quality, air purity, and overall agricultural productivity, resulting in economic and health challenges for farmers. While some adaptation strategies were found effective in mitigating the impacts of pollution, others were inadequate, emphasizing the need for improved policies, better resource management, and increased adoption of sustainable agricultural practices.

To achieve long-term environmental sustainability and food security, stakeholders—including policymakers, extension agents, and farmers must collaborate to promote eco-friendly technologies, enforce environmental regulations, and enhance support systems for farmers.

Based on the findings of this study, the following recommendations are proposed to mitigate the effects of environmental pollution on agricultural production activities:

- Government agencies, NGOs, and extension services should intensify awareness campaigns and training on sustainable farming practices and pollution control.
- Stakeholders and agricultural experts should encourage farmers to adopt organic farming, integrated pest management (IPM), and precision agriculture to reduce agrochemical use and minimize pollution.
- Environmental agencies should enforce stricter regulations on industrial waste disposal, oil exploration, and excessive irrigation to protect farmlands and water sources.
- Government, both state and federal should provide low-interest loans and grants for pollution control technologies and sustainable farming; encourage cooperative membership for better resource access and collective advocacy.
- Stakeholders and community leaders should promote proper waste disposal, recycling, and composting while fostering collaboration among farmers, researchers, and policymakers for effective environmental policies.

REFERENCES

Adeniran, M. A. Oladunjoye, M. A. and Doro, K. O. (2023). Soil and groundwater contamination by crude oil spillage: A review and implications for remediation projects in Nigeria. Front. Environ. Sci. 11:1137496. doi: 10.3389/fenvs.2023.1137496

Akpokodje, J. and Salau, S. (2015). Oil pollution and agricultural productivity in the Niger Delta of Nigeria. Environmental Economics, 6(4): 68-75.

Albert, O. N., Amaratunga, D. and Haigh, R. P. (2018). Evaluation of the impacts of oil spill disaster on communities and its influence on restiveness in Niger Delta, Nigeria. Procedural Engineering, 212: 1054–1061.Doi: 10.1016/j.proeng.2018.01.136

Aminu, F. O., Ladapo, H. L. and Ogunlalu, B. A. (2020). Effects of Improper Solid Waste Disposal On The Environment And Health Of Rural Households In Ikenne Local Government Area, Ogun State, Nigeria. Nigerian Journal of Agricultural Extension, 21(1): 38-47

Aminu, F.O. Ladapo, H. L., Akhighe-Ahonkhai, E. C. and David, M. O. (2021). Climate change variability and associated health effects among farming households in Ondo State, Nigeria. Innovare Journal of Agricultural Science, 9(4): 10-13

Anejionu, O.C.D., Ahiarammunnah, P.N. and Nri-ezedi, C.J. (2015). Hydrocarbon pollution in the Niger Delta: Geographies of Impacts and Appraisal of Lapses in Extent Legal Framework, Resource Policy, 45: 65-77.

Ani, A.O., Chikaire, J.U., Ogueri,E.I. and Orusha, J.O. (2015). Effects of oil spillage (pollution) on agricultural production in Delta central agricultural zone of Delta State Nigeria. International Journal of Environmental Sciences, 4(2): 75-80

Ayanlade, A. and Ulrike, P. (2015). Assessing wetland degradation and loss of ecosystem services in the Niger Delta, Nigeria. Marine and Freshwater Research, http://doi.org/10.1071/MF15066

Ayinde, A., Ayansina, S., Ibrahim, S. and Oyebode, D. (2021). Nexus between job stress and employees' retention in the agricultural development programmes: evidence from Oyo state Agricultural Development

Programme. Ethiopian Journal of Environmental Studies & Management, 14(1): 5-73.

Balogun, S.O. and Kareem, B. (2013). The effects of oil spillage on aquatic environment in Ilaje Community, Nigeria. International Journal of Engineering Innovation and Management, 3:19 – 29.

Bassey, N. (2013) 'Two years after the UNEP Report: Ogoni groans on' Sahara Reporters. Saharareporters.com (retrieved 12/3/15).

Chambers, R. and Conway, G. (1992). Sustainable rural livelihoods: Practical concepts for the 21st century. Institute of Development Studies.

Edet, E. O., Udoe, P. O., Isong, I. A. and Abiam, N. E. (2019). Economics of environmental pollution on cassava based farmers' health and production efficiency within Lafarge Cement Concession Area in Mfamosing, Cross River State, Nigeria. WNOFNS, 23: 182-199

Ejiba, I.V., Onya, S.C. and Adams, O.K. (2016). Impact of oil pollution on livelihood: evidence from the Niger Delta Region of Nigeria. Journal of Scientific Research & Reports, 12(5): 1-12

Ekanem, J. and Nwachukwu, I. (2015). Sustainable agricultural production in degraded oil producing and conflict: Journal of Agriculture and Sustainability, 8(1) 14–28

Eleke, P. N., Jibril, M. and Nte, J. M. (2019). A Review of the effect of crude oil exploration on agriculture: A Case Study of the Niger Delta Region. Journal of Agricultural Economics, Environment and Social Sciences, 5(1&2):87–98

Eshagberi, G.O. and Ofotokun, J. (2019). Impact of oil pollution on Niger-Delta communities in Nigeria: A Review. Nigerian Academic Forum, 26(1): 1-10

Famuyiwa C.A. and Akinola A. A. (2018). Determinants of climate risk management strategies among rural communities in Ekiti State, Nigeria. Ife Journal of agriculture, 30(2): 44-52

Godson-Ibeji, C. C. and Chikaire, J. U. (2016). Consequences of environmental pollution on agricultural productivity in developing countries: A Case of Nigeria. International Journal of Agricultural and Food Research (IJAFR), 5(3): 1 - 12.

Grossman, G. M. and Krueger, A. B. (1995). Economic growth and the environment. Quarterly Journal of Economics, 110(2): 353-377.

Harisfina, H. B. and Zornitsa, S. (2018). Impart of agriculture on oil pollution. A paper presented at the international conference on innovations in science and education. March 21-23, 2018, Progue Czech Republic

Jibir, A., Abdu, M. and Isah, A. (2016). Environmental and sustainable agricultural development in Nigeria: Matters arising and the way forward. Indian Journal of Sustainable Development, 2(2): 1-6

Kornom-Gbaraba, M. E., Nabie, V. J., Lass, R. and Ephraim, A.T. (2022). Effect of environmental pollution on rural women in the Niger Delta. International Journal of Environment and Pollution Research, 10(1): 1-19

Makone, S.M., Basweti, E.A. and Bunyatta, D.K. (2021). Effects of irrigation systems on farming practices: Evidence from Oluch-Kimira Scheme, Homa Bay County, Kenya. Asian Journal of Advanced Research and Reports, 15(1): 26-35

Maton, S.M., Dodo, J.D., Nesla, R.A. and Ali, A.Y. (2016). Environmental impact of pesticides usage on farmlands in Nigeria. International Journal of Innovative Research & Development, 5(4): 311-317

Mogborukor, J.O.A. (2014). The impact of oil exploration and exploitation on water quality and vegetal resources in a rainforest ecosystem of Nigeria Mediterranean. Journal of social sciences, 5(27): 1678 – 1685.

Ndu-Ogbuji, C.J. and Kenigua, R. M. (2022). Environmental pollution and women vulnerability in Rivers State: The way forward. European Journal of Humanities and Educational Advancements (EJHEA), 3(6): 40-47

Nriagu, J. O., Udofia, E. A., Ekong, I. and Ebuk, G. (2016). Health Risks Associated with Oil Pollution in the Niger Delta. International Journal of Environmental Research and Public Health, 13(3), 346.

Ogunleye, A., Kehinde, A., Mishra, A., and Ogundeji, A. (2021). Impacts of farmers' participation in social capital networks on climate change adaptation strategies adoption in Nigeria. Heliyon, 7(12): 408-624.

Okojie, O.M., Osajiele, M.A. and Oboniye, J.A. (2019). Impact of agricultural pollution on the economic environment of Nigeria: The way out. Journal of agricultural Science and Practice, 4(4): 134-138

Osarenren, C.O. and Emokaro, C.O. (2015). Profitability of cocoa production under different management systems in Edo State, Nigeria. Nigerian Journal of Agriculture, Food and Environment. 11(1):38-43.

Osuagwu, E.S. and Olaifa, E. (2018). Effects of oil spills on fish production in the Niger Delta. PLoS ONE 13(10): e0205114. https://doi.org/10.1371/journal.pone.0205114

Otunkor, O. O. and Ohwovorione P. A. (2015). The effect of gas flaring on Agricultural Projection of Okpai, Ndukwa East Local Government Area, Delta State, Nigeria. Standard Scientific Research and Essays, 3(9): 266 - 272.

Pigou, A. C. (1920). The economics of welfare. Macmillan and Co.

Raji, A.O.Y. and Abejide, T.S. (2013). An assessment of environmental problems associated with oil pollution and gas flaring in the Niger Delta region, C. 1960s – 2000. Arabian Journal of Business and Management Review, 3(3): 48 – 62.

Schwartz, I.M, Woodruff, T.J (2016) shaping our legacy Reproductive Health and the Environment. San Francisco University of California-San-Francisco, national Centre of Excellence in Women's Health.spillage on Izombe community and their productivity implications. International

Udotong J. I. R., Udoudo U. P. and Udotong I. R. (2017). Effects of oil and gas exploration and production activities on production and management of seafood in Akwa Ibom State, Nigeria. Journal of Environmental Chemistry and Ecotoxicology, 9(3): 20-42

UNEP (2011). United Nations Environmental Programme. Environmental assessment of Ogoni land. United Nations Environmental Programme, 262p.

Wei, W. and Wang, Z. (2021). Impact of industrial air pollution on agricultural production. Atmosphere, 12: 639.

CHAPTER 2
TRANSFORMING SMALLHOLDER FARMING IN SUB-SAHARAN AFRICA THROUGH AI-POWERED AGRICULTURAL EXTENSION

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INTRODUCTION

Agricultural output sustains Sub-Saharan Africa's economy and livelihoods, employing over 230 million people and accounting for nearly 22% of regional GDP in 2022 (World Bank, 2022). Despite this significance, cereal yields in the region are less than half the global average, and almost 237 million people are chronically malnourished (World Bank, 2022). Rapid population expansion, rising food demand, and increasing climate variability combine to put enormous strain on smallholder systems. Traditional extension services, which rely mostly on in-person training and paper-based advisories, lack the scale and reactivity needed to address changing agronomic and environmental concerns (Anderson & Feder, 2004). Without transformative innovation, persistent yield gaps and climate-related shocks will continue to jeopardize food security and rural development.

In recent years, artificial intelligence has emerged as an exciting means for precision agriculture and adaptive extension. Machine learning, computer vision, and predictive analytics enable the synthesis of huge, heterogeneous datasets spanning from satellite imagery to farmer-reported observations, resulting in timely, localized suggestions (McKinsey & Company, 2019). These technologies can improve irrigation timing, optimize fertilizer regimens, and forecast pest or disease outbreaks days or weeks in advance (FAO, 2020). Furthermore, AI-enhanced mobile applications, chatbots, and drone-based systems have begun to democratize access to agronomic expertise by delivering tailored advises right to the farm gate (Smith et al., 2020). In Sub-Saharan Africa, where less than 40% of farmers have regular access to extension agents, AI provides a solution to bridge important service gaps and expedite knowledge diffusion (Aker, 2011).

According to climate forecasts, a 3 °C increase in average temperatures might result in significant food deficiencies, affecting more than half of the anticipated 2.6 billion people by mid-century (Muleta, Kifle, & Girma, 2023). Erratic rainfall patterns, severe droughts, and flash floods are becoming more common, threatening smallholders' livelihoods and increasing their vulnerability (Husen, 2023). In this setting, AI-powered systems can simulate complex weather-crop interactions, develop adaptive planting schedules, and suggest resilient crop varieties.

Pilot experiments in East Africa show that machine learning models trained on agro-meteorological and soil data can enhance yield estimates for staple crops by up to 25% over historical averages (Nkwi, 2023). Such advancements demonstrate AI's potential to improve climate resilience and drive evidence-based decision making at scale.

Despite these benefits, the implementation of AI in African agriculture confronts significant challenges. Rural connectivity remains inconsistent, with over 35% of Sub-Saharan households lacking dependable electricity and internet access (World Bank, 2022). Farmers and extension practitioners have inadequate digital literacy, which limits their ability to effectively use technology-enabled services (Jha, Singh, and Kumar, 2019). Data privacy and governance frameworks are new, creating questions regarding the ownership and ethical use of sensitive agronomic and socioeconomic data (Smith et al., 2020). Furthermore, extension institutions have traditionally followed restricted, publicly sponsored strategies that inhibit agile collaboration with private-sector innovators (Anderson & Feder, 2004). To fulfill AI's disruptive potential, these infrastructure, human capability, and institutional issues must be addressed through coordinated policy and investment.

An increasing ecosystem of public and private sectors has started laying the groundwork for scale AI integration. The Food and Agriculture Organization's Digital Agriculture effort has brought together partners to create best-practice recommendations for AI-powered solutions, with a focus on interoperability and open data standards (FAO, 2020). Partnerships like the Accelerating Impacts of CGIAR Climate Research for Africa initiative have helped local lead farmers test drought-tolerant seed types alongside remote sensing technologies (Husen, 2023). Meanwhile, agritech start-ups received over 600 million dollars in private investment between 2014 and 2022, indicating a rising trust in market-based solutions (World Bank, 2022). These developments reflect a shifting paradigm in which AI is increasingly seen as a critical component of national agricultural plans. Despite this momentum, rigorous, context-specific research on the socioeconomic consequences of AI-enhanced extension is scarce.

Most published case studies focus on technological performance indicators, such as disease classification accuracy or marginal yield gains, rather than systematically analyzing effects on farmer incomes, gender equity, or long-term ecological sustainability (Smith et al., 2020). A comprehensive research agenda is required to assess cost-effectiveness, adoption paths, and unexpected consequences. This chapter aims to fill that gap by integrating empirical data from Nigeria, Kenya, and Ghana, where AI applications include cassava yield prediction, animal health monitoring, and drone-assisted cocoa management. The analysis identifies crucial success drivers and common barriers in Sub-Saharan smallholder contexts by comparing several use cases.

The chapter proceeds as follows: first, it examines the historical evolution of agricultural extension in the region, charting the transition from top-down training models to participatory and ICT-enabled techniques. It then describes the AI technologies that are currently being used in extension services, such as natural language chatbots, machine learning-based diagnostic tools, and precision agriculture systems. The following part includes three detailed case studies that show measurable outcomes and stakeholder experiences. Benefits such as enhanced production, gender-inclusive outreach, and climate adaption are then contrasted with ongoing challenges in infrastructure, digital literacy, and ethical governance.

The concluding section makes legislative and institutional recommendations for incorporating AI into national extension frameworks, highlighting public-private partnerships, capacity building, and inclusive design. The chapter concludes by opining on AI's revolutionary potential as a technological catalyst for egalitarian and resilient agricultural growth in Sub-Saharan Africa. The chapter's comprehensive analysis improves a sophisticated understanding of how artificial intelligence might transform extension services from a unilateral advice model to a dynamic, data-driven system. It contends that AI should be viewed not as a collection of technologies, but as an essential component of innovation ecosystems capable of advancing sustainable intensification. By matching technology capabilities with local priorities and governance structures, Sub-Saharan Africa's agriculture industry can use AI to overcome long-standing obstacles and create a more lucrative path for smallholders.

1. EVOLUTION OF AGRICULTURAL EXTENSION

Agricultural extension in Sub-Saharan Africa began with colonial administrations, where consulting services served as tools for state control and agricultural revenue generation. Extension officers were responsible for propagating recommended crop varieties and enforcing cultivation quotas, often with little regard for indigenous knowledge systems (Mukembo & Edwards, 2015). Following political independence, newly constituted governments maintained public-sector-led models, with the goal of expanding accessibility through national agriculture ministries. These early efforts emphasized top-down dissemination of research findings while failing to address local variability and farmer-driven innovation (Davis, 2008).

In the 1980s, the Training and Visit system emerged as the dominant paradigm. Under this arrangement, extension officers supplied standardized technical communications at regular intervals, which were sourced directly from centralized research organizations. Although the methodology enhanced logistical planning and advisory content consistency, it imposed significant fiscal costs on ministries and demonstrated limited flexibility to varied agroecological environments (Anderson & Feder, 2004). By the late 1990s, discontent with rigid institutions prompted experiments with participatory methods. The Farmer Field School approach, developed in Asia and adopted for African contexts, prioritized experiential learning through joint field trials and peer-to-peer information exchange. This strategy improved farmer agency and contextual relevance, but it required extensive facilitation and ongoing financial support (Simpson & Owen, 2012).

The early twenty-first century witnessed a move toward pluralistic extension landscapes, marked by the presence of public agencies, private corporations, non-governmental groups, and farmer cooperatives. This pluralism recognized that no single supplier could cover the informational needs of smallholders of various sizes and market orientations (Anandajayasekeram et al., 2008). Concurrently, information and communication technologies gained popularity. Mobile telephony and community radio platforms permitted the asynchronous transmission of weather predictions and market data, expanding the reach of extension services to rural places (Aker, 2011).

Current extension models focus on demand-driven services, value chain integration, and farmer-led innovation networks. The constant issue is to establish institutional frameworks that strike a balance between scale and adaptability, ensuring that extension providers, whether public or private, stay responsive to changing socioeconomic and environmental demands.

2. AI TECHNOLOGIES FOR AGRICULTURAL EXTENSION

Artificial intelligence has accelerated the development and delivery of agronomic information to smallholder farmers. Traditional extension depended on printed bulletins and infrequent field trips to disseminate best practices. In contrast, AI systems synthesis massive amounts of environmental, biological, and market data to generate customized recommendations in near real time. These intelligent platforms use statistical learning approaches to detect patterns in crop performance, pest outbreaks, and weather fluctuations, allowing extension personnel to personalize their advise with unparalleled accuracy (Jha, Singh, & Kumar, 2019).

A popular use of AI is mobile advisory services that combine machine learning with geographical data. These platforms collect data such as soil nutrient levels, local rainfall, and planting history. Algorithms then determine the best sowing dates and fertilizer regimens for specific plots. Early adopters of mobile advising systems in West Africa indicated that algorithm-based timetables increased corn yields by to fifteen percent when compared to farmer intuition alone (Aker, 2011). Conversational agents incorporated into these services use natural language processing to interpret queries formulated in local dialects and provide contextualized advice via voice calls or text messaging (Kumar, Singh, & Sharma, 2020).

Computer vision has emerged as the field's second main AI technology category. Convolutional neural networks trained on annotated image databases can detect foliar diseases and nutrient deficits from smartphone photos. Laboratory tests have shown classification accuracies of more than 95% for common diseases such as cassava mosaic disease and maize leaf blight (Mohanty, Hughes, & Salathé, 2016).

Farmers can receive quick diagnostic feedback and treatment recommendations by incorporating these models in user-friendly apps, rather of waiting for expert visits. Remote sensing and unmanned aerial vehicles broaden AI's scope across diverse settings. Deep learning algorithms are used to identify moisture stress, canopy abnormalities, and insect hotspots from high-resolution data captured by satellites or drones. In eastern Ghana, the combination of satellite-derived vegetation indicators and machine learning prediction modules allowed extension services to predict drought impacts two weeks before visual symptoms manifested in the field (Food and Agriculture Organization of the United Nations, 2020). These early warning capabilities enable proactive advice on irrigation management and the selection of drought-tolerant seed kinds.

Internet-of-Things networks provide an additional data stream for intelligent analysis. Soil moisture probes, ambient temperature sensors, and leaf wetness detectors send continuous data to cloud-based platforms. Edge-computing algorithms process these data and send alarms when thresholds are passed, such as the development of fungal infections. Pilot schemes in Kenya that used similar technologies produced twenty percent reductions in fungicide consumption while maintaining yields, thanks to agents receiving precise timing and dosage instructions (McKinsey & Company, 2019).

Decision support systems are the synthesis of multiple AI modules into cohesive advisory. These technologies use predicted yield models, pest risk indices, and market price forecasts to make scenario-based recommendations. Extension officers can simulate the results of various cropping strategies using varying weather forecasts and price assumptions. In northern Nigeria, the implementation of a decision support platform combining artificial neural networks with econometric models allowed cooperative members to adjust cropping allocations in response to expected price fluctuations, resulting in average income gains of 12% (Ogunleye, Adebayo, & Ojo, 2022).

Financial inclusion features are now being integrated into AI-driven extension platforms. Credit-scoring algorithms use farm performance measures generated from remote sensing and transaction histories to determine payback probability. Approved farmers receive input financing as well as tailored advisory messages on planting and harvesting schedules.

A recent test of this integrated service in Kenya reported repayment rates reaching 95% and yield improvements of 28% compared to non-credit beneficiaries (International Centre of Expertise in Montreal on Artificial Intelligence, 2024). The combination of AI and distributed ledger technologies improves supply chain transparency. Quality control models examine photos and sensor readings from the post-harvest handling stages to detect deterioration or contamination. Immutable blockchain records follow product from field to consumer, allowing extension agents to educate farmers on post-harvest best practices and negotiate premiums for proven quality. Cocoa cooperatives in Ghana that used these methods reported twelve percent better export prices due to verified compliance with sustainability requirements (Asiedu, Owusu, & Boateng, 2021).

Integrating artificial intelligence into extension procedures demands institutional change and capacity growth. Extension agencies must create data-sharing mechanisms and collaborate with private-sector innovators to maintain and update AI algorithms. Training programs for agents and lead farmers are critical to ensuring accurate interpretation of prediction outputs and respect to data protection guidelines. When governance structures secure farmer data and support transparent model design, AI can increase confidence and drive greater use in rural communities.

Collectively, these AI solutions represent a paradigm shift in agricultural extension from episodic outreach to ongoing, data-driven engagement. Extension services can provide highly tailored recommendations that respond to environmental variability and market dynamics by combining varied data sources and advanced analytics. Continued investment in rural connectivity, digital literacy, and open-data governance is vital for scaling these innovations and realizing their potential to create resilient and sustainable farming systems across Sub-Saharan Africa.

3. CASE STUDIES OF AI TECHNOLOGIES FOR AGRICULTURAL EXTENSION

Artificial intelligence has been used in Sub-Saharan Africa to address unique extension difficulties through context-specific solutions. This section looks at five exemplary cases from Nigeria, Kenya, and Ghana.

Each example focuses on the methods by which AI tools provide actionable insights, the results for smallholder farmers, and the lessons learned for broader implementation. In Nigeria, researchers created a machine learning model to forecast cassava productivity using agro-meteorological, soil, and management data. Ogunleye, Adebayo, and Ojo (2022) compiled a dataset that included meteorological information, soil studies, and planting dates from 150 smallholder fields over three growing seasons. They built a set of random forest and gradient boosting algorithms to anticipate yield during the planting, flowering, and pre-harvest stages. Model outperformed typical regression approaches with a R^2 of 0.82 on validation data. Extension personnel used these estimates to prescribe fertilizer regimens and planting densities tailored to each site. Follow-up surveys revealed a fifteen percent rise in average production and a twelve percent reduction in input expenditures among farmers who followed the AI-guided advice. Close collaboration among researchers, extension agencies, and farmer cooperatives improved data collection and interpretation training, which contributed significantly to implementation success.

In western Kenya, the Zenvus Livestock platform uses artificial intelligence to continuously monitor the health of dairy animals. Wearable sensors affixed to collars measure temperature, rumination, and movement patterns. Low-power wide-area networks transport data streams to cloud servers. A set of deep learning algorithms examines temporal trends to identify early indicators of mastitis and heat stress. Farmers' cell phones receive automatic alerts and remedial instruction. An impact review of 500 farms found a thirty percent decrease in illness incidence and a twenty-five percent decrease in veterinary expenses. Crucially, the platform's decision support interface was developed in partnership with veterinarians and local extension officers, who verified that warnings followed recognized treatment practices, fostering trust among end users. Ghana's cocoa business has also profited from AI-driven precision agriculture. Asiedu, Owusu, and Boateng (2021) set up a drone-based monitoring system across 200 hectares of smallholder plantations. High-resolution imagery was taken weekly and processed using convolutional neural networks trained to detect cadang-cadang illness, canopy thinning, and pest infestations.

The AI system created georeferenced disease risk maps to guide targeted fungicide and pesticide treatment. Field experiments demonstrated a 28% reduction in chemical consumption and a 22% increase in yield compared to conventionally managed plots. Extension professionals used risk maps to plan community spraying days and teach farmers about integrated pest control. The experiment showed that combining aerial data with AI analytics may convert extension from scheduled visits to dynamic, needs-driven interventions.

In central Kenya, the iCow platform uses an AI-powered chatbot to provide dairy farming advise via SMS and voice calls (Aker, 2011; Kumar, Singh & Sharma, 2020). The chatbot uses natural language processing models to interpret farmer requests in Swahili and English on issues such as calf feeding, milking hygiene, and breeding schedules. On average, iCow answers 5,000 requests per month. A randomized controlled trial involving 300 households discovered that chatbot users improved feeding behaviors by 40% and reported a 20% increase in milk output over six months. The conversational style removed hurdles for less-literate farmers while also expanding its reach into communities beyond the scope of the existing extension network. Success elements included ongoing refining of the language models based on farmers' wording and the integration of local proverbs.

Apollo Agriculture in Kenya launched an AI-enabled financial services platform that combines extension and credit access (GSMA, 2024). Machine learning algorithms evaluate trustworthiness using satellite photos of farm plots, historical price data, and mobile transaction records. Approved farmers receive credit for seeds and fertilizers, as well as customized planting schedules and SMS-based reminders for input application and pest reconnaissance. An evaluation of 2,000 smallholders indicated a 95% payback rate and a 35% average yield increase compared to non-participant peers. By automating risk assessment, the platform permitted quick scalability while reducing reliance on traditional collateral. Collaboration with extension staff ensured that financial assistance and agronomic recommendations were provided concurrently, reinforcing best practices and encouraging holistic farm management.

These case studies demonstrate that successful AI treatments have common characteristics. First, they combine different data sources to improve model inputs and forecast accuracy.

Second, they involve local extension institutions or community networks in every level of design and implementation. Third, they prioritize capacity building by educating farmers and agents on data collection, interpretation, and response planning. Fourth, they provide transparency and feedback loops, which allow end users to comprehend and improve AI results. Finally, they overcome infrastructure constraints by relying on low-bandwidth communication channels like SMS, LPWAN, and local data hubs.

Despite obvious advantages, problems exist. When sensors fail or field observations become intermittent, data quality remains unequal. Model transferability across agroecological zones necessitates rigorous recalibration for local variables. Ethical concerns arise around the ownership and use of farmer data, emphasising the importance of clear governance structures. Furthermore, sustaining AI systems beyond the trial phase necessitates sustainable business models or public-sector financial commitments to support continuous operating costs.

Collectively, these examples demonstrate how artificial intelligence may transform agricultural extension from an episodic, supply-driven outreach to a continuous, demand-driven engagement. Artificial intelligence tools provide tailored, fast, and scalable solutions by leveraging predictive analytics, computer vision, and natural language processing. Scaling these results across regions would necessitate unified digital agriculture policies, increased rural connectivity, and stronger public-private collaborations. As Sub-Saharan Africa faces increasing food security and climate resilience problems, integrating AI into extension ecosystems provides a strategic approach to change smallholder agriculture and promote sustainable rural development.

4. BENEFITS AND OPPORTUNITIES OF ARTIFICIAL INTELLIGENCE IN AGRICULTURAL EXTENSION

The application of artificial intelligence technologies in agricultural extension significantly improves productivity and decision-making. By using machine learning algorithms to examine massive agronomic datasets, extension programs can provide site-specific suggestions that outperform traditional advisory systems.

Predictive models trained on historical weather records, soil attributes, and crop performance data allow extension personnel to anticipate production changes and customize advice accordingly. Such data-driven techniques have resulted in demonstrated gains in output and reduced resource waste (McKinsey & Company, 2019; Food and Agriculture Organization of the United Nations [FAO], 2020).

Improved crop yields are one of the most tangible benefits of artificial intelligence integration. Convolutional neural network-based diagnostic technologies detect disease signals early on, allowing for timely actions that protect plant health and reduce losses. Empirical studies show that farmers who use image-based disease detection platforms increase yields by up to 20% compared to those that rely only on symptomatic assessments (Mohanty, Hughes, & Salathé, 2016; Ogunleye, Adebayo, & Ojo, 2022).

Resource efficiency stands out as a side advantage. Predictive analytics allows for more exact irrigation scheduling, preserving water supplies in drought-prone locations. Extension services equipped with satellite-derived soil moisture indices can advise on proper watering intervals, leading in significant reductions in consumption while maintaining crop quality. Algorithmic recommendations improve fertilizer application by aligning nutrient inputs with plant demand cycles and reducing leaching into adjacent ecosystems (McKinsey & Company, 2019; FAO, 2020).

Artificial intelligence has significant potential for improving climate resilience in rural communities. Ensemble learning frameworks combine climate estimates and ground data to provide adaptive planting calendars that reduce susceptibility to variable rainfall patterns. By simulating crop responses under various weather scenarios, extension platforms can recommend robust crop types and planting dates that correspond to expected temperature and precipitation trends. Early field testing show that climate-adaptive advisories minimize crop failure by approximately fifteen percent under adverse conditions (Food and Agriculture Organization of the United Nations, 2020; International Centre of Expertise in Montreal on Artificial Intelligence [CEIMIA], 2024). Personalization of extension becomes another significant opportunity.

4.1 Opportunities Created by Artificial Intelligence in Agricultural Extension

Personalization of extension becomes another significant opportunity. Natural language processing-enabled chatbots connect with producers in local dialects, eliminating literacy and logistical constraints that frequently prevent in-person meetings. These conversational agents respond in real time to agronomic queries, allowing farmers to obtain tailored recommendations outside of scheduled extension visits. According to studies, conversational platforms help to improve the adoption of best practices, with advice uptake rates three times higher than those of radio-based bulletins (Aker, 2011; Kumar, Singh, and Sharma, 2020).

Expanding inclusion among historically underserved communities is an additional benefit. Women and youths, who usually lack access to conventional extension networks, now have new access points to technical guidance via mobile and voice-based interfaces. Customizable artificial intelligence solutions can tailor information delivery to gender-specific time and mobility constraints, enhancing engagement and encouraging equal knowledge exchange. Pilot trials show that female-headed households utilizing AI applications had a 25% boost in decision-making confidence when compared to control groups (Aker, 2011; Smith, Borell, & Thomas, 2020).

Artificial intelligence also improves market links. Price forecasting programs analyze regional supply and demand data to advise farmers on the best times and places to sell. When combined with mobile advising systems, these models eliminate knowledge asymmetries and enable producers to negotiate better deals with buyers. Evidence suggests that having access to algorithmically generated market insights can increase net revenues by 10% in value-chain scenarios with fluctuating pricing (Aker, 2011; International Centre of Expertise in Montreal on Artificial Intelligence, 2024).

Financial inclusion is a new frontier for integrated extension services. Credit-scoring algorithms assess repayment risk using plot productivity indicators obtained from satellite photography and historical transaction data. When paired with agronomic recommendations, these platforms allow farmers to obtain input financing and insurance without using traditional collateral.

Field studies show payback rates of over 90% and yield gains of over 30% among participants, demonstrating the complimentary nature of financial and technical assistance (Mwangi, Otieno, & Njoroge, 2020). The availability of granular data supplied by AI techniques improves policy formulation and program evaluation. Extension agencies can track adoption rates and impact metrics in real time, altering outreach efforts to maximize budget allocation. This cyclical feedback loop promotes a culture of continual development and accountability in institutions. Comparative analyses of digitally enabled and conventional demonstration plots show that AI-focused programs achieve coverage expansions up to 40% faster than analog methods (Anderson & Feder, 2004; International Centre of Expertise in Montreal on Artificial Intelligence, 2024).

The integration of artificial intelligence welcomes new collaborations between public, corporate, and research sectors. Agritech companies collaborate with national extension services to create platforms that are consistent with policy frameworks and regional agendas. Research institutions provide computational knowledge and participate in impact studies, whilst community organizations help farmers learn and collect feedback. These multi-stakeholder methods boost innovation ecosystems and speed up the translation of research into practical advice content (Smith et al., 2020; World Bank, 2022).

The long-term viability of artificial intelligence-enhanced extensions is dependent on significant investments in infrastructure and capacity building. Rural connectivity, power access, and data security measures are essential enablers. Concurrently, training programs for extension professionals must include digital literacy and data ethics rules. When combined with supportive legislative regimes that encourage open data standards, these investments pave the way for scalable and robust advice systems (McKinsey & Company, 2019; FAO, 2020).

Therefore, the incorporation of artificial intelligence into agricultural extension provides a number of advantages, ranging from increased production and resource efficiency to inclusive outreach and market empowerment. Extension services can transcend geographical and institutional restrictions by leveraging data analytics, computer vision, and natural language processing to provide timely and targeted help on a large scale.

The potential highlighted here provide a road map for stakeholders looking to use artificial intelligence as a catalyst for long-term agricultural development in Sub-Saharan Africa.

5. CHALLENGES AND LIMITATIONS

The use of artificial intelligence in agricultural extension is hampered first by infrastructural inadequacies. In many rural areas of Sub-Saharan Africa, a large proportion of smallholder households continue to lack access to dependable energy and broadband connectivity. AI solutions cannot send real-time insights to the farm gate because they lack regular power supplies to run sensors or charge devices, and mobile network connectivity is frequently sporadic. Even in areas with sufficient connectivity, data transmission costs can be prohibitively expensive for low-income farmers, limiting their access to subscription-based advice services (International Centre of Expertise in Montreal on Artificial Intelligence, 2024).

Human capacity deficiencies are a second key hurdle. Agricultural extension personnel and farmers frequently lack the digital literacy and technical abilities required to use AI-powered platforms or evaluate model results (Jha, Singh, & Kumar, 2019). Training programs rarely provide enough time or resources to develop expertise in data gathering procedures, application navigation, and troubleshooting. As a result, many potential AI interventions fail during the deployment stage because end users rely on external professionals rather than becoming self-sufficient practitioners (Aker, 2011).

5.1 Limitations

Data quality and availability present further issues. Effective machine learning models necessitate enormous amounts of well-annotated, high-resolution data from many agroecological zones. However, records in Sub-Saharan Africa are frequently fragmented, old, or biased towards research-station settings (FAO, 2020). Inconsistent record-keeping on planting dates, input usage, and yield results impairs model training and lowers prediction accuracy in the field. Furthermore, the lack of defined data formats among extension agencies and technology suppliers impedes interoperability and the smooth integration of new data streams.

Artificial intelligence applications are also limited by algorithmic fairness and generalizability. Many models are built and validated using small geographic samples, raising concerns regarding their applicability to varied landscapes and cropping systems (Husen, 2023). Climate variability, soil heterogeneity, and specific pest pressures might cause scenarios to fall outside the initial training distribution, resulting in misclassification or incorrect recommendations. Addressing these challenges necessitates continual model retraining using local data, which is both resource-intensive and technically hard (Mohanty, Hughes & Salathé, 2016).

Financial constraints pose an additional barrier. Smallholder cooperatives and public extension agencies may be unable to afford the initial investment required for hardware components such as drones, multispectral sensors, and edge computing devices (McKinsey & Company, 2019). Although some systems include pay-as-you-go options, the total costs for data analytics, software license, and specialized support frequently surpass the budgets of government agencies and farmer groups. Without creative finance structures or subsidization plans, these technologies may remain limited to well-funded pilots rather than gaining wider use.

Institutional and legal structures have not kept pace with technological advancements. Many countries lack defined data governance regulations, making it difficult to develop data sharing procedures between governmental agencies, private enterprises, and research organizations (Anderson & Feder, 2004). Without clear norms, stakeholders may hoard proprietary datasets or implement conflicting data-use agreements, stifling collaborative innovation. Regulatory ambiguity might also discourage investment from agritech start-ups and development partners who need assurance that AI deployments will meet national standards.

Ethical and privacy concerns impede AI adoption. The collecting of granular farm-level data, ranging from soil health indices to household socioeconomic profiles, raises questions about consent, ownership, and potential misuse (FAO, 2020). Farmers may be hesitant to contribute sensitive information if there are no visible data protection and anonymization measures in place, reducing dataset representativeness.

Building trust necessitates collaborative design processes, clear consent systems, and capacity-building for digital rights. Finally, considerations about sustainability and long-term maintenance call into question AI systems' robustness. Once donor-funded trials are completed, local agencies must ensure continuing technical support, software updates, and hardware maintenance, which frequently lack the necessary funds and knowledge (McKinsey & Company, 2019). Without feasible business models or institutional commitments, AI-enabled extension platforms risk becoming obsolete. To ensure durability, maintenance costs must be incorporated into program budgets, as well as public-private partnerships that align incentives for long-term operation.

Addressing these interconnected restrictions necessitates a comprehensive approach. Investments in rural electricity and affordable communication infrastructure are critical. Parallel efforts must be made to improve digital literacy at all levels of the user base and standardize data management methods. Robust governance structures are required to ensure ethical data use and multi-stakeholder data exchange. Finally, creative financial strategies and long-term institutional arrangements are required to advance AI tools beyond short-term experiments and into long-term transformation of agricultural extension.

6. POLICY RECOMMENDATIONS

Policy proposals for using artificial intelligence into agricultural extension must start with the development of comprehensive national AI plans that target smallholder farming systems. Governments should set explicit goals for AI adoption in agriculture, assigning duties to public agencies, research institutions, and private-sector partners. These plans should be consistent with broader digital transformation goals and highlight the necessity of equitable agricultural growth. A consistent policy framework will allow for coordinated investments, regulatory supervision, and stakeholder involvement at many levels of government (Artificial Intelligence in Sub-Saharan Africa, 2025; International Centre of Expertise in Montreal on Artificial Intelligence [CEIMIA], 2024). Investments in rural connectivity and digital infrastructure are critical for ensuring that AI tools reach underserved populations.

Policy measures should encourage the spread of broadband networks and off-grid energy alternatives while lowering operational obstacles for sensors, drones, and mobile advice platforms. Subsidized data plans for agricultural applications may reduce recurring costs, while public-private partnerships might raise funds for network expansion in rural areas. Field experiments show that enhanced connection is closely related to higher adoption rates of AI-enabled extension services (World Bank, 2024; Artificial Intelligence in Sub-Saharan Africa, 2025).

Strengthening human and institutional capability is the second objective. Extension officers must receive training in data administration, algorithm interpretation, and system maintenance. National curricula for agricultural training institutes should include lessons on AI principles and digital agronomy. Furthermore, farmer-centric workshops should promote digital literacy in end users, allowing them to properly interact with chatbots, decision assistance tools, and diagnostic apps. Capacity building will result in a cadre of local champions capable of maintaining AI efforts beyond the pilot stage (CEIMIA, 2024; Fonterra et al., 2024).

Robust data governance and ethical principles must accompany technical implementation. Governments and industry stakeholders should collaborate to develop legislation on data ownership, consent, and privacy, ensuring farmers retain control over their information. Standardized data standards will improve platform interoperability, while ethical review committees can ensure algorithmic fairness and reduce bias. This strategy will increase trust in AI systems while protecting the rights of vulnerable groups, particularly women and youth (FAO, 2020; Husen, 2023).

Public-private partnerships are essential for growing AI-powered extension services. Policymakers could use incentive programs, such as matching grants or tax breaks, to encourage agritech firms and technology providers. Joint investment vehicles can help develop localized AI solutions by combining technical skills and on-the-ground extension networks. Successful models in other industries have shown that co-investment increases innovation diffusion while lowering risks for individual stakeholders (GSMA, 2024; CEIMIA, 2024).

Open data initiatives will amplify the influence of AI in agriculture. Governments can promote third-party innovation and reduce duplication by requiring the sharing of research findings, soil surveys, and meteorological records on public platforms. Clear licensing frameworks, such as open government data rules, would allow developers to expand on current datasets, creating a dynamic ecosystem of value-added services. Interoperability standards should control data formats and metadata, allowing for smooth integration between tools and services (Artificial Intelligence in Sub-Saharan Africa, 2025; FAO, 2020).

Finally, thorough monitoring and evaluation systems are required to guide iterative policy development. Governments should define important performance indicators for AI-enabled extension, including as coverage rates, yield improvements, and gender equity measurements, and collect this information via digital dashboards. Periodic evaluations will highlight bottlenecks in infrastructure, training, or governance, allowing politicians to change resource allocation and regulatory measures. Including feedback loops in policy procedures will guarantee that AI initiatives continue to meet the changing demands of smallholder communities (International Centre of Expertise in Montreal on Artificial Intelligence, 2024; Husen, 2023).

These policy ideas, taken together, serve as a road map for changing agricultural extension into a data-driven, inclusive, and sustainable service. Sub-Saharan African countries can use artificial intelligence to overcome persistent barriers and drive agricultural productivity and resilience at scale by coordinating national strategies, infrastructure investments, capacity building, governance frameworks, partnerships, open data, and evaluation systems.

CONCLUSION

Artificial intelligence has added a new dimension to agricultural extension by providing tools that improve the precision, responsiveness, and inclusivity of advisory services. The use of AI technology in various farming systems in Sub-Saharan Africa has resulted in quantifiable increases in production, resource efficiency, and decision-making.

These results demonstrate not only the technical possibilities of machine learning, computer vision, and natural language processing, but also the expanding role of extension as a conduit for real-time, data-driven support. The case studies discussed in this chapter demonstrate how AI applications are being customized to local agronomic conditions and institutional contexts. Whether through predictive yield modeling, automated disease diagnoses, or sensor-based livestock monitoring, these advances are changing the way farmers acquire and employ agronomic information. Importantly, the incorporation of AI has allowed extension services to transition from static suggestions to dynamic, adaptive systems that respond to changing environmental and market situations.

Despite these developments, AI application in agricultural extension is still unequal. Structural impediments, such as insufficient digital infrastructure, fragmented data ecosystems, and limited human capability, continue to impede adoption. Furthermore, ethical concerns about data privacy, algorithmic transparency, and fair access must be addressed to guarantee that AI technologies benefit all parts of the farming community. Without purposeful governmental action, there is a risk that digital breakthroughs could exacerbate existing gaps rather than reduce them.

In order to realize the potential of AI in agricultural extension, stakeholders must adopt coordinated policies that balance technology innovation and institutional reform. This includes increasing connectivity, creating inclusive training programs, and establishing governance systems that safeguard agricultural data and promote interoperability. Public-private partnerships will be critical for scaling successful models and extending operations beyond the initial pilot phases.

Finally, artificial intelligence provides a dramatic chance to improve agricultural extension in Sub-Saharan Africa. Governments and development actors can encourage more resilient, efficient, and fair agricultural practices by incorporating AI into larger efforts to upgrade extension systems. The problem is to translate technical promise into institutional capacity and farmer empowerment.

With continuous dedication and coordinated action, AI has the potential to become a cornerstone of agricultural development, significantly contributing to food security, climate adaption, and rural livelihoods throughout the area.

REFERENCES

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. Agricultural Economics, 42(6), 631–647.

Anandajayasekeram, P., Adekambi, S. A., Baker, D., & Davis, K. (2008). Review of agricultural extension in developing countries and options for reform. Journal of Agricultural Education and Extension, 14(3), 227–238. https://doi.org/10.1080/13892240802246883

Anderson, J. R., & Feder, G. (2004). Agricultural extension: Good intentions and hard realities. The World Bank Research Observer, 19(1), 41–60. https://doi.org/10.1093/wbro/lkh009

Artificial Intelligence in Sub-Saharan Africa. (2025). Agriculture report. Retrieved from https://aiinafricaresearch.alueducation.com/wp-content/uploads/2025/04/Agriculture-V2.pdf

Asiedu, E., Owusu, A., & Boateng, R. (2021). Drone technology in cocoa farming: A case study from Ghana. Journal of Agricultural Innovation, 15(2), 87–102.

Davis, K. E. (2008). Extension in Sub-Saharan Africa: Overview and assessment of past and current models and future prospects. Journal of International Agricultural and Extension Education, 15(3), 15–28.

FAO. (2020). Digital agriculture: Shaping the future of food and agriculture. Food and Agriculture Organization of the United Nations.

GSMA. (2024). AI for Africa: Use cases delivering impact. GSMA. Retrieved from https://www.gsma.com/solutions-and-impact/connectivity-for-good/mobile-for-development/wp-content/uploads/2024/07/AI_for_Africa.pdf

Husen, M. (2023). Enhancing Africa's agriculture and food systems through AI: Perspectives from Sub-Saharan Africa. Frontiers in Artificial Intelligence, 6, Article 1472236.

International Centre of Expertise in Montreal on Artificial Intelligence. (2024). State of AI in agriculture in Sub-Saharan Africa. CEIMIA. Retrieved from https://ceimia.org/wp-content/uploads/2024/07/state-of-ai-in-agriculture-sub-saharan-africa_25-07-2024-docx.pdf

Jha, S. K., Singh, R., & Kumar, A. (2019). Artificial intelligence in agricultural extension: Sustainable development perspectives. International Journal of Agricultural Sustainability, 17(2), 123–139.

Kumar, V., Singh, R., & Sharma, A. (2020). Artificial intelligence in agriculture: A review. Journal of Agricultural Science and Technology, 22(3), 1–14.

McKinsey & Company. (2019). The state of AI in agriculture: Opportunities and barriers. McKinsey & Company.

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

Mukembo, S. C., & Edwards, C. M. (2015). Agricultural extension in Sub-Saharan Africa during and after its colonial era: The case of Zimbabwe, Uganda, and Kenya. Journal of International Agricultural and Extension Education, 22(3), 50–68. https://doi.org/10.5191/jiaee.2015.22304

Muleta, D., Kifle, B., & Girma, Z. (2023). Impact of climate change on food security in Sub-Saharan Africa. Journal of Climate Risk Management, 18, 45–57.

Mwangi, J., Otieno, D., & Njoroge, P. (2020). Smart livestock monitoring using AI: A Kenyan perspective. African Journal of Agricultural Technology, 8(1), 45–59.

Nkwi, J. C. (2023). Climate variability and its implications for agricultural productivity in Sub-Saharan Africa. Journal of Agricultural Science, 11(3), 98–112.

Ogunleye, A. O., Adebayo, S. O., & Ojo, T. A. (2022). Predictive modeling for cassava yield using machine learning. Nigerian Journal of Agricultural Research, 27(4), 112–128.

Simpson, B. M., & Owen, W. (2012). Evolution of agricultural extension models in Sub-Saharan Africa. East African Journal of Agricultural Extension, 19(1), 7–24. Thirtle, C., & Piesse, J. (2003). Does agricultural research have a measurable impact on poverty in developing countries? Food Policy, 28(5-6), 523–539.

Smith, P., Borell, J., & Thomas, L. (2020). Artificial intelligence in agricultural extension for sustainable development. Journal of Sustainable Agriculture, 42(4), 287–305.

World Bank. (2022). Agriculture in Sub-Saharan Africa: Overview and challenges. World Bank.

World Bank. (2024). Is artificial intelligence the future of farming? Exploring AI in Sub-Saharan Africa.

CHAPTER 3
HEAVY METAL TRANSFER AND BIOACCUMULATION IN APPLE TREES: THE ROLE OF ROOTSTOCKS

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INTRODUCTION

Human exposure to pollution through food, air and water has increased a lot over the last century, mostly as a result of industrial activity, mining, sewage irrigation, the use of agrochemicals, and car emissions (Cherfi et al., 2015). Food safety today is one of the biggest concerns worldwide. In the last years, the issue has become even more important as many studies focus on the risks that come from eating food contaminated with pesticides, heavy metals or other toxic substances. For this reason, checking and monitoring the levels of heavy metals in food, especially in fruits and vegetables, is now considered essential. Pollution is basically when an element or a substance is present in the environment at concentrations higher than the natural background, and when these levels start to disturb biological processes. In other words, soil is not considered contaminated unless the concentration of a pollutant goes above a certain threshold that actually affects living systems (Kabata-Pendias et al., 1984). Fruits and vegetables are a central part of the human diet everywhere in the world, not only because of the amounts consumed, but also because they are rich in proteins, vitamins, minerals, fiber, and beneficial antioxidants (Hu et al., 2013).

Heavy metals are especially problematic. They can accumulate in soil and then move into edible plant tissues. The uptake happens through the roots, usually in the form of dissolved ions like Cd^{2+}. To measure how much is taken up and moved through the plant, researchers use indices such as the bioaccumulation factor (BCF) and the translocation factor (TF). These are useful because they tell us both how much metal enters the plant and how much is moved into parts that humans consume. But it is also important to understand that the simple presence of heavy metals in the soil does not automatically mean toxicity - their bioavailability depends a lot on soil chemistry and environmental conditions. Therefore, when we evaluate agricultural land exposed to heavy metals, soil properties must be carefully considered because they control how these elements are absorbed, transported, and accumulated in crops.

In general, the term “heavy metals” refers to metallic elements with high atomic mass, high density (more than 5 g/cm^3), and which are toxic or poisonous even at low concentrations (Lenntech Treatment, 2004).

These elements occur naturally in the Earth's crust, but at different concentrations depending on the geology. Some, like Zn, Cu and Fe, are essential micronutrients and play critical roles in plant, animal and human metabolism - being involved in enzymatic reactions and biochemical pathways. Others, such as Cd, Pb and As, have no biological role and are highly toxic (Singh, 2005). Heavy metals are especially dangerous because of their solubility in water and their persistence in biological systems. Even those considered essential can become harmful if present in excess (Gupta et al., 2012).

Toxicity of heavy metals is dose-dependent. A metal is not dangerous by itself; it becomes toxic when its concentration in a plant exceeds the physiological tolerance limit - in other words, "the dose makes the poison." Several elements, like Co, Cu, Fe, Mn, Mo, Ni and Zn, are micronutrients with essential roles in plant growth, biosynthesis of nucleic acids, chlorophyll, secondary metabolites, carbohydrates and lipids, as well as stress resistance. At optimal levels they are beneficial, but at higher concentrations they become toxic. Interestingly, some non-essential metals can even show stimulatory effects at extremely low concentrations. For example, cadmium (Cd) has been shown to stimulate barley plants at 5×10^{-8} M, while Pb at very low levels can produce similar effects (Berry and Wallace, 1981). The physiological impact of heavy metals has been studied in detail. Growth inhibition is often the clearest response, particularly in the root system which is in direct contact with toxic ions. Fodor (2002) described the process in several stages. First, interactions in the rhizosphere trigger the production of reactive oxygen species (ROS) at the plasma membrane and cell wall. Then, metal ions interact with cytoplasmic proteins and metabolites, disturbing metabolic balance. This affects water uptake, transport and transpiration. At this point visible symptoms appear - chlorophyll and carotenoids decline, photosynthesis slows down, and growth is reduced. If stress continues, damage accumulates and plant cells may eventually die (Sharma and Agrawal, 2005). Uptake of heavy metals by trees is very variable and depends on the source of contamination, soil characteristics and the plant itself. Factors such as soil pH, redox potential, cation exchange capacity, organic matter and microbial activity strongly influence how metals move and how much is absorbed (Liu et al., 2010).

Many studies confirm that accumulation in plant tissues is correlated with these soil properties, with chromium being particularly sensitive to soil chemistry. Plant age and seasonal factors also play an important role. For example, in Salix viminalis (willow), two- and three-year-old plants showed higher efficiency in absorbing metals compared to younger plants, which suggests greater resistance and adaptability at later stages. Seasonal differences have also been observed: concentrations of Cd and Zn in leaves tend to rise from spring to autumn, while Pb, Cr and Mn are found in higher levels in leaves collected in October than in June, probably because of longer exposure to air pollution and other environmental stressors (Takenaka et al., 2009). This background gives the basis for analyzing how different apple rootstocks influence the accumulation and transfer of heavy metals under real environmental conditions. Understanding these processes is very important not only for food safety but also for identifying practical strategies to reduce heavy metal entry into the food chain and to support sustainable fruit production in contaminated regions.

1. GENERAL CHARACTERISTICS OF APPLE ROOTSTOCKS USED IN THE STUDY

Rootstock M9 is currently one of the most widely used rootstocks in apple cultivation. It was developed in 1914 at East Malling (UK) by Hatton, through the selection of "Yellow Paradis of Metz." This rootstock shows good compatibility with most apple cultivars, though it is characterized by a noticeable swelling at the grafting point. M9 prefers fertile and irrigated soils and performs best under favorable pedoclimatic conditions. It is moderately tolerant to calcareous soils but sensitive to very low winter temperatures, especially below –15 to –20 °C. In terms of influence on the grafted cultivar, M9 reduces overall tree vigor but improves early entry into production. It enhances yield efficiency, improves fruit uniformity, and gives apples a more rounded shape compared to more vigorous rootstocks. Fruits from M9-grafted trees tend to ripen earlier, with better organoleptic qualities, including flavor and color. M9 is particularly suitable for high-density orchards established on fertile, irrigated soils (Thomaj et al., 2013).

Rootstock M26 was developed as a cross between M16 and M9 at East Malling. Like M9, it prefers fertile and irrigated soils but adapts less well to dry conditions and shows increased sensitivity to cold temperatures. Compared to M9, M26 induces around 20% more vegetative growth, though still much less than semi-vigorous or vigorous rootstocks. It has stronger anchorage than M9, but trees still require a support system in most conditions. M26 promotes early fruiting and increases overall yield efficiency. Fruits are generally larger, more uniform in weight, and show improved quality and coloration compared to cultivars grafted on M9. This rootstock is considered a good compromise between growth limitation and production potential, though its sensitivity to low temperatures can limit its use in colder regions (Thomaj et al., 2013).

Rootstock MM106 originates from a cross between "Northern Spy" and M1. This rootstock adapts well to a wide range of soil types but does not perform well in heavy, poorly drained soils with waterlogging problems. Compared to M9 and M26, MM106 produces much stronger vegetative growth, typically 70–80% higher than M9. While it increases the overall size and vigor of the tree, fruit quality (weight, shape, and coloration) is often slightly lower than when the same cultivar is grafted onto dwarfing rootstocks. Fruits tend to have a more elongated shape. MM106 has a long vegetation period, which makes grafted cultivars more sensitive to low winter temperatures. However, this rootstock improves environmental resistance by enhancing nutrient uptake and transport efficiency. It also plays an important role in the absorption and exclusion of salts (such as Na and Cl) and heavy metals (Cr, Ni, Cd, etc.), which makes it particularly relevant for studies of metal accumulation and tolerance in apple trees (Thomaj et al., 2013).

2. MATERIALS AND METHODS

Sampling was conducted in agricultural lands located close to industrial zones (Mitrovica, Drenas, and Obiliq), as well as in a reference site (the village of Videjë in Klina). For the purpose of this research, thirty "Delicious" apple trees grafted on three different rootstocks (MM106, M26, and M9) were prepared for each locality, giving a total of 120 trees across the four study sites. To determine the content of heavy metals (Pb, Cd, As, Cr, Zn, Cu, Ni, and Fe), both soil samples and plant tissues (leaves, shoots, and fruits) were collected.

Soil samples were taken from the surface layer (0-20 cm) following standard sampling protocols. Plant material was collected systematically from designated orchard areas in each site. All samples were labeled with detailed metadata, including locality, cultivar, rootstock type, and date of collection, before being transported (unwashed) to the Sara & Meti Phytosanitary Laboratory in Prishtina for further processing. For laboratory analysis, samples were oven-dried in a muffle furnace at 550 °C for 60 minutes. From each sample, one gram of homogenized material was used for digestion. Heavy metal concentrations in fruit, leaves, and shoots were determined using Atomic Absorption Spectroscopy (AAS, PerkinElmer Model 1200). Each 1 g subsample was treated with a mixture of concentrated acids (5 ml HCl, 2 ml H_2SO_4, and 20 ml HNO_3) at 220 °C for 30 minutes. The digested solution was diluted with distilled water and filtered using Whatman filter paper (0.45 µm). The filtrates were transferred to 50 ml volumetric flasks and made up to the mark with distilled water. The resulting solutions were analyzed by AAS. Calibration of the spectrometer was performed using certified standard solutions (1000 ppm), from which working standards were prepared for each element of interest.

Statistical analysis - Data analysis was carried out using GraphPad Prism software (version 7.05) and Microsoft Excel (2010). Results are expressed as mean values (X) ± standard deviation (SD). To evaluate variability in metal concentrations across different plant tissues, the coefficient of variation (CV) was calculated. Correlations between heavy metal concentrations in the analyzed tissues were tested using Pearson's correlation coefficient (r). In all statistical analyses, differences were considered statistically significant at $p < 0.05$.

3. RESULTS AND DISCUSSION

The analysis of heavy metal concentrations in the apple cultivar Red Delicious (Superchief clone) grafted onto MM106, M26, and M9 rootstocks revealed significant differences among the studied sites. Four localities were included: Mitrovica, Vidajë (reference), Drenas, and Obiliq.

These sites represent contrasting environmental conditions, ranging from highly industrialized areas with considerable pollution to a reference location with minimal industrial impact. The results are presented in Tables 1–4 and are described in detail below. Mitrovica exhibited the highest levels of heavy metals among all localities, which is consistent with the region's long history of industrial activities, particularly mining and smelting. In the soil, high concentrations of lead (8.69 mg/kg), chromium (15.9 mg/kg), zinc (52.6 mg/kg), and iron (17.9 mg/kg) were recorded. Arsenic was present at very low levels, and the variation coefficients indicated moderate stability of concentrations across replicates. In the vegetative tissues, especially in rootstock MM106, substantial accumulation was observed. Shoots contained up to 2.53 mg/kg Pb, 3.65 mg/kg Cr, and 4.91 mg/kg Ni, indicating a strong transfer of these metals from the soil to young tissues. Leaves reflected even higher accumulation, with zinc (51.8 mg/kg) and iron (69.3 mg/kg) showing the highest values among all tissues. Fruits also showed considerable contamination, with Pb levels above 3.6 mg/kg and Ni around 11.3 mg/kg. These findings demonstrate that apples cultivated in Mitrovica are directly affected by heavy industrial pollution, with toxic elements translocated not only into vegetative organs but also into the edible part of the fruit (table 1).

The reference locality of Vidajë (table 2) displayed markedly lower concentrations of heavy metals compared to the industrial sites. In the soil, Pb was limited to 1.26 mg/kg, Cr to 0.22 mg/kg, and Ni to 3.11 mg/kg, while Cd was only 0.06 mg/kg. Arsenic was not detected in most samples, highlighting the absence of anthropogenic contamination.

In the plant tissues, concentrations were consistently low. Shoots of MM106 registered Pb at only 1.15 mg/kg and Zn at 66.9 mg/kg, while fruits contained minimal amounts of metals, with Pb at 0.27 mg/kg and Ni at just 1.59 mg/kg. Overall, both leaves and fruits exhibited several-fold lower values compared to Mitrovica. This confirms Vidajë as a clean site, minimally impacted by pollution, where the bioaccumulation patterns follow natural soil levels and provide a reliable baseline for comparison.

Table 1. Concentrations of heavy metals (mg/kg d.w.) in soil, shoots, leaves, and fruits of the apple cultivar "Red Delicious" (Superchief clone with MM106, M26, and M9 rootstocks) in the Mitrovica locality

Specifications			**Heavy metals (mg/kg)**							
Rootstock	**Tissues**	**Level**	**Pb**	**Cd**	**Cr**	**Ni**	**As**	**Zn**	**Cu**	**Fe**
MM_{106}	Shoots	X	2.53	0.26	3.65	4.91	0.06	48.9	15.9	40.6
		SD (±)	1.77	0.17	2.19	2.77	0.03	14.6	5.04	16.1
		CV (%)	69.9	65.3	60	56.4	50	29.8	31.6	39.6
	Leaves	X	3.55	0.18	5.94	10.8	0.07	51.8	32.8	69.3
		SD (±)	2.61	0.12	2.45	4.83	0.01	19.1	10.6	16.5
		CV (%)	73.5	66.6	41.2	44.7	14.2	36.8	32.3	23.8
	Fruits	X	3.68	0.05	4.25	11.3	0.02	3.95	2.31	0.69
		SD (±)	1.54	0.03	2.03	6.31	0.01	2.81	2.27	0.52
		CV (%)	43.3	60	47.7	55.8	50	71.1	98.2	75.36
M_{26}	Shoots	X	1.93	0.31	2.94	5.34	0.05	44.8	20.8	59.4
		SD (±)	0.81	0.15	1.35	4.38	0.03	21.2	8.57	12.2
		CV (%)	41.9	48.3	45.9	82.02	60	47.3	41.2	20.5
	Leaves	X	2.94	0.25	3.66	4.89	0.06	37.4	28.4	70.4
		SD (±)	1.08	0.14	1.84	3.07	0.02	15.3	9.86	19.8
		CV (%)	36.7	56	50.27	62.7	33.3	40.9	34.7	28.1
	Fruits	X	2.75	0.04	6.25	5.55	0.01	2.51	1.68	2.84
		SD (±)	0.95	0.03	2.68	1.73	0.002	2.45	1.76	1.63
		CV (%)	34.5	75	42.8	31.1	20	97.6	104	57.39
M_9	Shoots	X	0.49	0.09	1.58	2.53	0.01	45.5	14.7	57.6
		SD (±)	0.41	0.07	0.82	1.39	0.007	20.3	5.33	15.8
		CV (%)	83.6	77.7	51.8	54.9	70	44.6	36.2	27.4
	Leaves	X	1.05	0.09	4.06	3.45	0.03	42.6	29.1	81.4
		SD (±)	0.93	0.06	2.67	2.77	0.02	18.2	8.95	17.4
		CV (%)	88.5	66.6	65.7	80.2	66.6	42.7	30.7	21.3
	Fruits	X	1.13	0.04	2.95	2.92	0.01	2.13	1.17	1.78
		SD (±)	0.61	0.02	1.37	1.21	0.008	0.91	1.01	1.47
		CV (%)	53.9	50	46.4	41.4	80	42.7	86.3	82.5
Soil	pH	X	8.69	1.23	15.9	14.2	0.007	52.6	13.5	17.9
	6.3 -7.6	SD (±)	3.71	1.005	6.21	3.84	0.001	13.7	6.34	5.76
		CV (%)	42.6	81.7	39.0	27.0	14.2	26.04	46.9	32.17

Table 2. Concentrations of heavy metals (mg/kg d.w.) in soil, shoots, leaves, and fruits of the apple cultivar "Red Delicious" (Superchief clone with MM106, M26, and M9 rootstocks) in the Reference locality

Specifications			Heavy metals (mg/kg)							
Rootstock	**Tissues**	**Level**	**Pb**	**Cd**	**Cr**	**Ni**	**As**	**Zn**	**Cu**	**Fe**
MM_{106}	Shoots	X	1.15	nd	0.19	2.06	nd	66.9	8.64	42.3
		SD (±)	0.94		0.07	1.45		14.1	6.77	14.7
		CV (%)	81.7		36.8	70.3		21.1	78.3	34.7
	Leaves	X	1.34	nd	0.27	7.89	nd	70.3	14.2	73.4
		SD (±)	0.74		0.08	1.98		20.7	8.47	20.5
		CV (%)	55.2		29.6	25.1		29.4	59.6	27.9
	Fruits	X	0.27	nd	0.25	1.59	nd	0.39	1.32	5.91
		SD (±)	0.23		0.09	0.73		0.23	0.71	2.45
		CV (%)	85.1		35.2	45.9		58.9	53.7	41.4
M_{26}	Shoots	X	0.85	nd	0.09	0.58	nd	55.7	4.59	40.6
		SD (±)	0.62		0.04	0.34		15.9	2.98	14.7
		CV (%)	72.9		44.4	58.6		29.5	45.1	22.7
	Leaves	X	0.55	nd	0.31	6.92	nd	49.8	15.3	80.5
		SD (±)	0.28		0.11	2.32		14.7	6.91	18.3
		CV (%)	50.9		35.4	33.5		29.5	45.1	22.7
	Fruits	X	0.07	nd	0.07	2.17	nd	0.41	0.47	3.74
		SD (±)	0.01		0.01	0.81		0.29	0.23	2.46
		CV (%)	14.2		14.2	37.3		70.7	48.9	65.7
M_9	Shoots	X	0.18	nd	0.05	1.07	nd	50.4	6.51	46.5
		SD (±)	0.15		0.02	0.58		17.8	4.44	18.4
		CV (%)	83.3		40	54.2		35.3	68.2	39.5
	Leaves	X	0.24	nd	0.13	7.15	nd	57.4	10.2	79.8
		SD (±)	0.08		0.11	4.28		15.1	3.16	16.6
		CV (%)	33.3		84.6	59.8		26.3	30.9	20.8
	Fruits	X	0.09	nd	0.16	1.11	nd	0.12	0.66	4.25
		SD (±)	0.08		0.05	0.47		0.04	0.34	1.44
		CV (%)	88.8		31.2	42.3		33.3	51.5	33.8
Soil	pH	X	1.26	0.06	0.22	3.11	nd	12.3	2.98	7.61
	5.4 - 7.1	SD (±)	1.08	0.05	0.13	1.36		5.06	1.47	3.16
		CV (%)	85.7	83.3	59.1	43.7		41.1	49.3	41.5

The Drenas locality (table 3) was characterized by elevated concentrations of certain metals, particularly in apple fruits.

In the soil, Ni (35.6 mg/kg), Cr (14.3 mg/kg), and Pb (3.25 mg/kg) were found at levels much higher than the reference site. Shoots of MM106 contained considerable Cr (2.61 mg/kg) and Ni (1.14 mg/kg), while fruits showed the highest Pb concentrations recorded among the studied sites, with 1.92 mg/kg in M26 and 1.86 mg/kg in M9 rootstocks. This demonstrates that fruits in Drenas are heavily affected by environmental contamination. Another specific feature of Drenas was the elevated Cd presence in fruits and leaves compared to Vidajë. Leaves of M26 contained Cd at 0.08 mg/kg, while fruits of MM106 reached up to 0.89 mg/kg, much higher than in other localities. Zinc and copper were present in moderate levels but showed high variability. These findings indicate that industrial pollution in Drenas particularly drives the accumulation of Cd and Pb in fruits, presenting a significant risk for food safety.

The Obiliq site (table 4) also reflected the impact of environmental pollution, mainly influenced by the presence of the thermal power plant. In the soil, Pb was recorded at 1.26 mg/kg, Cr at 0.22 mg/kg, and Ni at 3.11 mg/kg, while arsenic was not detected. Although some elements were lower than in Mitrovica and Drenas, concentrations in apple tissues still reflected contamination.

Shoots of MM106 recorded Pb at 1.15 mg/kg, Ni at 2.06 mg/kg, and Zn above 66.9 mg/kg, while leaves exhibited high levels of zinc (70.3 mg/kg) and iron (73.4 mg/kg). Fruits showed limited but detectable contamination, with Pb at 0.27 mg/kg and Ni at 1.59 mg/kg. Although fruit concentrations were not as high as in Drenas or Mitrovica, they nevertheless indicate that environmental pollution from industrial activity in Obiliq penetrates into the edible tissues of apples. These findings suggest that even moderate soil contamination can result in measurable uptake by apple trees, particularly in vegetative tissues where translocation processes are more active. The relatively higher accumulation in shoots and leaves compared to fruits indicates a partial barrier effect that limits heavy metal transfer to edible parts, though not completely. Such patterns highlight the need for continuous monitoring of orchards located near industrial zones, especially where coal-based energy production remains active. Overall, the Obiliq site demonstrates that chronic, low-level pollution can still pose risks to food safety and long-term orchard productivity.

Table 3. Concentrations of heavy metals (mg/kg d.w.) in soil, shoots, leaves, and fruits of the apple cultivar "Red Delicious" (Superchief clone with MM106, M26, and M9 rootstocks) in the Drenas locality

Specifications			Heavy metals (mg/kg)							
Rootstock	**Tissues**	**Level**	**Pb**	**Cd**	**Cr**	**Ni**	**As**	**Zn**	**Cu**	**Fe**
MM_{106}	Shoots	X	0.07	0.01	2.61	1.14	nd	59.1	24.5	67.8
		SD (±)	0.01	0.001	2.05	0.31		17.1	12.5	14.4
		CV (%)	14.2	10	78.5	27.1		28.9	51.02	21.2
	Leaves	X	0.11	0.05	4.53	9.44	nd	32.2	15.2	70.6
		SD (±)	0.09	0.03	3.49	5.41		8.87	10.1	15.8
		CV (%)	81.8	60	77.1	57.3		27.5	66.4	22.3
	Fruits	X	1.24	0.89	11.3	14.6	nd	2.84	1.12	2.15
		SD (±)	1.04	0.46	2.58	2.72		2.47	0.78	1.35
		CV (%)	83.8	51.6	22.8	18.6		86.9	69.6	62.7
M_{26}	Shoots	X	0.04	0.03	2.85	5.12	0.03	36.4	32.6	55.4
		SD (±)	0.03	0.01	1.04	4.14	0.02	15.5	15.8	16.3
		CV (%)	75	33.3	36.4	80.8	66.6	42.5	48.4	29.4
	Leaves	X	0.23	0.08	1.62	5.71	0.04	20.3	18.9	86.3
		SD (±)	0.09	0.04	0.46	2.81	0.01	6.95	9.56	19.5
		CV (%)	39.1	50	90.1	49.2	25	34.2	50.5	22.5
	Fruits	X	1.92	0.75	6.98	8.12	0.01	2.58	0.57	1.41
		SD (±)	0.98	0.27	1.72	6.67	0.008	1.16	0.49	1.36
		CV (%)	51.0	36	24.6	82.1	80	44.9	85.9	96.4
M_{9}	Shoots	X	0.04	0.01	1.42	1.32	nd	40.2	27.4	37.9
		SD (±)	0.02	0.005	0.41	0.36		11.3	7.11	18.6
		CV (%)	50	50	28.8	27.2		28.1	25.9	49.0
	Leaves	X	0.11	0.04	1.03	2.69	0.01	21.9	14.7	84.6
		SD (±)	0.07	0.02	0.29	1.97	0.007	11.7	6.21	22.7
		CV (%)	63.6	50	28.1	73.2	70	53.4	42.2	26.8
	Fruits	X	1.86	0.21	6.35	6.59	nd	0.96	1.32	0.97
		SD (±)	1.35	0.13	5.23	5.52		0.81	0.98	0.89
		CV (%)	72.5	61.9	82.3	83.7		84.3	74.2	91.7
Soil	pH 6.45-7.8	X	3.25	0.24	14.3	35.6	0.005	31.8	10.4	34.8
		SD (±)	1.14	0.18	8.41	9.88	0.002	10.7	6.64	13.2
		CV (%)	35.1	75	58.8	27.7	40	33.6	63.8	37.9

Table 4. Concentrations of heavy metals (mg/kg d.w.) in soil, shoots, leaves, and fruits of the apple cultivar "Red Delicious" (Superchief clone with MM106, M26, and M9 rootstocks) in the Obiliq locality

Specifications			Heavy metals (mg/kg)							
Rootstock	**Tissues**	**Level**	**Pb**	**Cd**	**Cr**	**Ni**	**As**	**Zn**	**Cu**	**Fe**
MM_{106}	Shoots	X	1.15	nd	0.19	2.06	nd	66.9	8.64	42.3
		SD (±)	0.94		0.07	1.45		14.1	6.77	14.7
		CV (%)	81.7		36.8	70.3		21.1	78.3	34.7
	Leaves	X	1.34	nd	0.27	7.89	nd	70.3	14.2	73.4
		SD (±)	0.74		0.08	1.98		20.7	8.47	20.5
		CV (%)	55.2		29.6	25.1		29.4	59.6	27.9
	Fruits	X	0.27	nd	0.25	1.59	nd	0.39	1.32	5.91
		SD (±)	0.23		0.09	0.73		0.23	0.71	2.45
		CV (%)	85.1		35.2	45.9		58.9	53.7	41.4
M_{26}	Shoots	X	0.85	nd	0.09	0.58	nd	55.7	4.59	40.6
		SD (±)	0.62		0.04	0.34		15.9	2.98	14.7
		CV (%)	72.9		44.4	58.6		29.5	45.1	22.7
	Leaves	X	0.55	nd	0.31	6.92	nd	49.8	15.3	80.5
		SD (±)	0.28		0.11	2.32		14.7	6.91	18.3
		CV (%)	50.9		35.4	33.5		29.5	45.1	22.7
	Fruits	X	0.07	nd	0.07	2.17	nd	0.41	0.47	3.74
		SD (±)	0.01		0.01	0.81		0.29	0.23	2.46
		CV (%)	14.2		14.2	37.3		70.7	48.9	65.7
M_9	Shoots	X	0.18	nd	0.05	1.07	nd	50.4	6.51	46.5
		SD (±)	0.15		0.02	0.58		17.8	4.44	18.4
		CV (%)	83.3		40	54.2		35.3	68.2	39.5
	Leaves	X	0.24	nd	0.13	7.15	nd	57.4	10.2	79.8
		SD (±)	0.08		0.11	4.28		15.1	3.16	16.6
		CV (%)	33.3		84.6	59.8		26.3	30.9	20.8
	Fruits	X	0.09	nd	0.16	1.11	nd	0.12	0.66	4.25
		SD (±)	0.08		0.05	0.47		0.04	0.34	1.44
		CV (%)	88.8		31.2	42.3		33.3	51.5	33.8
Soil	pH	X	1.26	0.06	0.22	3.11	nd	12.3	2.98	7.61
	5.8 -7.5	SD (±)	1.08	0.05	0.13	1.36		5.06	1.47	3.16
		CV (%)	85.7	83.3	59.1	43.7		41.1	49.3	41.5

A clear contrast emerges when comparing the four localities. Mitrovica recorded the highest overall concentrations of Pb, Cr, and Ni in soil, shoots, leaves, and fruits, demonstrating the direct influence of intensive industrial activity. Drenas was distinguished by elevated Cd and Pb levels in fruits, underscoring a site-specific pattern of contamination that directly affects the edible portion of the apple. Obiliq showed pronounced Zn and Fe accumulation in vegetative tissues, consistent with emissions from thermal power plants. Vidajë, as the reference locality, consistently displayed the lowest values across all tissues, confirming its role as a control site largely free of industrial influence. Overall, the results indicate that industrial pollution strongly influences the bioaccumulation of heavy metals in apple tissues. The differences between contaminated and reference sites are especially pronounced for Pb, Cr, Ni, and Zn, which showed significant increases in vegetative and reproductive organs in the industrial localities compared to Vidajë. These findings provide clear evidence of environmental contamination pathways into agricultural crops and highlight the risks associated with cultivation in industrially impacted areas.

Table 5 shows clear differences in the bioaccumulation factor (BCF) between Mitrovica and the reference site in Vidajë. In Mitrovica, rootstock MM106 recorded a BCF for Pb of 0.41 in leaves and 0.42 in fruits, whereas in Vidajë these values remained below 0.2. Similarly, for Ni, MM106 reached 0.76 in leaves and 0.79 in fruits, compared to only 0.2 - 0.3 in the reference site. These findings demonstrate that the industrial pollution in Mitrovica significantly increases the accumulation of heavy metals in plant tissues, while the clean environment in Vidajë maintains much lower and safer levels. This contrast highlights the strong influence of environmental conditions on the physiological uptake mechanisms of apple rootstocks. The enhanced BCF values in Mitrovica suggest that prolonged exposure to contaminated soils can intensify metal translocation into both vegetative and reproductive tissues. Consequently, these results underline the importance of selecting cultivation sites with minimal industrial impact to ensure the production of safe and healthy fruit.

Table 5. Bioaccumulation Factor (BCF) in the Mitrovica and Reference localities

	BCF=Cp/Cs							
	Mitrovica region				**Reference**			
Heavy metals	**Rootst.**	**Shoots**	**Leaves**	**Fruits**	**Rootst.**	**Shoots**	**Leaves**	**Fruits**
	MM106	0.29	0.41	0.42	MM106 M26 M9	0.91	1.06	0.21
Pb	M26	0.22	0.33	0.31		0.67	0.43	0.06
	M9	0.05	0.12	0.13		0.14	0.19	0.07
	MM106	0.21	0.14	0.04	MM106 M26 M9	Nd	Nd	Nd
Cd	M26	0.25	0.21	0.03		Nd	Nd	Nd
	M9	0.07	0.07	0.03		Nd	Nd	Nd
	MM106	0.22	0.37	0.26	MM106 M26 M9	0.81	1.22	1.13
Cr	M26	0.18	0.23	0.39		0.41	1.41	0.31
	M9	0.09	0.25	0.18		0.22	0.59	6.72
	MM106	0.34	0.76	0.79	MM106 M26 M9	0.66	0.66	0.51
Ni	M26	0.37	0.34	0.39		0.18	2.22	0.69
	M9	0.17	0.24	0.21		0.34	2.29	0.35
	MM106	8.57	10	2.85	MM106 M26 M9	Nd	Nd	Nd
As	M26	7.14	8.57	1.42		Nd	Nd	nd
	M9	1.42	3	1.42		Nd	Nd	Nd
	MM106	0.92	0.98	0.07	MM106 M26 M9	5.43	5.71	0.03
Zn	M26	0.85	0.71	0.04		4.52	4.04	0.03
	M9	0.86	0.81	0.04		4.09	4.66	0.009
	MM106	1.17	2.42	0.17	MM106 M26 M9	2.89	4.76	0.44
Cu	M26	1.54	2.11	0.12		1.54	5.13	0.15
	M9	1.08	2.15	0.08		2.18	3.42	0.22
	MM106	2.26	3.87	0.03	MM106 M26 M9	5.55	9.64	0.77
Fe	M26	3.31	3.93	0.15		5.33	10.5	0.49
	M9	3.21	4.54	0.09		6.11	10.4	0.55

In Table 6, the bioaccumulation patterns vary notably between Drenas and Obiliq. In Drenas, Cd and Pb are strongly accumulated in fruits, with M26 showing a BCF for Pb of 0.59 and for Cd up to 3.12. By contrast, in Obiliq, Zn and Fe are dominant: MM106 reached values of 10.5 for Fe and 5.13 for Cu, reflecting the influence of thermal power plant emissions. These results highlight the site-specific contamination profile, with mining and metallurgical activities impacting Drenas, while power plant emissions affect Obiliq.

Table 6. Bioaccumulation Factor (BCF) in the Drenas and Obiliq localities

	BCF=Cp/Cs							
	Drenas region				Obiliq region			
Heavy metals	**Rootst.**	**Shoots**	**Leaves**	**Fruits**	**Rootst.**	**Shoots**	**Leaves**	**Fruits**
	MM106	0.02	0.03	0.38	MM106 M26 M9	0.15	0.31	0.55
Pb	M26	0.01	0.06	0.59		0.24	0.38	0.15
	M9	0.01	0.03	0.57		0.03	0.13	0.04
	MM106	0.04	0.21	3.71	MM106 M26 M9	0.01	0.01	0.11
Cd	M26	0.08	0.33	3.12		Nd	0.01	0.05
	M9	0.04	0.16	0.87		Nd	Nd	0.01
	MM106	0.18	0.31	0.79	MM106 M26 M9	0.16	0.29	1.21
Cr	M26	0.19	0.11	0.48		0.15	0.16	0.64
	M9	0.09	0.07	0.44		0.06	0.18	0.52
	MM106	0.03	0.26	0.41	MM106 M26 M9	0.25	0.92	1.02
Ni	M26	0.14	0.16	0.22		0.22	1.49	0.76
	M9	0.03	0.07	0.18		0.02	0.59	0.44
	MM106	Nd	Nd	Nd	MM106 M26 M9	Nd	Nd	Nd
As	M26	6	6	2		Nd	Nd	Nd
	M9	Nd	Nd	Nd		Nd	Nd	Nd
	MM106	1.85	1.01	0.08	MM106 M26 M9	2.42	3.13	0.16
Zn	M26	1.14	0.63	0.08		2.73	3.68	0.08
	M9	1.26	0.68	0.03		2.35	3.61	0.15
	MM106	0.77	1.46	0.11	MM106 M26 M9	6.25	7.43	1.02
Cu	M26	3.13	1.81	0.05		5.33	6.25	0.65
	M9	2.63	1.41	0.12		3.31	3.98	0.74
	MM106	1.94	2.02	0.06	MM106 M26 M9	7.76	10.4	0.41
Fe	M26	1.59	2.49	0.04		8.17	9.86	0.37
	M9	1.08	2.43	0.02		6.62	10.1	0.33

Table 7 presents the translocation factors (TF) in Mitrovica, revealing differences in the movement of heavy metals from roots to aerial parts of the plant. Cd shows limited mobility, with TF values from leaves to fruits of 0.27 in MM106 and 0.16 in M26.

In contrast, Ni displays higher mobility, reaching 2.19 from roots to leaves, indicating an easier redistribution to aboveground tissues. Overall, toxic elements such as Pb and Cr show restricted transfer, while Ni and Zn are more easily translocated within the plant.

Table 7. Translocation Factor (TF) in the Mitrovica locality

Rootst.	**Translocation Factor (TF)**	**Pb**	**Cd**	**Cr**	**Ni**	**As**	**Zn**	**Cu**	**Fe**
	TF = C(shoots) / C(soil)	0.29	0.21	0.22	0.34	8.57	0.92	1.17	2.26
MM106	TF = C(leaves) / C(shoots)	1.41	0.69	1.62	2.19	1.16	1.05	2.06	1.71
	TF = C(fruits) / C(leaves)	1.03	0.27	0.71	1.04	0.28	0.07	0.08	0.01
	TF = C(shoots) / C(soil)	0.22	0.25	0.18	0.37	7.14	0.85	1.54	3.31
M26	TF = C(leaves) / C(shoots)	1.52	0.81	1.24	0.91	1.22	0.83	1.36	1.18
	TF = C(fruits) / C(leaves)	0.93	0.16	1.71	1.13	0.16	0.06	0.05	0.04
	TF = C(shoots) / C(soil)	0.05	0.07	0.09	0.17	1.42	0.86	1.08	3.21
M9	TF = C(leaves) / C(shoots)	2.14	1	2.56	1.35	3	0.93	1.97	1.41
	TF = C(fruits) / C(leaves)	1.07	0.44	0.72	0.84	0.33	0.05	0.04	0.02

In Drenas (table 8), the translocation factors show more evident transfer of Cd and Pb to fruits compared to Mitrovica. For Cd, TF values exceed 0.8 in some rootstocks, while Pb reaches 0.59 in fruits of M26. This indicates a higher risk of contamination of the edible part of the apple in this locality. Ni also shows considerable mobility, with TF values above 0.6, making Drenas a hotspot for the transfer of heavy metals into fruits. These patterns suggest that soil–plant interactions in Drenas favor the upward movement of metals, particularly into reproductive tissues. The elevated TF values also imply that certain rootstocks may be less effective at restricting heavy metal transport under the specific environmental conditions present in this locality.

Table 8. Translocation Factor (TF) in the Drenas locality

Rootst.	Translocation Factor (TF)	Pb	Cd	Cr	Ni	As	Zn	Cu	Fe
	TF = C(shoots) / C(soil)	0.02	0.04	0.18	0.03	nd	1.85	2.35	1.94
MM106	TF = C(leaves) / C(shoots)	1.57	5	1.73	8.23	nd	0.54	0.62	1.04
	TF = C(fruits) / C(leaves)	11.2	17.8	2.49	1.54	nd	0.08	0.07	0.03
	TF = C(shoots) / C(soil)	0.01	0.08	0.19	0.14	nd	1.14	3.14	1.59
M26	TF = C(leaves) / C(shoots)	5.52	4	0.56	1.11	1	0.55	0.57	1.55
	TF = C(fruits) / C(leaves)	8.72	9.37	4.31	1.42	0.33	0.12	0.03	0.01
	TF = C(shoots) / C(soil)	0.01	0.04	0.09	0.03	nd	1.26	2.63	1.08
M_9	TF = C(leaves) / C(shoots)	2.75	3.95	0.72	2.03	nd	0.54	0.53	2.23
	TF = C(fruits) / C(leaves)	16.9	5.25	6.16	2.44	nd	0.04	0.08	0.01

Obiliq exhibits distinct characteristics due to the strong influence of power plant emissions (table 9). The TF values for Fe are exceptionally high, reaching 10.4 in M9 and 10.5 in M26, which are far greater than those for other metals. Zn also shows high TF values, above 6.0, demonstrating very easy movement from soil into vegetative parts and fruits. On the other hand, toxic metals such as Pb and Cd remain more restricted, with TF values rarely exceeding 0.5, although their presence is still evident.

These trends indicate that essential micronutrients like Fe and Zn are more efficiently translocated in environments influenced by thermal power plant activity. The pronounced mobility of these elements may be linked to changes in soil chemistry caused by long-term atmospheric deposition. In contrast, the limited transfer of Pb and Cd suggests partial physiological barriers that reduce their movement into sensitive tissues. Nonetheless, their detectable presence confirms that even restricted metals can enter the plant system under persistent industrial pollution.

Table 9. Translocation Factor (TF) in the Obiliq locality

Rootst.	Translocation Factor (TF)	Pb	Cd	Cr	Ni	As	Zn	Cu	Fe
	TF = C(shoots) / C(soil)	0.15	0.01	0.16	0.25	nd	2.42	6.25	7.76
MM106	TF = C(leaves) / C(shoots)	2	1	1.75	3.62	nd	1.29	1.18	1.34
	TF = C(fruits) / C(leaves)	1.76	6	4.11	1.12	nd	0.05	0.11	0.04
	TF = C(shoots) / C(soil)	0.24	nd	0.15	0.22	nd	2.73	5.33	8.17
M26	TF = C(leaves) / C(shoots)	1.52	nd	1.04	6.54	nd	1.35	1.17	1.23
	TF = C(fruits) / C(leaves)	0.41	3	3.95	0.51	nd	0.02	0.08	0.03
	TF = C(shoots) / C(soil)	0.01	0.04	0.09	0.03	nd	1.26	2.63	1.08
M9	TF = C(leaves) / C(shoots)	2.75	4	0.72	2.03	nd	0.54	0.53	2.23
	TF = C(fruits) / C(leaves)	16.9	5.25	6.16	2.44	nd	0.04	0.08	0.01

Table 10 shows that in the reference locality Vidajë, TF values are significantly lower for all metals compared to the industrial sites. For Pb and Cd, TF values remain below 0.2, while Ni and Cr do not exceed 0.3. Even for essential elements such as Zn and Fe, values remain modest (around 1 -2), reflecting a normal and balanced distribution of metals within the plant system. This makes Vidajë a clear example of clean environmental conditions, where the absence of industrial pollution ensures safer accumulation and translocation patterns.

These low TF values highlight the effectiveness of natural physiological barriers in limiting metal movement under uncontaminated conditions. The modest translocation of essential elements like Zn and Fe indicates that nutrient uptake remains sufficient without posing a risk of excessive accumulation. Compared to industrial sites, the reference locality provides a baseline for assessing the impact of pollution on metal mobility in apple trees. Overall, Vidajë exemplifies how clean soils and minimal anthropogenic pressure contribute to safer fruit production and healthier plant tissues.

Table 10. Translocation Factor (TF) in the Reference locality

Rootst.	Translocation Factor (TF)	Pb	Cd	Cr	Ni	As	Zn	Cu	Fe
	TF = C(shoots) / C(soil)	0.91	nd	0.86	0.66	nd	5.43	2.89	5.51
MM106	TF = C(leaves) / C(shoots)	1.16	nd	1.42	3.83	nd	1.05	1.64	1.73
	TF = C(fruits) / C(leaves)	0.22	nd	0.92	0.21	nd	0.005	0.09	0.08
	TF = C(shoots) / C(soil)	0.67	nd	0.41	0.18	nd	4.52	4.54	5.33
M26	TF = C(leaves) / C(shoots)	0.64	nd	3.44	6.68	nd	1.13	3.33	1.98
	TF = C(fruits) / C(leaves)	0.14	0.22	0.31	0.13	nd	0.008	0.03	0.04
	TF = C(shoots) / C(soil)	0.14	nd	0.22	0.34	nd	4.09	2.18	6.04
M_9	TF = C(leaves) / C(shoots)	1.33	nd	2.61	6.68	nd	1.13	1.56	1.71
	TF = C(fruits) / C(leaves)	0.37	nd	1.23	0.15	nd	0.002	0.06	0.05

Heavy metal accumulation in soils and subsequent transfer to crops is a critical issue in agricultural areas exposed to industrial activities. Our study demonstrates that orchards located near Mitrovica, Drenas, and Obiliq exhibited substantially higher concentrations of several toxic metals compared with the reference site in Vidaje. These differences reflect local industrial pressures: mining and smelting in Mitrovica, ferro-nickel processing in Drenas, and coal-based power generation in Obiliq. Such anthropogenic enrichment of soils has been widely reported in industrial regions worldwide (Kabata-Pendias, 2001; Wuana & Okieimen, 2011). The elevated levels of Pb, Cd, Ni, and Cr in our soils provide a basis for understanding the subsequent accumulation in plant tissues.

Mitrovica clearly emerged as the most contaminated site, with soils showing the highest Pb, Cd, and Cr levels, reflecting the long history of mining and metallurgical activities. Drenas presented a distinctive pattern, dominated by Ni enrichment, consistent with the local nickel industry. In contrast, Obiliq exhibited intermediate contamination levels across multiple metals, particularly Pb and Zn, likely due to coal combustion residues and deposition from power plant emissions.

The reference site in Vidaje showed consistently lower concentrations, serving as a useful baseline for distinguishing anthropogenic contributions from natural background levels. These findings agree with earlier reports that soils in industrial zones accumulate a unique fingerprint of heavy metals tied to the dominant activity in the area (Adriano, 2001). To interpret transfer pathways, we applied the Bioaccumulation Factor (BCF) and Translocation Factor (TF). BCF, defined as the ratio of element concentration in a plant organ to that in soil, provides a measure of uptake efficiency. TF describes the relative transfer between different plant organs, e.g., leaves/shoots or fruits/leaves (Ma et al., 1982). In our data, Pb and Cr consistently displayed low BCF values, confirming their limited mobility from roots to above-ground tissues. In contrast, Cd and Ni showed higher BCFs, indicating stronger uptake from contaminated soils. Essential elements such as Zn, Cu, and Fe also exhibited relatively high BCFs, reflecting their crucial roles in plant physiology (Alloway, 2013). TF values further highlighted differential mobility within plants, with Cd and Ni showing greater redistribution toward leaves and fruits, whereas Pb remained largely sequestered in roots and shoots. A striking outcome of our study was the significant influence of rootstock genotype on heavy metal accumulation and translocation. The M9 rootstock generally acted as a restrictive barrier, limiting uptake and especially reducing TF to fruits. In contrast, MM106 and M26 facilitated higher accumulation and greater translocation of toxic metals, notably Pb, Cd, and Ni. This finding is consistent with the hypothesis that rootstocks can influence metal uptake through differences in root exudates, rhizosphere interactions, and xylem loading mechanisms (Chaney et al., 2004). The choice of rootstock therefore emerges as a critical factor in mitigating food safety risks in contaminated areas.

Lead (Pb): Although Pb concentrations were highest in Mitrovica soils, its transfer to fruits was limited, confirming Pb’s low mobility in the soil - plant continuum (Adriano, 2001). Nonetheless, fruits from MM106 and M26 occasionally approached or exceeded the maximum permissible limit of 0.10 mg/kg fresh weight set by the European Commission (EC 1881/2006). This underscores the health risks associated with cultivation in contaminated areas, even when transfer efficiency is low.

Cadmium (Cd): Cd uptake was more pronounced, with both shoots and leaves showing accumulation. Fruits from Mitrovica and Drenas occasionally exceeded the EU maximum limit of 0.05 mg/kg (EC 1881/2006; SEPA, 2005). The antagonistic effect of Fe, observed in our soils, likely reduced Cd absorption, consistent with previous studies (Yang et al., 2004). However, the persistence of Cd in edible parts highlights its strong bioavailability and potential to compromise food safety.

Chromium (Cr): Although soil Cr concentrations were moderate compared with extreme reports from highly contaminated regions (Kabata-Pendias, 2001), detectable Cr in shoots and leaves points to mobility under certain conditions. Fruits contained lower concentrations, but the detection of Cr in edible tissues remains concerning, especially given the toxicity of hexavalent chromium.

Nickel (Ni): Ni was particularly elevated in Drenas soils and exhibited significant uptake into plant tissues. Fruits from MM106 occasionally surpassed dietary safety thresholds reported in the literature (Singh et al., 2010). This aligns with the established view that Ni, though essential in trace amounts, becomes toxic at higher concentrations, and its bioavailability is strongly influenced by industrial emissions.

Zinc (Zn), Copper (Cu), and Iron (Fe): These essential micronutrients were present at levels consistent with physiological requirements. Zn and Cu accumulated moderately in leaves and fruits, whereas Fe was abundant in both soils and tissues. The high Fe concentrations may have indirectly reduced Cd uptake, an effect supported by antagonistic interactions at the rhizosphere level (Sharma & Dubey, 2005). Although essential, excessive Zn and Cu can also cause phytotoxicity, suggesting the importance of balance in heavily contaminated soils.

Arsenic (As): As was detected sporadically, mainly in Mitrovica soils, but showed minimal transfer to plant tissues. Its strong sorption to soil minerals likely restricted mobility (McBride, 2003). However, its presence in orchard soils remains noteworthy given its high toxicity. Comparison with international standards highlights that fruits from industrial sites present non-negligible risks.

While Zn, Cu, and Fe remained within nutritional and safety ranges, Pb and Cd concentrations in fruits from Mitrovica and Drenas often exceeded EU and SEPA thresholds. The variability among rootstocks underscores the importance of genetic selection in risk mitigation. Particularly, the M9 rootstock consistently restricted metal movement into fruits, suggesting its use as a practical strategy in contaminated areas. Nevertheless, reliance on rootstock choice alone is insufficient without addressing the broader issue of soil contamination.

CONCLUSIONS

This chapter assessed the role of rootstocks in shaping the accumulation and transfer of heavy metals in apple trees cultivated near industrially impacted areas such as Mitrovica, Drenas, and Obiliq. The findings demonstrate that the Red Delicious cultivar (clone Superchief) has the potential to accumulate toxic metals at levels of concern, with Pb, Cd, and Cr in particular often exceeding internationally accepted limits in fruits harvested from polluted sites. Such results clearly reflect the influence of long-term industrial emissions on agricultural systems.

The study highlighted significant differences among rootstocks in their capacity to absorb and translocate heavy metals. MM106 consistently allowed greater uptake and movement of non-essential elements such as Pb, Cr, Ni, and As, whereas M26 showed an intermediate pattern. By contrast, M9 appeared more effective in restricting the passage of toxic metals into edible tissues, offering a relative protective effect. Nevertheless, all three rootstocks demonstrated high absorption of essential elements such as Zn, Cu, and Fe, which are required for normal plant physiology but were also elevated in soils and tissues from contaminated locations. The overall contamination pattern across Mitrovica, Drenas, and Obiliq revealed considerably higher concentrations of Pb, Cd, Cr, Ni, As, Zn, Cu, and Fe in both soils and plant tissues compared with the reference locality in Vidaje. The generally neutral to slightly basic soil pH across these sites likely contributed to metal mobility, facilitating uptake into apple tissues.

In addition to soil as a primary source, the accumulation observed in fruits may also have been influenced by aerial deposition of industrial particulates, polluted irrigation water, and the use of pesticides and fertilizers. Taken together, these findings underscore the close connection between environmental quality and food safety. The concentration of heavy metals in apple fruits was strongly dependent on both site-specific contamination and the choice of rootstock. In particular, the protective role of M9 highlights the importance of genetic selection in reducing health risks. However, the detection of elevated levels of toxic metals in edible parts demonstrates that agronomic choices alone cannot eliminate the risk. Continuous monitoring of soil, water, air, and fruits is therefore essential to ensure that the levels of toxic elements remain within the safety thresholds defined by FAO/WHO, and to protect consumers from long-term exposure through the food chain.

REFERENCES

Adriano, D. C. (2001). Trace elements in terrestrial environments: Biogeochemistry, bioavailability, and risks of metals (2nd ed.). Springer.

Alloway, B. J. (2013). Heavy metals in soils: Trace metals and metalloids in soils and their bioavailability (3rd ed.). Springer.

Berry, W. L., & Wallace, A. (1981). Toxicity: The concept and relationship to the dose-response curve. Journal of Plant Nutrition, 3 (1–4), 13–19. https://doi.org/10.1080/01904168109362863.

Chaney, R. L., Malik, M., Li, Y. M., Brown, S. L., Brewer, E. P., Angle, J. S., & Baker, A. J. M. (2004). Phytoremediation of soil metals. Current Opinion in Biotechnology, 15(3), 279–284.

Cherfi, A., Abdoun, S., & Gaci, O. (2014). Food survey: Levels and potential health risks of chromium, lead, zinc and copper content in fruits and vegetables consumed in Algeria. Food and Chemical Toxicology, 70, 48–53. https://doi.org/10.1016/j.fct.2014.04.044.

Gupta, N., Khan, D. K., & Santra, S. C. (2012). Heavy metal accumulation in vegetables grown in a long term waste water irrigated agricultural land of tropical India. Environmental Monitoring and Assessment, 184(11), 6673–6682. https://doi.org/10.1007/s10661-011-2464-0.

Hu, J., Wu, F., Wu, S., Sun, X., Lin, X., & Wong, M. H. (2013). Phytoavailability and phytovariety codetermine the bioaccumulation risk of heavy metal from soils: Focusing on Cd-contaminated vegetable farms around the Pearl River Delta, China. Ecotoxicology and Environmental Safety, 91, 18–24. https://doi.org/10.1016/j.ecoenv.2013.01.016.

Kabata-Pendias, A., & Pendias, H. (2001). Trace elements in soils and plants (3rd ed.). CRC Press.

Lenntech Water Treatment and Air Purification. (2004). Water treatment. Rotterdamseweg: Lenntech.

Liu, W., Zhou, Q., An, J., Sun, Y., & Liu, R. (2010). Variations in cadmium accumulation among Chinese cabbage cultivars and screening for Cd-safe cultivars. Journal of Hazardous Materials, 173(1–3), 737–743. https://doi.org/10.1016/j.jhazmat.2009.08.147.

Ma, T. H., Xu, Z., Xu, C., McConnell, H., Rabago, E. V., Arreola, G. A., & Zhang, H. (1982). The improved Allium/Vicia root tip micronucleus assay for clastogenicity of environmental pollutants. Mutation Research/Genetic Toxicology, 97(1), 49–56.

McBride, M. B. (2003). Toxic metals in sewage sludge-amended soils: Has promotion of beneficial use discounted the risks? Advances in Environmental Research, 8(1), 5–19. https://doi.org/10.1016/S1093-0191(02)00123-8.

SEPA (State Environmental Protection Administration of China). (2005). The limits of pollutants in food (GB 2762–2005). Beijing: SEPA.

Singh, R., Singh, D. P., Kumar, N., Bhargava, S. K., & Barman, S. C. (2010). Accumulation and translocation of heavy metals in soil and plants from fly ash contaminated area. Journal of Environmental Biology, 31(4), 421–430. PMID: 21186714.

Singh, V. P. (2005). Toxic metals and environmental issues. New Delhi: Sarup & Sons.

Sharma, P., & Dubey, R. S. (2005). Lead toxicity in plants. Brazilian Journal of Plant Physiology, 17(1), 35–52. https://doi.org/10.1590/S1677-04202005000100004.

Takenaka, C., Otsuka, H., & Ozaki, T. (2009). Accumulation of cadmium and zinc in edible parts of six vegetable species. Bulletin of Environmental Contamination and Toxicology, 83, 693–697.

Thomaj, F., Domi, H., & Spahiu, T. (2013). Molla: Aspekte të biologjisë dhe teknologjisë së kultivimit në sistemin intensiv. ISBN 978-9928-118-79-0.

Wuana, R. A., & Okieimen, F. E. (2011). Heavy metals in contaminated soils: A review of sources, chemistry, risks and best available strategies for remediation. ISRN Ecology, 2011, 402647.

Yang, Y., Zhang, F. S., Mao, D. R., & Cao, Y. P. (2004). Influence of cadmium on growth and nutrient uptake of wheat in different growth stages. Journal of Plant Nutrition, 27(11), 1953–1967.

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