



**UNIVERSITY OF RWANDA
COLLEGE OF SCIENCE AND TECHNOLOGY
AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THINGS**

**MONITORING AGRICULTURAL PEST INSECTS USING
DUAL-POLARIZATION RADARS**

**PhD Thesis Submitted in the Fulfillment of the Requirements for the
Award of the Degree of Doctor of Philosophy in Internet of Things –
Embedded Computing Systems.**

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SEPTEMBER 2024

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Computing Systems**

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To my wife, and children,

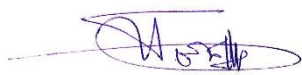
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Declaration

I hereby declare that the dissertation entitled “**Monitoring Agricultural Pest Insects Using Dual-Polarization Weather Radars**” to be submitted for the Degree of Doctor of Philosophy on the Internet of Things: Embedded Computing Systems at the University of Rwanda, College of Science and Technology, African Center of Excellence in Internet of Things is my original work and has not formed the basis for the award of any degree, diploma, associateship, or fellowship of similar other titles. I also declare that all source of information used was acknowledged by a complete list of references and were cited.

Done at Kigali, on 16th Septembe 2024



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Foreword

This dissertation represents years of dedication to advancing knowledge in agricultural pest monitoring through the innovative use of radar technology. The research was conducted at the African Centre of Excellence in Internet of Things (ACEIoT), College of Science and Technology (CST), University of Rwanda. The study aimed to address a critical agricultural challenge in Rwanda: the monitoring and controlling of crop pest insects, particularly the Fall Armyworm (FAW). The research utilized data from Meteo Rwanda's C-band dual-polarization weather radar to investigate maize field infestations in the Nyanza, Huye, and Gisagara districts during the Fall Armyworm outbreak from September 2020 to January 2021.

This study is structured around three key objectives: first, improving the detection of agricultural pest insects by addressing the challenges posed by ground clutter in radar data; second, developing and refining algorithms for insect detection, particularly for Fall Armyworm monitoring; and third, quantifying pest migration patterns using radar data to provide insights into pest behavior and distribution. These research goals were approached through rigorous analysis of weather radar data, literature review, and the development of new methods and algorithms for insect identification.

Acknowledgment

The completion of this research would not have been possible without the invaluable support and guidance of numerous individuals and institutions. I owe my deepest gratitude to my supervisor, Professor Anthony Vodacek, whose expertise, mentorship, and belief in my potential have been pivotal throughout this process. His critical feedback and constant encouragement have greatly shaped this work and my development as a researcher.

I am also deeply thankful to my co-supervisors, Dr. Emmanuel Ndashimye, Dr. Gerard Rushingabigwi, and Professor Kwang Soo Kim. Their collective wisdom, insightful feedback, and specialized knowledge significantly enriched this research. Each has played a critical role in different aspects of my work, and their support has been essential in navigating the complexities of this field.

The journey has also been made more enjoyable and intellectually rewarding thanks to the camaraderie and support of my colleagues and friends, Eric Nizeyimana, Barbara Kabwiga Asiingwire, and Prudence Mavhemwa. Their encouragement, insightful discussions, and shared commitment have made the challenges of this journey easier to navigate. I also want to express my appreciation to my neighbors and friends, particularly the Gwiza family, whose kindness and steadfast support helped ease the pressures of balancing work and life during periods of absence.

To my beloved family, my wife Evelyne Kabasinga, and our daughters Enxhi Imena Tinsley and Easley Irebe Shyra, my deepest thanks. Evelyne, your unwavering love, patience, and emotional strength have been the foundation of my success. Your sacrifices have allowed me to dedicate myself fully to this work. To my daughters, your joy and curiosity have been a constant source of inspiration, reminding me of the importance of striving for a better future through knowledge.

I am immensely grateful to PASET-RSIF for the scholarship that made this academic journey possible. I also wish to express my gratitude to Prof. Damien Hanyurwimfura, whose exceptional leadership and support at ACEIoT have been instrumental in my development. Thanks also go to Dr. Omar Gatera and the entire ACEIoT team, as well as to the Rwanda Meteorology Agency, for their mentorship and career guidance.

Lastly, I extend my profound thanks to God Almighty for His grace and blessings throughout this journey. His guidance has provided the strength to overcome challenges, and without His support, none of this would have been possible.

I dedicate this work to all those who have supported and believed in me. While it represents a personal achievement, this research contributes to the broader field of weather radar applications in agricultural pest management. I hope it inspires further innovation and contributes to improving the lives of farmers and communities reliant on sustainable agricultural practices.

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Abbreviations

ACEIoT	African Centre of Excellence in Internet of Things
AUC-PR	Area Under the Curve-Precision-Recall
C250P	C-band, 250-kilometer range, Polarimetric Weather Radar
CAPPI	Constant Altitude Plan Position Indicator
CIDD	Cartesian Interactive Data Display
CST	College of Science and Technology
DBZ	Reflectivity
DEM	Digital Elevation Model
DR	Depolarization Ratio
ESDS	Earth Science Data Systems
FAW	Fall Armyworm
FEI	Fraction of Echoes Correctly Identified
FL	Fuzzy Logic
FL_DR	Fuzzy logic integrating depolarization ratio
FMQ	File Message Queue
FRAHCC	Fuzzy Radar Algorithm for Hydrometeor Classification at C-band
GCMD	Ground Clutter Mitigation Decision
GHTC	Global Humanitarian Technology Conference
HCA	Hydrometeor Classification Algorithm
HSS	Heidke Skill Score

IEEE	Institute of Electrical and Electronics Engineers
IQ	In-Phase and Quadrature
IWRF	Integrated Weather Radar Facility Format
KDP	Specific Differential Phase
MDV	Meteorological Data Volume
MGEN/PGEN	Moment and Product Generator
MTR	Migration Traffic Rate
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCP	Normalized Coherent Power
NEXRAD	Next-Generation Radar
OPERA	Operational Programme for the Exchange of Weather Radar Information
PASET	Partnership for Skills in Applied Sciences, Engineering and Technology
PHIDP	Differential Phase
PID	Particle Identification
PPI	Plan Position Indicator
Py-ART	Python ARM Radar Toolkit
RAB	Rwanda Agriculture Board
RCS	Radar Cross-Section
REC	Radar Echo Classifier

RHOHV	Correlation Coefficient
RSIF	Regional Scholarship and Innovation Fund
SNR	Signal to Noise Ratio
TITAN	Thunderstorm Identification Tracking Analysis and Nowcasting
UR	University of Rwanda
VEL	Mean Doppler Velocity
VID	Vertically Integrated Density
VIR	Vertically Integrated Reflectivity
WIDTH	Doppler Spectrum Width
WSR-88D	Weather Surveillance Radar, 1988 Doppler
ZDR	Differential Reflectivity

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Symbols

ε	: Misclassification error
η	:Radar reflectivity
σ	:Radar cross-section
η	:Reflectivity,
dbz	: Equivalent reflectivity factor
K	:Refractive index Constant of the scatterer
λ	:Radar wavelength in cm,
ρ_{insect}	:Insect density
σ_{insect}	:Radar cross section of an insect
ρ_{FAW}	: Radar cross section of FAW

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Abstract

The Fall Armyworm (FAW), *Spodoptera frugiperda*, is a migratory pest originally native to tropical and subtropical regions of the Americas, but it has emerged as a global threat to agriculture, particularly in Africa since its arrival in 2016. FAW larvae feed on more than 80 different crops, including staple foods such as maize, rice, sorghum, and sugarcane, making it a significant concern for food security across the continent. In Rwanda, where FAW was first detected in 2017, conventional pest monitoring and control methods have often proven insufficient in preventing large-scale crop damage due to delayed detection of infestations.

This research introduces a novel approach to FAW monitoring by leveraging dual-polarization weather radar technology traditionally used for meteorological applications to detect and classify airborne biological entities, including insect swarms. Specifically, this study employs the Meteo Rwanda C-band polarimetric Doppler radar to track FAW infestations and outbreaks in southern Rwanda. Dual-polarization radars are uniquely suited for such applications because they can detect both the size and shape of targets, allowing them to distinguish between meteorological (e.g., rain) and biological (e.g., insects) targets using key radar parameters such as horizontal reflectivity (DBZH), differential reflectivity (ZDR), correlation coefficient (RHOHV), and specific differential phase (KDP).

A significant contribution of this research is the development and application of a neuro-fuzzy logic-based classification algorithm, which combines fuzzy logic with neural networks to improve the accuracy of FAW detection from radar data. This neuro-fuzzy approach enables more precise classification of FAW by processing radar signals and accounting for the inherent uncertainties in radar measurements. The introduction of a new radar parameter, the Depolarization Ratio (DR), further enhances the ability to distinguish biological targets like FAW from meteorological phenomena. By integrating DR into the fuzzy logic classification algorithm, the study achieved significant improvements in insect identification accuracy, particularly in separating FAW from other biological entities such as birds and smaller insects.

Through extensive analysis of radar data collected during the FAW infestation period from September 2020 to January 2021 across the Nyanza, Huye, and Gisagara districts of

Rwanda, the research demonstrates that dual-polarization weather radar can detect FAW adult moths up to four weeks earlier than ground-based monitoring techniques. Early detection is crucial for enabling timely interventions, such as targeted pesticide application or biological control measures, which can substantially reduce crop damage. This proactive approach to pest management not only helps mitigate the economic losses associated with FAW infestations but also promotes more efficient use of resources, reducing the reliance on blanket pesticide applications.

The study also provides a comprehensive analysis of FAW migration and infestation patterns using advanced radar data processing tools like the bioRad R package. Metrics such as Vertically Integrated Reflectivity (VIR), Vertically Integrated Density (VID), and Migration Traffic Rate (MTR) were used to quantify the spatial and vertical distribution of FAW swarms. The results highlight distinct nocturnal activity patterns of FAW, with peak migration occurring at specific altitudes, typically between 300 and 700 meters above ground level. These findings offer valuable insights into the behavior of FAW, enabling the development of more targeted pest control strategies that are aligned with the pest's movement and activity patterns.

This research advances the use of meteorological radar technology in agricultural pest management, showing that dual-polarization weather radar can effectively monitor pests like the Fall Armyworm (FAW). This cost-effective method has proven successful in Rwanda and has the potential to be scaled to other regions facing similar pest challenges. Integrating radar-based detection into agricultural monitoring frameworks can provide real-time data, improving pest management and contributing to more sustainable agricultural practices. This study highlights how technology can reduce crop losses and enhance food security in vulnerable areas.

Key Words: Dual-Polarization Weather Radar, Crop Pest Insect Detection, Fall Armyworm (FAW), Neuro-Fuzzy Logic, Agricultural Pest Management

Chapter 1. Introduction

1.1. Background and Significance

Arthropod pests alone cause about 20% of global annual crop losses [1], [2], [3], significantly threatening food security. This issue is particularly severe for poor and small-scale farmers in low-income countries, where pest infestations can lead to total crop destruction, exacerbating poverty and food scarcity [4]. In these regions, rapid population growth often outpaces crop yield improvements, resulting in pre-harvest losses ranging from 15% to 100% and post-harvest losses from 10% to 60% [1], [5], [6], [7]. The migration of insects exacerbates these infestations by spreading pests and diseases, causing extensive pre-harvest damage [3], [8].

In a crucial turning point for FAW, 2016 marked its official identification in West and Central Africa, signifying its introduction to the African continent. Subsequently, the pest rapidly spread across various African nations, impacting countries such as Nigeria, São Tomé and Príncipe, Cameroon, Ghana, Ethiopia, Kenya, Uganda, Burundi, and Rwanda [1], [8], [9]. In February 2017, the presence of FAW was initially reported in Rwanda, in the Mushishito maize marshland area, situated within the Uwinkingi and Kibilizi sectors of Nyamagabe District. By March 13 of the same year, this pest had spread to all districts within the Southern Province of Rwanda [10], [11]. Due to the lack of early detection and control, the outbreak rapidly spread, hampering the timely application of control measures [12], [13][14]. The infestation rapidly expanded, affecting nearly every one of Rwanda's 30 districts. The FAW infested approximately 15 699 hectares of land across the country, which constitutes about 24.7% of the total area of 63 499 hectares of maize and sorghum cultivation nationwide[15]. This rapid spread of FAW is particularly concerning in Sub-Saharan Africa, where millions are reliant on maize and sorghum as staple crops for food security and livelihoods. Therefore, the implementation of tools to track airborne pest outbreaks becomes essential to alleviate the burden of agricultural pests on farmers [1], [15], [16].

To effectively combat these pest infestations, farmers and agricultural decision-makers need access to precise, effective, and timely information on agricultural pest and disease outbreaks. Such information is crucial for informed decision-making and effective resource allocation, including the use and application of pesticides. Without timely and accurate data, efforts to manage and mitigate pest impacts are significantly hampered,

leading to greater crop losses and heightened food insecurity. Access to this information allows for better planning and the implementation of integrated pest management strategies, which are essential for sustaining agricultural productivity and ensuring food security, particularly in vulnerable regions.

Monitoring airborne insects in Africa, particularly agricultural pests like FAW faces significant challenges due to resource limitations and technological disparities compared to more developed regions such as Europe and North America[17], [18], [19] [20], [21]. While weather radars in these advanced areas offer valuable insights into insect behavior and migration, aiding pest management and ecological research, financial constraints, technological gaps, and skills shortages in Africa hinder the acquisition and maintenance of such monitoring systems. This results in an incomplete understanding of the movements of airborne biological targets, such as insects and birds, within the continent's diverse ecosystems[17].

Fall Armyworm, originally indigenous to tropical regions extending from the United States to Argentina in the western hemisphere[19], the FAW has emerged as a substantial threat to global agriculture and food security. Notably, in its early stages, FAW's young caterpillars and larvae exhibit a voracious appetite, feeding on more than 80 plant species, including crucial crops like maize, rice, sorghum, and sugarcane [22], [23]. This extensive feeding behavior significantly contributes to the severity of the menace and food security globally. Furthermore, the adult FAW moths, distinguished by their high-flying capabilities and migratory behavior, play a crucial role in the rapid dispersion of this pest across diverse regions[24]. Recognizing the dual impact of both the larvae's crop consumption and the moth's ability to cover vast distances is imperative for formulating effective strategies to address the challenges posed by FAW to global agricultural practices.

Modern polarimetric dual-polarization weather radars, designed to detect airborne hydrometeors like rain, hail, and snow, also can detect airborne biological entities such as birds, bats, and agricultural pest insects due to their high sensitivity to particle shape and size [25], [26]. Studies have shown a correlation between insect movements and echoes detected by weather radars, highlighting the potential of these radars as tools for monitoring non-meteorological targets like insects, birds, and bats [25], [26]. However,

the challenge lies in developing algorithms to detect and separate meteorological echoes from non-meteorological ones.

Africa has lagged behind developed regions in adopting weather radar technology for ecological and environmental monitoring. While North America and Europe have extensively used this technology to study airborne animal movements and ecological patterns [25], [27], its application in Africa remains limited. This discrepancy is evident in the scarcity of operational weather radar systems across the continent, which hampers African researchers' ability to leverage these tools for ecological studies.

Although some African countries, like Rwanda, possess advanced weather radar systems such as the Meteo Rwanda C-band polarimetric Doppler radar, their utilization has primarily been restricted to tracking weather patterns and precipitation. This study in Rwanda aims to broaden the scope by exploring the potential of weather radar for environmental monitoring, specifically focusing on airborne crop pest insect migration such as FAW. By analyzing data from the Meteo Rwanda weather radar, this study assesses the radar's ability to classify, identify, monitor, and quantify the movement and density of FAW. Adopting the fuzzy logic algorithm to identify insect radar echoes from weather radar data and the bioRad R package tools for biological analysis of weather radar data [17], [18], alongside the Meteo Rwanda C-band Doppler radar, we strive to attain a comprehensive understanding of insect movement across the country. This includes analyzing seasonal variations, preferred flight altitudes, and the geographical and quantitative spatial and vertical distribution of different insect populations, filling a critical gap in African ecological research and providing real-time data on insect migration.

The emergence of FAW as a significant threat to African agriculture underscores the critical need for effective monitoring and management strategies. Leveraging weather radar data with advanced algorithms, this research aims to develop precisely targeted control measures based on real-time insights into FAW movement patterns. This approach empowers farmers with the knowledge to prioritize scouting efforts and optimize resource allocation for effective pest control.

This research aims to utilize dual-polarization weather radars to monitor agricultural pest insects, specifically targeting FAW in Rwanda. By developing and refining radar-based

detection algorithms, the study seeks to provide a robust and cost-effective tool for early warning and management of pest outbreaks, thereby protecting crops and enhancing food security in regions most vulnerable to agricultural pest infestations. This approach will help inform decision-makers and enable the effective allocation of resources such as pesticides, ultimately improving agricultural productivity and resilience.

1.2. Problem Statement

Agricultural pests, particularly the Fall Armyworm (FAW), present a severe threat to crop production, significantly impacting food security and economic stability in regions like Rwanda. FAW infestations can lead to devastating crop losses, undermining the efforts of farmers and complicating food supply chains. Traditional pest monitoring and management methods often lack the precision and timeliness needed to effectively combat such threats, resulting in delayed responses and insufficient data for informed decision-making.

Weather radars, specifically dual-polarization C-band Doppler radars, offer a promising technological solution for enhanced pest monitoring. These radars are capable of detecting faint biological signals amidst complex environmental and meteorological clutter. However, several challenges impede their effectiveness: ground clutter masks weak insect echoes, dynamic insect movement alters radar signal polarization, and existing detection algorithms struggle to differentiate between meteorological and biological targets.

To address these challenges, there is a critical need to develop and refine methods for mitigating radar clutter, improving target identification, and quantifying insect migration. Effective integration of advanced radar technology with sophisticated data analysis techniques is essential for providing actionable insights into pest behavior and supporting more efficient pest management strategies.

1.3. Research Questions

The following research questions guide the investigation into enhancing radar detection capabilities, improving algorithmic accuracy, and understanding insect migration patterns:

- 1. How can ground clutter and beam blockage be effectively mitigated to improve the detection and quality of insect echoes in weather radar data?**

- This question focuses on exploring techniques to reduce interference from ground features and correct beam obstruction, thereby enhancing the radar's ability to detect weak insect signals.
2. **What radar detection and identification algorithms can be optimized to improve the accuracy of Fall Armyworm (FAW) classification?**
 - This question investigates the development and optimization of radar-based algorithms, aiming to enhance the accuracy of FAW detection compared to traditional methods.
 3. **How can weather radar data be utilized to quantify the spatial and vertical distribution patterns of Fall Armyworm (FAW) during an outbreak, and what insights can this provide for crop pest management strategies?**
 - This question aims to use radar data to analyze the movement patterns of FAW and derive actionable insights to improve pest management and control strategies.

These research questions are designed to tackle the core challenges of using weather radar for pest monitoring, aiming to advance the precision and effectiveness of pest management strategies through technological innovation and improved data analysis.

1.4. Research Aims and Objectives

1.4.1. Main Objective

The main objective of this work is to develop and refine radar-based Insect detection and identification algorithms to enhance the monitoring and management of the Fall Armyworm (FAW) in agriculture. This involves leveraging dual-polarization weather radar technology to improve the accuracy of FAW detection, classification, and understanding of its migration patterns.

1.4.2. Specific Objectives

To achieve the main goal of enhancing FAW monitoring, this research addresses three specific objectives: improving insect detection by mitigating ground clutter in radar data, refining detection and classification algorithms with radar parameters and fuzzy logic, and analyzing FAW migration patterns and distribution using weather radar data.

Objective 1

Enhancing Detection of Insect Signatures by Mitigation of Ground Clutter in Polarimetric C- Band Doppler Weather Radar.

Activities:

- Developed and implemented methods for ground clutter mitigation, significantly improving the detection and identification of insect signatures using polarimetric C-band Doppler weather radar.

Objective 2

Development and Enhancement of Insect Detection and Identification Algorithms.

Activities:

- Evaluate the effectiveness of key radar polarimetric parameters for insect detection and classification, such as Reflectivity, Correlation Coefficient, Differential Reflectivity, and Specific Differential Phase, in distinguishing FAW signature from other targets.
- Optimize detection methods and algorithms to improve classification accuracy compared to traditional approaches.
- Adopt fuzzy logic methods with polarimetric radar data to detect, classify, and monitor FAW.
- Compute the Depolarization Ratio (DR) and integrate it into the fuzzy logic algorithm, enhancing the identification of meteorological and biological targets, specifically focusing on FAW outbreak detection.

Objective 3

Quantifying Insect Migration and Evaluating Spatial and Vertical Distribution Using Weather Radar Data During the Fall Armyworm (FAW) Outbreak

Activities:

- Quantified the migration patterns of FAW using weather radar data, assessing their spatial, and temporal dynamic movement preference as well as vertical distribution, including flying altitude, preferable activity times, and migration traffic rates.

1.5. Overview of Major Contributions

The major contributions of this research are as follows:

1. Comprehensive Literature Review on Radar-Based Pest Monitoring:

- This thesis provides an extensive review of existing literature on the use of weather radar for agricultural pest monitoring. It critically analyzes the advancements and limitations of current methods, laying the foundation for the research by identifying key gaps and opportunities in the field. The literature review also situates the study within the broader context of radar technology applications in agriculture, emphasizing the need for improved detection and monitoring techniques.

2. Development of Ground Clutter Mitigation Techniques:

- The thesis introduces novel methods for mitigating ground clutter in C-band polarimetric weather radar data, specifically designed to enhance the detection of weak insect echoes. These techniques significantly improve the radar's ability to accurately identify and monitor agricultural pest insects, particularly in areas with complex terrain, where traditional methods fall short.

3. Optimization of Insect Detection and Identification Algorithms:

- The research presents advanced algorithms for the detection and classification of the Fall Armyworm (FAW) using dual-polarization radar data. By incorporating neuro-fuzzy logic and other innovative approaches, these algorithms enhance the precision of FAW identification, distinguishing it from other biological and meteorological targets with greater accuracy than traditional methods.

4. Quantification of Insect Migration and Distribution Patterns:

- This thesis contributes to the understanding of pest insect behavior by quantifying the spatial and vertical distribution patterns of the Fall

Armyworm during outbreaks. Utilizing weather radar data, the study provides detailed insights into FAW migration and distribution, offering valuable data that can be used to inform more effective pest management strategies.

These contributions collectively advance the field of agricultural pest monitoring and management by leveraging weather radar technology to address critical challenges in the detection, classification, and control of pest insects. The inclusion of a thorough literature review ensures that the research is well-grounded in existing knowledge while pushing the boundaries of current methodologies. These contributions also address the research questions and align with the objectives of the study. The outcomes have been consolidated into four research papers.

1.6. Thesis Outline

This thesis is organized into eight chapters, each addressing different aspects of the research on monitoring agricultural pest insects using dual-polarization weather radars. The structure ensures a logical flow from the introduction of the research problem to the conclusions and recommendations.

Chapter1:Introduction

Chapter 1 introduces the background and significance of using dual-polarization weather radars for monitoring agricultural pests, with a focus on the Fall Armyworm (FAW). It defines the research problem, outlines the study's objectives, and presents the key research questions that guide the investigation.

Chapter2:LiteratureReview

Chapter 2 provides a comprehensive review of existing literature related to agricultural pest monitoring and the application of radar technology. It examines the current methods and technologies, identifies gaps in the research, and justifies the need for this study.

Chapter 3: Methodology

Chapter 3 outlines the research design and methods used in this study. It details the data collection process, describes the study area, and explains the techniques employed for mitigating ground clutter and correcting beam blockage. The chapter also covers the development of insect detection and identification algorithms.

Chapter 4: Enhancing Detection of Insect Signatures by Mitigation of Ground Clutter in Polarimetric C-Band Doppler Weather Radar

Chapter 4 focuses on the implementation of techniques to mitigate ground clutter and correct beam blockage in radar data. It explains the methods used to enhance the quality of the radar data, ensuring more accurate detection of pest insects.

Chapter 5: Development and Enhancement of Insect Detection and Identification Algorithms

Chapter 5 discusses the creation and optimization of algorithms for detecting and identifying FAW in radar data. It describes the application of advanced methods, such as neuro-fuzzy logic, to improve the accuracy of pest detection and classification.

Chapter 6: Quantify insect migration and evaluate spatial and vertical distribution using weather

Chapter 6 analyzes the spatial and vertical distribution patterns of the Fall Armyworm during outbreaks using weather radar data. It provides insights into the behavior and movement of FAW, contributing to a better understanding of pest dynamics. It also explores how the findings from this study can be integrated into practical pest management strategies. It emphasizes the use of radar technology to inform and enhance decision-making in agricultural pest control.

Chapter 7: Conclusion and recommendation for future research directions

Chapter 7 concludes the thesis by summarizing the key findings, discussing their implications, and suggesting areas for future research. It reflects on the contributions of the study to the field of agricultural pest monitoring and management.

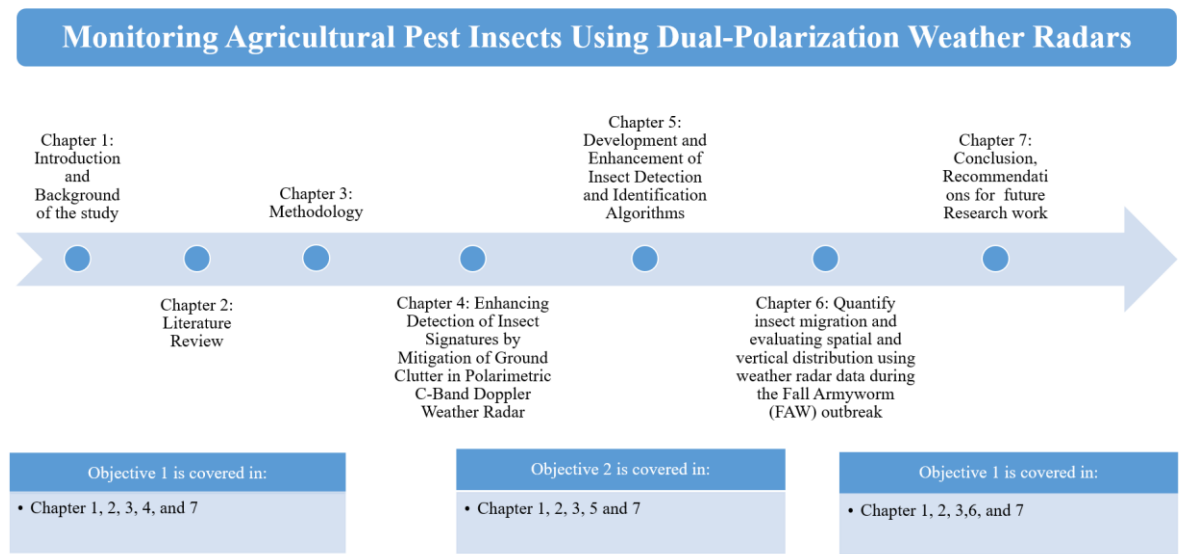


Figure 1: Thesis structure

Figure 1 illustrates the correlation between the chapters of this research and their respective objectives. Each chapter is aligned with specific research goals, showcasing the logical and cohesive progression of the study. It highlights the structured approach adopted to address the research questions, beginning with the literature review and methodological framework, followed by the development and implementation of the proposed solutions. By mapping the chapters alongside their objectives, Figure 1 provides a clear roadmap of the research process, underscoring the systematic efforts made to achieve the desired outcomes and advance agricultural pest monitoring.

Chapter 2. Related Literature

This chapter provides an overview of the application of weather radar technology for environmental monitoring, with a focus on detecting and classifying biological targets focusing on monitoring airborne pest insects such as Fall armyworm. Weather radar, originally developed for meteorological observations, has evolved to support ecological applications such as tracking biological targets like insects. The review highlights advancements in dual-polarization radar, which allows for more accurate detection and examines various algorithms and methodologies, including fuzzy logic and machine learning, that enhance the classification of insect radar echoes.

Special attention is given to the use of weather radar technology in monitoring and managing the Fall Armyworm (FAW), a significant agricultural pest. The review discusses research showing how radar data can track FAW migration patterns, assess their distribution, and predict outbreaks. It also explores how radar-based insect monitoring impacts agricultural practices, providing real-time data for timely interventions to mitigate crop damage.

2.1. Evolution and Historical Overview of Weather Radar Technology

Radar technology, an acronym for Radio Detection and Ranging, has its roots in the early 20th century. The concept was developed in the 1930s and became crucial during World War II for detecting enemy aircraft and ships [28], [29], [30]. Early radar systems emitted radio waves and detected objects by analyzing the reflected signals, known as echoes. This technology was primarily focused on military applications.

After World War II, radar technology transitioned from military to civilian use. Researchers noticed that radar echoes were not only returned by aircraft but also by weather phenomena like rain, snow, and storms. The first weather radars, developed in the late 1940s and early 1950s [28], [31] were adapted from military radar systems [34]. These early weather radars provided meteorologists with a new tool to observe and study weather patterns, leading to significant advances in weather forecasting and meteorology.

In the post-war era, radar operators encountered unexplained echoes termed "angels" which did not match the characteristics of known weather patterns or man-made objects [31] - [34]. Further investigation revealed that these echoes were caused by biological targets such as birds. This discovery, which occurred in the 1950s and 1960s [32], [33] marked the beginning of radar ornithology, the study of bird movements using radar technology. In 1966, a groundbreaking discovery revealed that clear air scattering echoes detected by weather surveillance radar primarily originated from biological sources, including birds, bats, and insects [35]. Shortly thereafter, insects were recognized as contributors to these mysterious echoes. Since then, radar has become a valuable tool for detecting, monitoring, and quantifying the movements of birds [36] - [38] bats [39], [40], and insects [41] - [43] in the atmosphere.

The 1970s and 1980s saw significant advancements in radar technology with the development of Doppler radar [44]. Doppler radar could measure the velocity of detected objects, not just their location. This advancement allowed meteorologists to not only detect precipitation but also measure wind patterns within storms, greatly enhancing severe weather prediction and tracking capabilities.

Polarimetric radar technology, developed in the late 20th and early 21st centuries [36], [45], further improved weather radar systems. Polarimetric radars transmit and receive both horizontal and vertical pulses, allowing for more detailed information about the shape, size, and type of precipitation particles. This capability enhances the identification and differentiation of precipitation types (rain, snow, hail) and improves the accuracy of weather forecasts [36].

Today, weather radar technology is utilized across various fields such as environmental monitoring [46], flight safety [47], and crop disaster prediction [48], [49]. Dual-polarization radar has revolutionized weather observations in several ways. Firstly, it improves precipitation estimation by analyzing parameters like differential reflectivity (ZDR), Correlation Coefficient (RHOHV), and specific differential phase (KDP), providing more accurate assessments of precipitation intensity and type [49], [50]. This capability enhances flood forecasting and water resource management. Secondly, it enhances hydrometeor classification by analyzing polarimetric variables, which offer detailed insights into the shape and orientation of precipitation particles [51], [52]. Thirdly, dual-polarization radar distinguishes between meteorological targets (such as

raindrops and snowflakes) and biological targets (such as birds and insects) based on their distinct polarimetric signatures [27], [47]. Biological targets such as birds and insects display polarimetric characteristics that differ from hydrometeors, making it possible to track their movements and behaviors in the atmosphere [53], [49]. This capability is valuable for biological research, enabling ornithologists and entomologists to study animal behavior and migration patterns effectively.

2.2. Insect radar signature, Classification algorithms and methods

Biometeors like insects and birds exhibit distinct radar signatures that separate them from rain and other weather phenomena. These signatures include low reflectivity (DBZ) ranging from -10 to 37 dBZ, high differential reflectivity (ZDR) values from -4 to 14 dB due to their elongated shape, and relatively low correlation coefficient (RHOHV) typically measuring less than approximately 0.86. Additionally, the differential phase (KDP) for insects is near zero, indicating clear air conditions. However, high insect densities can mimic precipitation due to exceptionally high RHOHV values, reaching up to 0.9 [54]. This is where polarimetric radar proves valuable. By analyzing these additional properties, we can differentiate between insects, birds, and precipitation.

Various algorithms have been developed for insect identification from radar data, including fuzzy logic [55], [56] decision trees [57], statistical methods[58], [59], and neural networks[60]. Fuzzy logic, with its ability to handle uncertainties and non-linearities, offers a robust approach. It works by converting numerical radar data (like DBZ, ZDR, RHOHV, and KDP) into fuzzy sets and then back into numerical values, enabling a nuanced classification process.

Fuzzy logic algorithms leverage these polarimetric characteristics to effectively distinguish between insects, birds, and precipitation [55],[61]. By using membership functions as filters, fuzzy logic extracts specific signatures from radar data, allowing for the analysis of multiple airborne objects simultaneously.

One major strength of fuzzy logic is its use of adaptable membership functions [63]. These functions act as filters to remove data that doesn't match insect signatures (typically low DBZH, high ZDR, low RHOHV, and near-zero KDP), followed by a classification

tailored to various airborne targets [58],[61], [62]. This flexibility allows for more accurate insect detection, especially when dealing with complex data sets. Additionally, fuzzy logic facilitates the simultaneous analysis of multiple airborne objects within a single dataset, providing a comprehensive understanding of the atmospheric conditions. This capability is beneficial for applications beyond entomology, such as weather forecasting and environmental monitoring.

However, fuzzy logic is not without limitations. Overlapping membership function values can lead to misidentifications [52], [63]. To mitigate this, subjective thresholds are often used, but this introduces an element of arbitrariness that can impact accuracy. Furthermore, the selection of appropriate membership function shapes (Gaussian, trapezoidal, triangular) is crucial for optimal performance [52], [55], [64].

Some researchers have addressed these limitations by combining fuzzy logic with neural networks, creating a neuro-fuzzy system [60]. This approach leverages the learning capabilities of neural networks along with the rule-based structure of fuzzy systems, potentially improving classification performance and incorporating prior observations into the process.

2.3. Application of Weather Radar in Biological Target Monitoring

Africa has lagged behind developed regions in adopting weather radar technology for weather forecasting, biological, and environmental monitoring applications [21], [55], [56], [65], [66]. While North America and Europe have extensively used this technology to study airborne animal movements and ecological patterns, its application in Africa remains limited. This discrepancy is evident in the scarcity of operational weather radar systems across the continent, which hampers African researchers' ability to leverage these tools for ecological studies.

Hardy et al. in 1969 associated clear air radar echoes with insects and birds [67]. Weather radar has become indispensable for monitoring airborne biological entities such as insects, birds, and bats, with applications in epidemic control, environmental preservation, flight safety, and crop disaster prediction [68].

Over the past decade, significant progress has been made globally in extracting biologically relevant information from low-level radar data [55], [15], [53]. These advancements align with a growing ecological need to understand and predict the movements of airborne animals. Consequently, the use of weather radar in ecological research has surged, particularly in developed nations where it has become crucial for monitoring bird migrations and insect movements [68] - [71].

Gauthreaux et al. [71] used reflectivity data from weather radar to establish a quantitative model for bird migration. The introduction of dual-polarised radar by Zrnic enabled detailed measurements of insects and birds [36], [72]. Cui et al. quantified insect migration across the Bohai Strait [73], while Nussbaumer et al. [74] used European radar networks to estimate nocturnal bird migration densities. These efforts have laid the groundwork for large-scale phenology research and improved the separation of birds and insects in radar data. For example, insect migration often takes place at significant heights, commonly hundreds of meters above the ground. They harness the power of strong winds to facilitate their long-distance journeys. This phenomenon is characterized by the concentration of migrating insects within specific altitude bands, typically between 40 and 290 meters above ground level. The range of altitudes for insect migration varies widely, spanning from 150 to 1200 meters, with a notable preference for medium-sized migrants weighing between 10 and 70 milligrams [75], [76], [77].

A key factor contributing to the widespread adoption of weather radar in these regions is the development of user-friendly radar biological software packages. A good example is the bioRad package for the R programming language, developed by Dokter et al. [53], which provides researchers with accessible tools for biological analysis of weather radar data. This package lowers the barrier to entry by offering functionalities that simplify the analysis of biological information within radar data.

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Chapter 3. Research Methodology

This chapter outlines the research design, data collection procedures, analytical techniques, and overall strategy used in this study. The methodology is structured into five main sections: research strategy, study area, data collection, ground clutter mitigation and data correction, and the development and optimization of detection algorithms.

3.1. Research Strategy

The research strategy provides a comprehensive plan for achieving the study's objectives through a combination of quantitative and qualitative methods. A mixed-methods approach was utilized to ensure a robust analysis, incorporating experimental techniques, algorithm development, and data analysis.

The experimental and algorithmic approach involved the creation and implementation of methods to mitigate ground clutter and enhance the radar's capability to detect weak insect echoes. This included applying advanced algorithms for clutter reduction and radar data correction. Detection and classification algorithms were developed using fuzzy logic and other computational techniques to improve the accuracy of identifying biological targets, with a specific focus on the Fall Armyworm (FAW).

A practical case study was conducted in maize fields across Nyanza, Huye, and Gisagara districts in Rwanda. This case study aimed to validate the effectiveness of the radar-based detection system by analyzing FAW outbreaks during the agricultural season from September 2020 to January 2021. Table 1 summarizes the research methods employed.

Table 1: Proposed research strategies

S/N	Research Focus	Method Used	Application
1	Clutter reduction and radar data cleaning	Experimental and Algorithmic, Case study	Developed techniques to reduce radar clutter and enhance data accuracy for improved insect detection
2	Developing Insect Detection Algorithms	Algorithm Development, Case study	Implemented fuzzy logic and other methods for accurate detection
3	Analyzing and quantifying Insect Migration	Data analysis and modeling	Quantified migration patterns and assessed spatial and vertical distribution

3.2. Study Area

The study was conducted in the southern province of Rwanda, focusing on the districts of Nyanza, Huye, and Gisagara (Figure 2), which experienced significant Fall Armyworm (FAW) outbreaks. These districts are located within 25 to 95 kilometers from the Meteo Rwanda C-band polarimetric Doppler weather radar site, which was pivotal in monitoring weather patterns and biological activity. Maize cultivation dominates the region, and FAW infestations have led to substantial crop damage [17], [32], [18].

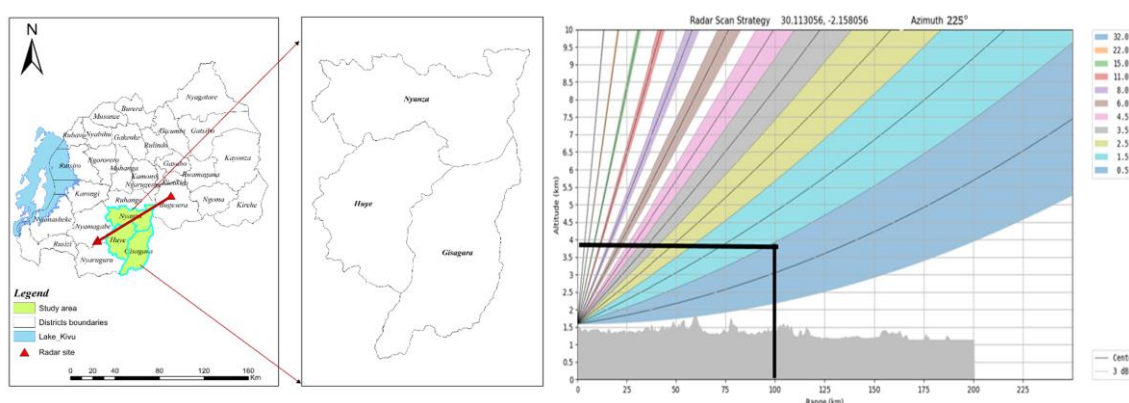


Figure 2. Study area and Meteo Rwanda weather radar scan strategy, with the red arrow pointing southwest at 2250 toward the study area, showing a clear view with no beam blockage.

The radar beam pointed specifically toward the infested areas. The beam height ranged from 200 to 2000 meters across the first three elevation angles (0.5, 1.5, and 2.5 degrees), optimizing the detection of insect flights. This clear air beam profile shows the minimized ground clutter and the radar's potential and ability to capture FAW signatures at typical insect flight altitudes.

3.3. Data Collection

This retrospective study relies on FAW outbreak observations recorded by the Rwanda Agriculture Board (RAB) and local farmers, as well as corresponding radar data from Meteo Rwanda. Data collection was centered on the FAW outbreak period from September 2020 to January 2021, aligning with reported infestation peaks in the study districts.

3.3.1. Weather Radar Data

Weather radar data were collected using the Meteo Rwanda C-band polarimetric Doppler weather radar. This radar operates at a frequency of 5625 MHz, with a wavelength of 5.3 cm, and features a beam width of 1°(see Table 2). It provides high-resolution observations with a temporal resolution of 5 minutes, which is crucial for capturing detailed meteorological and biological echoes, including those from Fall Armyworm (FAW) activity[17], [32], [18].

The radar key polarimetric parameters include reflectivity (DBZH), differential reflectivity (ZDR), correlation coefficient (RHOHV), and specific differential phase (KDP). These parameters are essential for differentiating between weather events and insect activity, particularly for FAW detection. The radar data are archived in Meteorological Data Volume (MDV) format and are processed using Thunderstorm Identification Tracking Analysis and Nowcasting (TITAN) and Cartesian Interactive Data Display (CIDD) software developed by the National Center for Atmospheric Research (NCAR)[78].

The selected radar data, coinciding with the FAW outbreaks, provided a robust dataset for radar analysis. Despite a notable data gap between 2015 and 2017, the period from September 2020 to January 2021 was rich in data critical for understanding FAW movements. This timeframe aligned with peak FAW activity, ensuring that the radar data collected were highly relevant for analyzing and characterizing the behavior and migration patterns of the pests.

Table 2: Radar Features and Parameters

S/N	Parameter	Value/Status
1	Status	Active
2	Owner	Meteo Rwanda
3	Longitude/Latitude	30.113056, -2.158056
4	Ground Height	1567 m
5	Tower Height	20 m
6	Band/Frequency	C / 5625 MHz
7	Beam Width	1°
8	Pulse Repetition Frequency (PRF) Min	160 Hz

9	PRF Max	2500 Hz
10	Transmitter Type	Magnetron
11	Power	250 kW
12	Receiver Type	Digital
13	Polarization	Dual
14	Manufacturer	Advanced Radar Corporation
15	Minimum Detectable Signal (MDS)	-112 dBm

The radar measurements include Equivalent Reflectivity factor at horizontal and vertical polarization (DBZH, DBZV), Differential Reflectivity (ZDR), Mean Doppler Velocity (VEL), Doppler Spectrum Width (WIDTH), Normalized Coherent Power (NCP), Cross Correlation Ratio (RHOHV), Differential Phase (PHIDP), Specific Differential Phase (KDP), Signal to Noise Ratio (SNR), and Received Power at Horizontal and Vertical channels (DBMHC and DBMVC). These parameters are assessed with a temporal resolution of 5 minutes and a radial range resolution of 150 m [32].

This comprehensive dataset from the radar, coupled with the temporal alignment with FAW outbreaks, provided valuable insights into FAW's migration patterns and behaviors. This rich dataset was pivotal in refining detection algorithms and improving the accuracy of radar-based pest monitoring systems.

3.3.2. Ground Reference FAW Data

Ground observation data on FAW outbreaks and maize infestations from three districts (Nyanza, Huye, and Gisagara) form the foundation and reference for this research. This retrospective study relies on FAW outbreak observations recorded by the Rwanda Agriculture Board (RAB) Rubona station. Field data were collected from 1160 hectares of maize fields in these districts, with farmers reporting infestations by sighting caterpillars and observing adult moth movements. As FAW are nocturnal, these observations were typically made after sunset and before sunrise in the early morning. During the day, farmers could only see the damage caused by the larvae (or caterpillars). The data collected are crucial for understanding the spread and impact of FAW, providing valuable insights into infestation patterns and timing. Additionally, these observations help inform the correlation between ground and radar observations, contributing to the development of effective identification algorithms.

Initial monitoring in October 2020 revealed FAW presence among 156 farmers, with the situation worsening within five weeks of planting, affecting over 280 hectares, highlighting the severity of FAW infestations [17]. Additionally, this study incorporates nocturnal clear-air weather radar data collected over infested maize fields during the infestation period. It is assumed that night clear air echoes over these fields and marshlands primarily originate from insects rather than birds, considering the unimodal pattern of tropical regional bird activity and foraging concentrated towards the end of the day [79], [80]. Further elaboration on the data used in this study is provided in [17] detailing the increasing trend of insect radar echoes detected before and during the infestation period. It's important to note that FAW are nocturnal insects, while most birds in tropical regions, including Rwanda, are active during the day and at the end of the day. Nocturnal bird species like owls and nightjars are not abundant in this region.

FAW ground reports were collected by farmers from three districts in the Southern Province (Nyanza, Huye, and Gisagara) to assess the distance between the radar and the FAW infestation reports. Figure 2 includes a map of Rwanda, highlighting the radar site and the districts reporting FAW infestations. The distances from the radar to Nyanza, Huye, and Gisagara Districts are between approximately 25 km and 95 km. Bold black lines in the right panel indicate the distance and height from the radar to the study area and the elevation angles used, considering the height or insect flight layer.

Figure 2 also outlines Meteo Rwanda's scanning strategy, showing that the radar beam points toward the infested areas. The beam height ranges from 200 meters to 2000 meters for the first three elevation angles (0.5, 1.5, and 2.5 degrees). This range encompasses the typical flight altitudes of migratory insects, which usually fly between 150 and 1200 meters above ground level [77], [75]. Additionally, the figure demonstrates that the beam profile is not obstructed by ground clutter, as evidenced by a clear air beam profile for a beam pointed at 225 degrees toward Nyanza and Huye Districts.

Insect migration predominantly occurs at high altitudes, often hundreds of meters above the ground, where insects utilize strong winds to travel quickly and cover long distances. The majority of these migrations take place between 150 and 1200 meters above ground level, with medium-sized insects, weighing between 10 and 70 milligrams, being the most common travelers. These insects include species like butterflies, dragonflies, and moths including FAW [81].

3.4. Data Preprocessing

The radar data underwent several preprocessing steps to ensure accuracy. Ground clutter mitigation was a critical first step, achieved by using Digital Elevation Models (DEM) to divide the radar's volume scans into blocked and unblocked areas. The Ground Clutter Mitigation Decision (GCMD) algorithm, complemented by beam blockage correction, was applied to filter out non-insect echoes, such as those caused by terrain or buildings. The ClutterRemove function was automatically applied to regions identified as cluttered by the GCMD algorithm, ensuring that only relevant biological signals were retained.

3.5. Algorithm Development and Analysis

After data cleaning, advanced detection algorithms were developed using fuzzy logic methods. These algorithms were designed to distinguish between meteorological phenomena and biological targets, focusing on FAW detection. Key polarimetric parameters, such as the Depolarization Ratio (DR), were computed and integrated into the fuzzy logic framework, improving the accuracy of FAW classification.

The bioRad R package was employed for the biological analysis of radar data, enabling the classification, identification, tracking, and quantification of FAW activity. Time series of vertical profiles were analyzed, including parameters such as insect ground speed (west-to-east and south-to-north components), vertical and horizontal flight speeds, and radar reflectivity factors. These analyses provided detailed insights into the spatial and vertical distribution of FAW during the outbreak period, helping to understand the insects' nocturnal migration patterns.

3.6. Research Outcome

The integration of radar data with ground observations successfully identified distinct radar signatures associated with Fall Armyworm (FAW) activity, particularly during nocturnal flights. Polarimetric radar parameters, such as Differential Reflectivity (ZDR) and the Correlation Coefficient (RHOHV), were instrumental in distinguishing FAW from other biological or meteorological targets. This study was able to identify FAW-specific radar signatures, marking a significant advancement in radar-based pest detection.

By validating radar-based detection algorithms with ground truth observations, the study contributed to the development of more accurate pest monitoring systems. These findings are essential for enhancing real-time pest management strategies, allowing for more proactive responses to FAW outbreaks. The integration of radar data in this manner supports sustainable agricultural practices, particularly in regions susceptible to similar infestations.

3.6.1. Research Publications

The outcomes of this research have been extensively documented in peer-reviewed journals and conferences, showcasing the significant advancements in radar-based detection of agricultural pests like the Fall Armyworm (FAW). These publications not only highlight the innovative methodologies used, such as ground clutter mitigation and neuro-fuzzy logic algorithms but also emphasize the successful integration of radar data with field verification. The findings contribute to the development of advanced monitoring tools that can aid in sustainable pest management strategies. Below is a summary of the key publications stemming from the research objectives.

Objective 1 was published as:

- F. Maniraguha, A. Vodacek, E. Ndashimye, and G. Rushingabigwi, "Ground Clutter Mitigation and Insect Signature Detection for Polarimetric C-Band Doppler Weather Radar," 2021 IEEE Global Humanitarian Technology Conference (GHTC), Seattle, WA, USA, 2021, pp. 289-296, doi: 10.1109/GHTC53159.2021.9612449.

Objective 2 was achieved through two publications:

- F. Maniraguha, A. Vodacek, K. S. Kim, E. Ndashimye, and G. Rushingabigwi, "Adopting a Neuro-Fuzzy Logic Method for Fall Armyworm Detection and Monitoring Using C-Band Polarimetric Doppler Weather Radar with Field Verification," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-10, 2024, Art. no. 5105910, doi: 10.1109/TGRS.2024.3395281.
- F. Maniraguha, A. Vodacek, K. S. Kim, E. Ndashimye, and G. Rushingabigwi, "Enhancing Identification of Meteorological and

Biological Targets Using the Depolarization Ratio for Weather Radar: A Case Study of FAW Outbreak in Rwanda," *Remote Sensing*, 2024; 16(14):2509, doi: 10.3390/rs16142509.

Objective 3 was published as:

- F. Maniraguha, A. Vodacek, K. S. Kim, E. Ndashimye, and G. Rushingabigwi, "Quantifying Insect Migration with Weather Radar: Case Study on Fall Armyworm Outbreak in Rwanda," Submitted for publication (under review).

Chapter 4. Enhancing the detection and Identification of insect signatures by mitigating ground clutter in polarimetric C-band doppler weather radar systems

4.1. Overview

Weather radar systems are designed to detect and monitor meteorological phenomena, but they also capture returns from non-meteorological targets such as insects, birds, dust, and other airborne particles. These non-meteorological echoes, particularly from insects, are common in clear-air conditions. However, a significant challenge in weather radar data processing is the contamination caused by ground clutter and unwanted radar returns from stationary objects like buildings, terrain, and other surface features. Ground clutter can obscure weaker radar echoes, such as those from insects, making it difficult to extract clear-air data[32], [82].

To address this issue, the study presents a Ground Clutter Mitigation Decision (GCMD) system combined with a radar scanning strategy. This system leverages topographic information obtained from a digital elevation model (DEM) to evaluate areas where the radar beam is blocked by terrain. The radar coverage area is classified into three distinct categories: fully blocked, partially blocked, and unblocked regions. These classifications are crucial for validating the GCMD algorithm and generating accurate clutter maps, which are essential for minimizing ground clutter interference[32].

Once ground clutter is mitigated, the study focuses on assessing the potential of the Meteo Rwanda Polarimetric C-Band weather radar to detect and monitor insect signatures in clear-air conditions. By analyzing key polarimetric parameters such as reflectivity (DBZ), differential reflectivity (ZDR), and correlation coefficient (RHOHV) the study evaluates the radar's ability to capture insect activity. These observations provide insights into how polarimetric radar can be used to distinguish insect echoes from other clear-air targets, enhancing the radar's utility in environmental monitoring and pest management[32].

4.2. Introduction and background

Weather observation radars are designed to monitor the skies to detect precipitation and extreme weather. Weather radar provides a mechanism for continuous monitoring of

airspace over a wide geographic coverage that is beneficial to meteorologists who are primarily interested in hydrometeor particles such as rain, snow, and hail. However, dual-polarization weather radars are sensitive to the properties and characteristics of all aerial objects, making it possible to separately identify bio-meteors such as birds, bats, and insects. Thus, this remote sensing meteorological infrastructure also has a broad undervalued capacity for detecting, quantifying, and tracking biological targets in the airspace[53], [68], [26], [83].

Biologists and entomologists who are interested in monitoring, observing, and studying airborne animal activities on a wide range of temporal and spatial scales can use weather radar as a remote sensing tool. Based on assumptions of certain weather radar parameters, the signatures of aerial biological particles can be determined by analyzing weather radar data [84], which is the purpose of this research.

However, since the inception of weather radar more than 50 years ago, one cause of poor data quality has been echoes that result from reflections from the earth itself and objects on the earth, such as rocks, bare ground, trees, shrubs, buildings, etc. Reflections off these ground targets are termed ground clutter echoes or simply ground clutter [85], [86].

To properly analyze radar reflectivity data, it is necessary to know how much of a radar view is blocked by surrounding obstacles. Users of radar data for meteorological and non-meteorological applications must be aware of the application limitations when there is a beam blockage. A significant factor to consider in weather radars operating in complex topography areas is the impact of adjacent hills of equivalent or higher altitudes blocking radar beams[87].

Rwanda is located along the Western Branch of the East African Rift Valley and is characterized by a complex terrain, particularly along the western part of the country. The volcanic Virunga Mountains, which border the Republic Democratic of Congo and Uganda, are in the northwest of the country and present high mountains causing low-elevation radar beam obstruction. The land gradually falls away from the west to the central plateau and the east. The Meteo Rwanda weather radar is installed in the southern east part of Rwanda. For the Meteo Rwanda weather radar, with processing to a nominal 150 m horizontal spatial resolution and 11 elevation angles, the beams of the lowest angles are partially or blocked by mountains to the west and north, although the beam is almost

clean to the east. Fortunately, polarimetric weather radars have the potential to mitigate this beam blockage problem to enhance the detection of biological targets.

4.3. Related Work

4.3.1. Ground Clutter Mitigation and Beam Blockage Correction

To mitigate ground clutter effects and improve radar data quality, studies have been conducted and different approaches have been proposed over the years. A clutter detection algorithm named dual-polarization and dual scan was proposed in [88], where ground clutter and weather echo discrimination are achieved from estimations from auto- and cross-correlation functions from two consecutive scans.

Due to the omnipresence of insects during warm and dry weather, traditional methods using the likelihood of detection often struggle to distinguish between ground clutter and insects. Thus, Rennie et al. created a way for separating ground clutter and insects based solely on velocity and reflectivity [89], by constructing a pseudo-probability clutter diagram [87].

Mitigation of radar data contamination may consist of a) calculation of a Dynamic Elevation Map which provides the minimum clutter-free antenna elevation for each pixel within the radar coverage; b) correction for residual by checking the vertical reflectivity gradients within the radar volume; and c) topographical beam blockage estimation and correction [84], [90], [91].

Partial beam blockage (PBB) of the main lobe of the radar antenna pattern by objects in the radar field of view (e.g., hills, terrain, trees, etc.) causes biases in radar reflectivity at ranges beyond the blockage. There are several techniques to correct such biases. For example, using digital terrain maps to create digital elevation models (DEMs) and using self-consistency of the polarimetric variables [27]. The DEM technique requires very accurate digital terrain maps; however, it cannot account for blockages due to trees and other ground structures. Additionally, blockage due to trees can vary from season to season.

4.3.2. Weather Radar and Flying Insect Detection

Meteorological radar operators prefer to concentrate on delivering clean meteorological radar scans from meteorological weather targets, and the signal received from non-meteorological targets such as clutter [92], [41], birds, and insects are regarded as contamination to be eliminated rather than as valuable data [36],[93]. Furthermore, operational technology solutions need to be developed to process non-hydrometeors radar signals such as biological signals, and produce valuable products such as insect monitoring as a tool for the eventual forecasting of the propagation of insect vector-borne crop diseases. This is why we seek to raise an understanding of the benefits of using a meteorological radar to track aerial animals (birds, bats, and insects) migrations and other non-meteorological applications.

Generally, radar echoes in the clear air come from insects, birds, and some other particulates in the atmosphere that are large enough to return some power to the radar. In warmer seasons, insects frequently fill the skies in almost every region in the world at temperatures above $>10^{\circ}\text{C}$ [48], [94]. Studies showed that the Rwanda temperatures annual climatology from 1961 to 1992 are above 20°C in most of the regions with elevation below 1500 m, while the mean annual temperature is below 15°C in the Virunga mountains in northwest Rwanda [95].

However, ground clutter is problematic for extracting the weak echoes of insects, since the returns from clutter are greater than the returns from insects. Polarimetric radars such as the Meteo Rwanda C250P C-Band Polarimetric Weather Radar have demonstrated capabilities of quantifying biological phenomena in the airspace that are not possible with standard weather radars. Thanks to its ability to track and control individual particles in clouds, which was not possible with conventional Doppler weather radars, the key features of modern Polarimetric radars such as C250P are Particle Identification (PID) and Radar Echo Classifier (REC) capabilities, which help to differentiate hydrometeor particles from non-hydrometeor particles such as ground clutter, bats, insects, and birds. Insect signatures can be specifically identified, where insect signatures are characterized by very high differential reflectivity ZDR (4 to 14 dB), low reflectivity Z (-10 to 6 dBZ), and low correlation coefficient RHOHV (≤ 0.9) [32], [96], [97].

Low RHOHV (<0.70) indicates a low consistency between radar H and V channel signals in the estimation and the heterogeneity of the scatterers. In general, RHOHV <0.70 is so diverse that scatters are almost certain to be non-meteorological, like birds or insects. On the other hand, a high RHOHV (>0.97) implies consistency estimation of polarization between H and V. This means the scatterers are very uniform in shape and size, as is common for rain or snow. The capability of Doppler and Polarimetric weather radar has been exploited to evaluate its capability to track and monitor flying insects in monitored radar areas using different types of radar around the globe such as WSR-88D, OPERA, and NEXRAD [53], [98].

C-band Polarimetric weather radar algorithms developed for rainfall measurements, severe weather detection, and particle identification in other parts of the world may not always directly apply to the situation of Rwanda. This research is performed to develop and adapt these algorithms to the region since no previous work in this regard has been done in Africa.

4.4. Methodology

4.4.1. Proposed Ground Clutter Mitigation Integrated with Beam Blockage Correction

As weather radars become more widely used for meteorological and non-meteorological measurement applications, it is important to resolve the major issues with radars for this purpose to ensure the highest quality data for reliable measurements and application.

The proposed ground clutter mitigation integrated with beam blockage correction is classified into three main parts as presented in Figure 3:

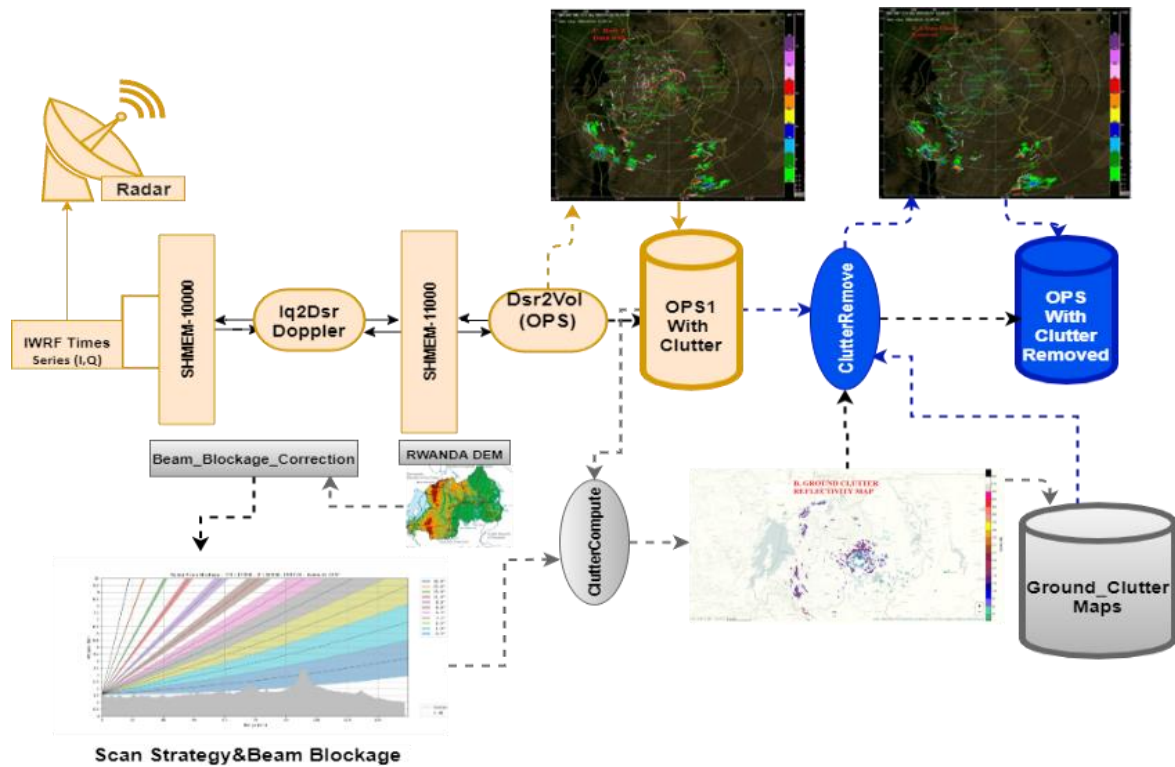


Figure 3. Proposed Ground clutter mitigation integrated with beam blockage correction

Real-time raw radar data generation: As presented in Figure 3, the orange shaded part, this consists of Level 0 moments and Level 1 raw radar data real-time generation in MDV format, where the dual polarized radar beam-by-beam data “in-phase” and “quadrature” (IQ) time series signal data in Integrated Weather Radar Facility format (IWRF) is loaded into a File Message Queue (FMQ), which is handled by first-in, first-out (FIFO) queues. Shmem indicates that the real-time time series data are available. The time series data are converted into moment data by the process Iq2Dsr stored under `output_fmqs_url="$(DATA_DIR)/fmq/moments"`. The moments produced by the (ops) instance of Iq2Dsr are packaged into polar format Meteorological Data Volumes MDVs by the (ops) instance, which are used for registration with procmap of Dsr2Vol. The output MDV data are radar polar volume data stored under OPS1 as cluttered data `polar_files = {450, 0, 90, "mdvp:://localhost:0:mdv/radarPolar/op1"}`. `Start_Iq2Dsr.ops` and `start_Dsr2Vol.ops` scripts registered under process Mapper keep track of real-time data availability.

Ground clutter compute and beam blockage correction: The method proposed for detecting clutter shaded in orange in Figure 3, is based on the consistency of ground clutter returns between scans and beam blocked areas. The beam blockage correction is derived from the terrain profile algorithm, which results in creating a map of areas with the highest likelihood of clutter. The proposed clutter mitigation strategy uses beam blockage identification and Clutter Mitigation Decision, which is a real-time fuzzy logic-based algorithm. The process generates/updates a new clutter map with the GlabClutterMap algorithm was developed to update the clear-air ground clutter. The clutter map is automatically applied to regions identified as ground clutter by GCMD. This strategy removes the ground clutter while minimizing the impact of the clutter filter on radar echoes, which biases zero velocity and near-zero velocity radar return signals. The ClutterCompute routine computes the auto-correlation for points in a series of incoming radar MDV files, the output of Dsr2Vol program. The auto-correlation, standard deviation and mean data are written out to MDV files. ClutterCompute computes the median values from a series of input clear-air MDV input files, the near zero standard deviation of radial velocity over time, and the consecutive input MDV file. Points with high correlation are regarded as having a high likelihood of representing clutter. ClutterCompute computes the clear-air scan media reflectivity values. The computation is based on the consistency of the ground clutter return echoes between successive returns. The output is an MDV clutter map used by ClutterRemove for clutter removal and is stored in G_ Clutter Map.

Using a digital elevation model (DEM) and a scan strategy, we evaluated the blockage of radar beams and other ground uncertainty phenomena. We created a scan strategy for all 11 elevation angle sweep scans from 0-360 azimuth angles, with terrain profile showing beam. An example of beam blockage is demonstrated in Figure 5, where the 0.5o sweep beam is partial blocked by one of the volcanoes located at around 75 km from radar site at azimuth 330o. Low elevation angle data are mostly blocked by high hills and mountains at the azimuth of 240-360 degrees. Therefore, data at 0.5o and 1.5o are blocked and severely contaminated with ground clutter if the CAPPI height is set below 1.5 km (Figure 4).

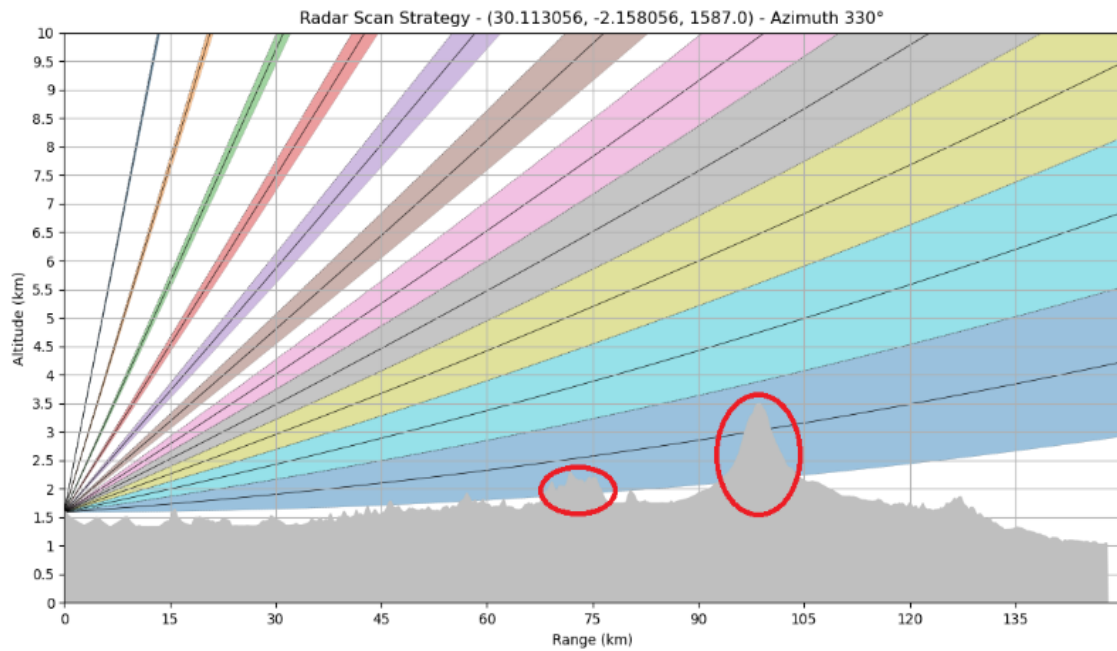


Figure 4. Scan strategy with Rwanda Train DME Profile showing radar beam blocked by Muhabura Volcano at AZ=330 degree.

3. ClutterRemove: The clutter map generated by ClutterCompute algorithm is used by ClutterRemove application to remove clutter from the MDV radar polar data with clutter, and the results of MDV radar polar data with clutter removed. The output of ClutterRemove Algorithm is clean MDV data that is stored under OPS clutter removal as it is depicted in Figure 4.

Table 3. A Python clutter mitigation algorithm

Clutter Mitigation Algorithm
<pre> # list of fields to read fields = ["GCMD_FLAG", "DBZ", "ZDR", "RHOHV"] ## sweep 0 ~ angle 0.5 sweep = 0 ## get projected coordinates at sweep 0 lat, lon, alt = radar.get_gate_lat_lon_alt(sweep) ## get slice (index) at sweep 0~ 0.5 Elevation sweep_slice = radar.get_slice(sweep) ### get dbz raw data data dbz = radar.fields['DBZ']['data'] ### Apply Clutter Mitigation Decision Flag&get GCMD_FLAG data GCMDF = radar.fields['GCMD_FLAG']['data'] ## Apply GCMD mask1 = (GCMDF == 1.).data dbz1 = np.ma.masked_where(mask1, dbz) ### get data at sweep 0 dbz_sweep0 = dbz[sweep_slice] gcmd_sweep0 = GCMDF[sweep_slice] dbz1_sweep0 = dbz1[sweep_slice] </pre>

The Python based algorithm is provided in Table 3. The algorithm combines the clutter Compute and Clutter Remove algorithm, Radar reflectivity dBZ data at 0.5o elevation angle sweep 0, which is likely blocked by ground clutter, are used for the clutter mitigation decision algorithm. The clutter map is computed as $gcmd_sweep0 = GCMDF[sweep_slice]$ and the clutter filtered reflectivity is generated by applying the mask from the clutter mitigation decision from the polar radar volume on the reflectivity field, resulting to $dbz1_sweep0 = dbz1[sweep_slice]$.

4.5. Results and discussion

4.5.1. Clutter Mitigation

Figure 4 above depicts the clutter mitigation process from ClutterCompute application to ClutterRemove application. Clutter maps are generated and computed from low elevation angle (Sweep0), where lower elevation angles are severely affected (Figure.4), either partially or full blocked by high mountains and high elevation regions in Western, Southern, and Northern part of Rwanda. Figure 5 also shows that ground clutter from

echoes from low elevation beams are observed within 10-15 km around the radar station. Less clutter is observed in low altitude regions, from the central part of the country and to the east. The clutter map, and clutter filtered data used in this example was collected by Meteo Rwanda weather radar on 11 April 2020 at 21:23:53, at 0.5° elevation. An example of proposed ground clutter mitigation decision applied to Meteo Rwanda ground clutter is given in Figure 5.

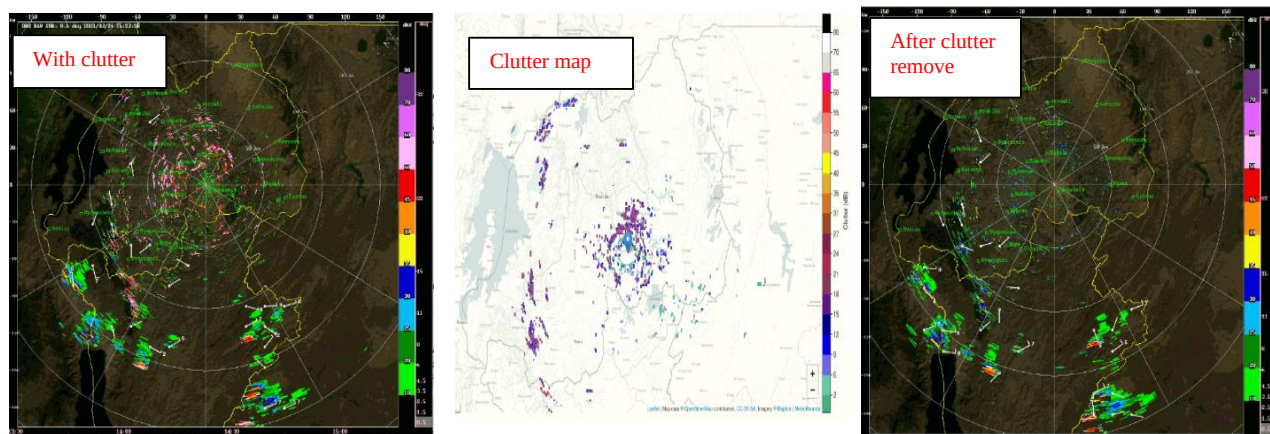


Figure 5. Clutter mitigation decision process. Left: Raw reflectivity data with clutter, Center: Clutter map, Right: Clutter removed reflectivity data. Collected on 24 March 2021.

4.6. Insect Signatures: Polarimetric Parameters

4.6.1. The reflectivity factor DBZ

The reflectivity factor DBZ of weather radars, which is measured in $\text{mm}^6 \text{m}^{-3}$, normally indicates the amount of precipitation (dBZ). The obtained power is proportional to the sum of the sixth power of the particles' equivolumetric spherical diameters per unit volume for particles with diameters much smaller than the transmitted wavelength (Rayleigh scattering). In the heart of a thunderstorm, typical values are 50 dBZ and higher, 20 dBZ in light rain and much less in clear air return [93], [99],[100], [101].

4.6.2. The Differential Reflectivity (ZDR)

The Differential Reflectivity (ZDR) reflects the disparity in returned energy between the radar's horizontal and vertical pulses. The difference between the horizontal and vertical reflectivity factors in dBZ units is referred to as differential reflectivity. It can have decibel values ranging from -15 to +30 (dB). Positive values indicate targets that are larger

horizontally than vertically, whereas negative values indicate targets that are larger vertically than horizontally. Near-zero values indicate that the target is spherical, with horizontal and vertical dimensions approximately equal [97], [101] [102], [72],.

The low reflectivity region (DBZ) corresponds with high differential reflectivity values (ZDR). Insects are less reflective than precipitation targets, and their horizontal width is typically greater than their vertical width while traveling through the air.

4.6.3. The Correlation Coefficient (RHOHV)

RHOHV is a measurement of how similar horizontally and vertically polarized pulses behave within a pulse volume. It has unitless values ranging from 0 to 1, with higher values suggesting identical behavior and lower values indicating dissimilar behavior [2]. The Correlation Coefficient is useful for identifying meteorological echoes from non-meteorological echoes (such as birds, insects, and ground clutter). To create a complex scattering pattern, allowing the horizontal and vertical pulses of the radar to differ significantly from pulse to pulse, resulting in RHOHV values of less than 0.8. Homogenous meteorological echoes, such as the one seen in rain and hail, create well-behaved scatter patterns with RHOHV exceeding 0.97 from pulse to pulse [103].

Non-meteorological targets, such as insects, are indicated by areas of lower reflectivity and by lower RHOHV values.

4.7. Insect signatures

In radar echoes, insect signatures are distinguished by predominantly low reflectivities (–10 to 6 dBZ), extremely high ZDR (3 to 14 dB), and low RHOHV (≈ 0.86) [32], [26], [83], [84], [36], [101], [104].

4.7.1. Case studies

The Meteo Rwanda polarimetric weather radar was used to collect clear air cases, i.e. days or selected area without precipitation. The data is analyzed at a distance from 10 to 150 km from the radar. Gates less than 10 kilometers far from the radar may be contaminated by ground clutter and are excluded. The resolution volumes become gradually too low beyond 150 kilometers from the radar to resolve the biological echoes due to beam

broadening with distance effects. Since biological scatters are typically found at low heights of up to 3 km above ground, in this study only data from the 0.5 and 1.5 elevation degree elevation are used.

4.7.1.1. Cases with potential insect signatures

During continuous observation of weather radar reflectivity data on 26th and 27th March 2021, potential insect signatures were spotted for different locations. One was identified on 26th March after sunrise 2021 between 7:45-10:40am at about 25 to 40 km to the southeast of the radar site. On 27 March 2021 insect signatures appeared from the radar returns between 6:50-10:40am and 3:00-5:35pm local time respectively at 40-60 km east of the radar site in the areas covering the eastern part of Akagera National Park in Kayonza District.

Case study 1: 26 March 2021

The first case presented took place on 26 March 2021 between 7:45-10:40am local time during a clear-air, continuous observation of the radar data collected by Meteo Rwanda Polarimetric weather radar. Insect signatures appeared at about 40 km to the southeast of the radar site. The echo region red encircled covers the Lake Rweru and the surrounding valley, at the northern border of Burundi with southern-south East of Rwanda in Bugesera district of Rwanda. The region also covers Gako and Karama dry natural forests in Bugesera, a region with more diverse insects, birds and other animals.

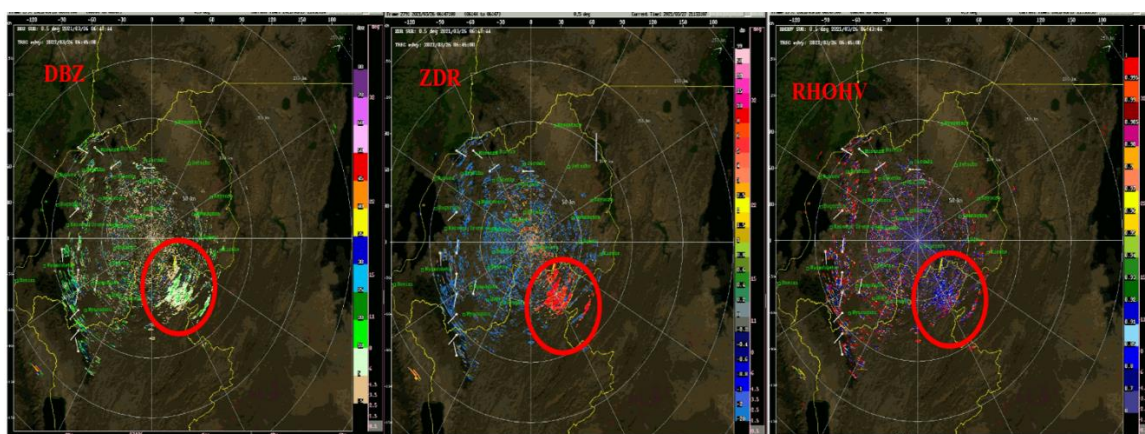


Figure 6: Insect signatures(Z,ZDR, RHOHV),Appeared on 26th March 2021 at 08:00:24 am Kigali Time during continuous observations on Meteo Rwanda Polarimetric C-band Weather Radar.

Radar images shown in Figure 6 show the reflectivity (DBZ), Differential Reflectivity (ZDR), and Correlation Coefficient (RHOHV) Plan Position Indicator (PPI) scans at 0.5° elevation angle gathered at 08:00:24 Kigali Time 26 March 2021. The local time is UTC plus 2 hours. The radar echoes spotted on March 26, 2021, between 7:45-10:40am local time, for a clear-air sky day, the red encircled region presented unique characteristics as is shown in Figure.6, with reflectivity between (-3 to 6 dBZ Figure 6, left) and very high ZDR (3 to 15 dB; Figure 6 middle), likely due to horizontally oriented insects, and low RHOHV ($< \approx 0.86$ Figure 6, Right), which is the signature of insects.

Case study 2: 27 March 2021

Continuous observation of Meteo Rwanda polarimetric radar data through 27 March 2021 gives us the second case which took place during the sunset time and sunrise time on 26-27 March 2021, where insect signatures appeared from the radar returns between 6:50-10:40am and 3:00-5:35pm local time respectively between 40-60 km to the east in Bugesera district and in the northern part of Lake Rweru Valley, where the same insect signature was spotted the day before in southern west part of the Lake valley. The same insect signatures appear south east of Akagera National Park 80-100 km away from the radar site.

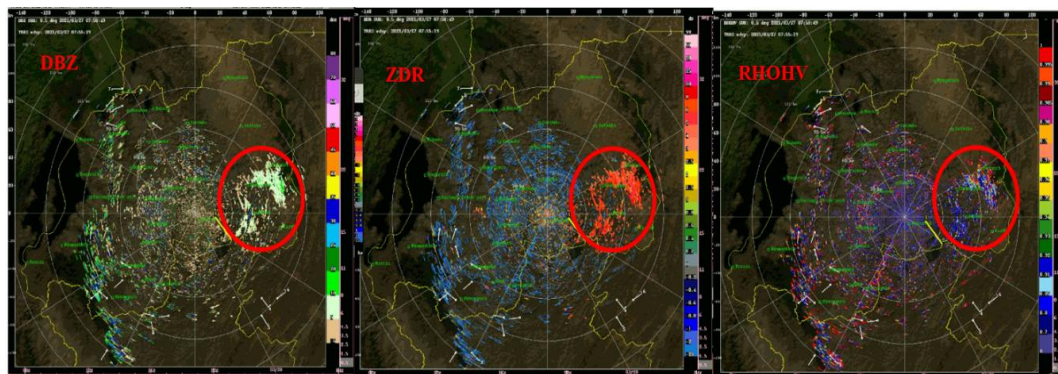


Figure 7. Insect signatures(Z,ZDR, RHOHV) appeared on 27th March 2021 at 9:15:14 am Kigali Time during continuous observations Meteo Rwanda Polarimetric C-band Weather Radar.

The radar image presented in Figure 7 taken on 27 March 2021 exactly at 9:15:14 am Kigali Time which is 7:15:14am UTC, shows the reflectivity (DBZ), Differential Reflectivity (ZDR), and Correlation Coefficient (RHOHV) Plan Position Indicator (PPI) scans at 0.5° elevation angle gathered three hours after sunrise. During this clear-air sky morning an increased reflectivity appeared at encircled regions at about 80-100 km away

from the radar over southern east part of Akagera National Park and at 40-60 km over eastern part of Bugesera district and in the northern part of Lake Rweru Valley. The radar returns in these two regions were characterized by reflectivity between (-5 to 8 dBZ, Fig 7 left) and very high ZDR (-2 to 15 dB; Figure.7 middle). This is may be due to horizontally oriented insects and vertically oriented insects for negative ZDR, and low RHOHV (≈ 0.86 Figure 7 right), which is the signature of insects.

4.8. Conclusion

We examined a method for correcting radar reflectivity data for ground clutter and beam blocking, specifically for data collected by Meteo Rwanda Polarimetric weather radar. To ensure excellent quality data, a digital elevation model (DEM) is used to identifying beam blockage of the main lobe of the radar antenna pattern by objects in the radar field of view. Using this DEM and radar scan strategy, the radar volume scan is classified into blocked and unblocked areas to improve real-time radar signal processing for the clutter problem. The algorithm, termed Ground Clutter Mitigation Decision (GCMD) complemented by beam blockage correction with DEM is presented, the clutter ClutterCompute to Clear-air MDV data for Clutter map computation and ClutterRemove is automatically applied to regions identified as ground clutter by GCMD. This strategy removes the ground clutter while minimizing the impact of the ClutterRemove on radar returns, which biases zero velocity and near-zero velocity radar signals. The capability of Meteo C250P weather radar to detect and monitor insect signatures is also discussed through analysis of polarimetric parameters (DBZ, ZDR and RHOHV) identified in clear area day case studies. Signatures consistent with flying insects are observed from the data collected by Meteo Rwanda weather radar on 26-27 March 2021 after sunrise.

Chapter 5. Development and Enhancement of Insect Detection and Identification Algorithms

In this chapter, we focus on advancing algorithms for the detection and identification of insects, specifically the Fall Armyworm (FAW), using C-Band Polarimetric Doppler Weather Radar. The development process began with the adoption of a Neuro-Fuzzy Logic (FL) method, an algorithm initially designed for hydrometeor identification. Here, the goal is to distinguish flying adult FAW moths by leveraging four key polarimetric radar parameters: horizontal reflectivity (DBZHC), correlation coefficient (RHOHV), differential reflectivity (ZDR), and specific differential phase (KDP). This approach facilitates the detection and monitoring of FAW populations, with field verification complementing the radar data.

One of the major challenges in insect detection lies in distinguishing biometeors such as birds, bats, and insects from other meteorological targets. Biometeors exhibit unpredictable behavior, including changes in direction and position, which affect radar wave polarization. This behavior complicates detection using conventional radar techniques, which were primarily developed for hydrometeors like rain or snow. To overcome this challenge, we introduced a novel methodology that utilizes Rwanda's C-Band Polarization Radar to improve detection accuracy. Specifically, we analyzed radar parameters like differential reflectivity (ZDR) and correlation coefficient (RHOHV) to compute the Depolarization Ratio (DR). While existing radar metrics provide useful information, they are limited in capturing the full extent of depolarization effects. To address this limitation, we developed an advanced fuzzy logic algorithm (FL_DR) that integrates the DR parameter for more accurate identification.

This chapter is divided into two main parts. The first part focuses on the Adoption of a Neuro-Fuzzy Logic Method for Fall Armyworm Detection and Monitoring Using C-Band Polarimetric Doppler Weather Radar. The second part explores Enhancing the Identification of Meteorological and Biological Targets Using the Depolarization Ratio for Weather Radar. These developments contribute to the overall goal of improving insect detection and identification algorithms.

5.1. Adopting a Neuro-Fuzzy Logic Method for Fall Armyworm Detection and Monitoring Using C-Band Polarimetric Doppler Weather Radar with Field Verification

5.1.1. Overview

In response to the persistent challenges posed by fall armyworm (FAW) outbreaks in Rwanda's maize production since 2017, this research introduces an innovative strategy integrating fuzzy logic and neural network methodologies, originally developed for hydrometeor identification. The focus is on distinguishing flying adult FAW moths using four polarimetric radar parameters: horizontal reflectivity (DBZHC), correlation coefficient (RHOHV), differential reflectivity (ZDR), and specific differential phase (KDP). Demonstrating a remarkable accuracy with a fraction of echoes correctly identified (FEI) of 98.42% for FAW and 87.02% for other weather phenomena, validated by a Heidke skill score (HSS) of 0.9801, the system proves adept at discerning between weather and nonweather events. A significant strength of the developed method lies in its ability to detect FAW adult moths approximately four weeks earlier than ground-based observations identifying infestation outbreaks. This was evident in the context of FAW infestation in maize fields within the surveyed districts of Nyanza, Huye, and Gisagara in the Southern Province of Rwanda. This positions the weather radar method as a promising early warning system for FAW outbreaks, especially beneficial in less-monitored regions like East Africa. The study underscores the potential application of polarimetric C-band Doppler weather radar, providing valuable insights into the intricate dynamics of agricultural insect pest outbreaks. The method offers practical solutions for timely interventions and enhanced crop management strategies, contributing to more effective pest control and promoting sustainable agriculture practices.

5.1.2. Introduction

The fall armyworm (FAW) is originally indigenous to tropical regions extending from the United States to Argentina in the western hemisphere [19], and the voracious FAW has emerged as a substantial threat to global agriculture and food security. Notably, in its early stages, FAW's young caterpillars and larvae exhibit a voracious appetite, feeding on more

than 80 plant species, including crucial crops such as maize, rice, sorghum, and sugarcane [22], [23]; this extensive feeding behavior significantly contributes to the severity of the menace and food security globally. Furthermore, the adult FAW moths, distinguished by its high-flying capabilities and migratory behavior, plays a crucial role in the rapid dispersion of this pest across diverse regions [24]. Recognizing the dual impact of both the larvae's crop consumption and the moth's ability to cover vast distances is imperative for formulating effective strategies to address the challenges posed by FAW to global agricultural practices.

In 1966, a groundbreaking discovery revealed that clear-air scattering echoes detected by Doppler weather surveillance radar primarily originated from biological sources, including birds, bats, and insects. Since then, weather radars have been crucial for monitoring the dynamic movement and quantifying migrating aerial animals (biometeors) [93], [38], [105], as well as identifying hydrometeors. Biometeors, comprising insects and birds, exhibit distinct radar signatures such as low horizontal reflectivity (DBZHC) ranging from -10 to 37 dBZ, high differential reflectivity (ZDR) values ranging from -4 to 14 dB due to their elongated shape, relatively low correlation coefficient (RHOHV) usually measuring less than approximately 0.86, and near-zero differential phase (KDP) indicating the absence of rain particles and clear-air conditions [32], [48], [54], [50], [106]. However, the presence of numerous airborne insects can lead to misclassification as precipitation due to exceptionally high RHOHV values, up to 0.96 [60]. Various detection methods, including decision trees, statistical decision theory, neural networks, and fuzzy logic algorithms, have been developed to address this challenge [93], [60], [56], [55]. Fuzzy logic, in particular, offers a promising solution by drawing distinct conclusions even from overlapping and noise-corrupted input radar data collected at different heights, representing various air column particles of different types and sizes [55], [107], [61].

Fuzzy logic, introduced by Zadeh [108], offers a concise approach to categorization through IF-THEN rules and logical operators. This method involves four key stages: fuzzification, inference, aggregation, and defuzzification, allowing for the conversion of numeric values into fuzzy sets and their subsequent transformation into numerical values [51], [109]. Recognized for its robustness in handling uncertainties and nonlinearities, fuzzy logic is highly effective in characterizing complex systems, making it ideal for identifying airborne particles [96], [109], [110], [111]. Liu and Chandrasekar [60] further

enhanced this approach by introducing a neuro-fuzzy system for hydrometeor detection, combining neural network learning capabilities with rule-based fuzzy systems, thereby improving classifier performance and incorporating prior observations into the classification process [54], [60], [63].

5.1.3. Methods and Materials

5.1.3.1. Neuro-Fuzzy Logic for FAW Identification

The effectiveness of the neuro-fuzzy logic identifier is significantly influenced by the design of the membership functions [60], [112]. The membership functions were developed by combining theoretical and empirical information. Manually adjusting the functions is time-consuming and inefficient. The development of a system that can learn from data and automatically adjust the membership functions would be quite advantageous and this is accomplished via the neuro-fuzzy FAW identifier [60], Figure 8 shows one implementation of the neuro-fuzzy logic system for detecting insects (FAW). The backpropagation path is depicted by dotted lines, whereas the feedforward path is represented by solid lines. The IF layer updates the membership function parameters based on the misidentification error $\epsilon \neq 0$. This is a very effective and efficient way to build a good classification method gradually.

The neuro-fuzzy logic system's learning algorithm is as follows: let X be the vector of radar observations used as inputs to the system, and let Y_0 be the known class of biometeor for this measurement set, which in our scenario Y represents the FAW.

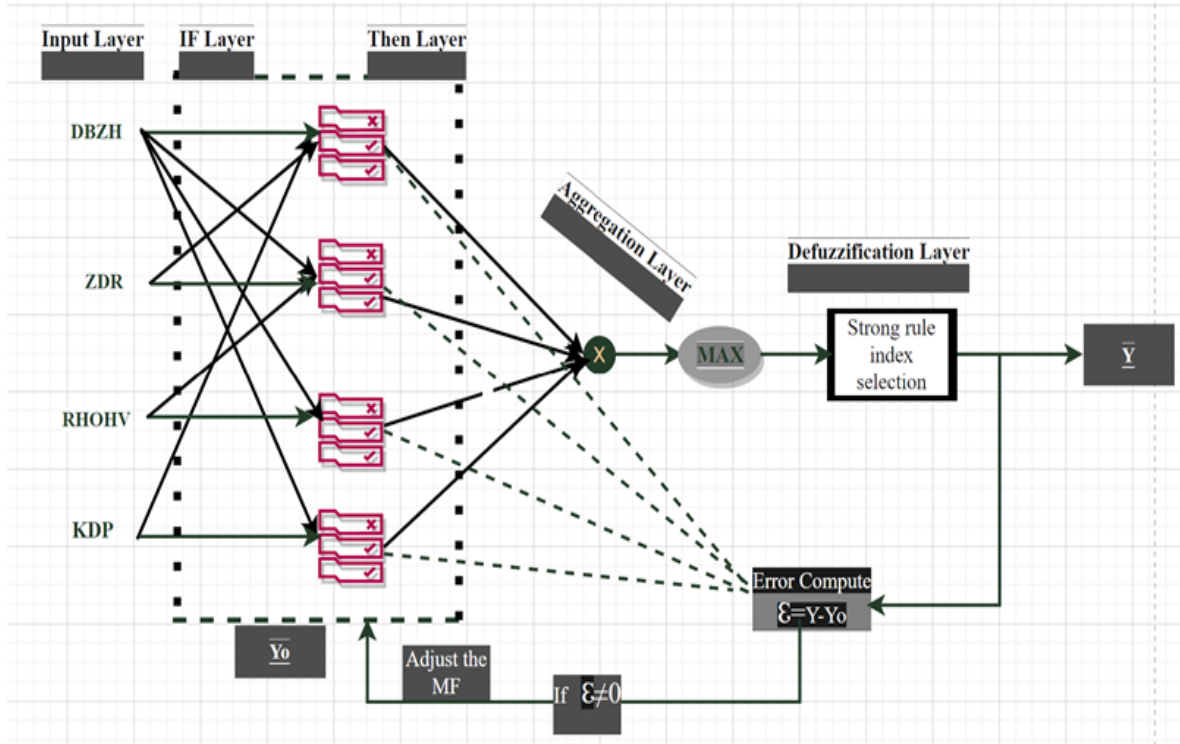


Figure 8. Proposed Neuro-Fuzzy logic system for FAW identification and classification.

The fuzzy logic system generates output Y when input vector X is applied, and the error is computed based on the output Y and known characteristics Y_0 , corresponding to inferences with the highest detection score. If the error ε is not equal to zero, the Neuro Network algorithm engages in learning and adjusts the membership functions accordingly. This adjustment process is illustrated by the backpropagation path represented by dotted lines in Figure 8. The output (Y) is determined by the strongest rule with the highest inference score, compared with the maximum aggregated FAW inference (Y_0). The neural network algorithm dynamically refines membership functions by considering errors and selecting optimal ones corresponding to radar input parameters. These refined functions are then integrated into the fuzzy logic of the TITAN system, enabling real-time monitoring of FAW. In this integrated system, hydrometeor particles are assigned Particle Identification (PI) numbers ranging from 0.5 to 14.5, while PID values between 14.5 and 16.5 are designated for biometeor (airborne insects) targets. Next, we describe the membership function development focused on insect signatures, these insect signatures

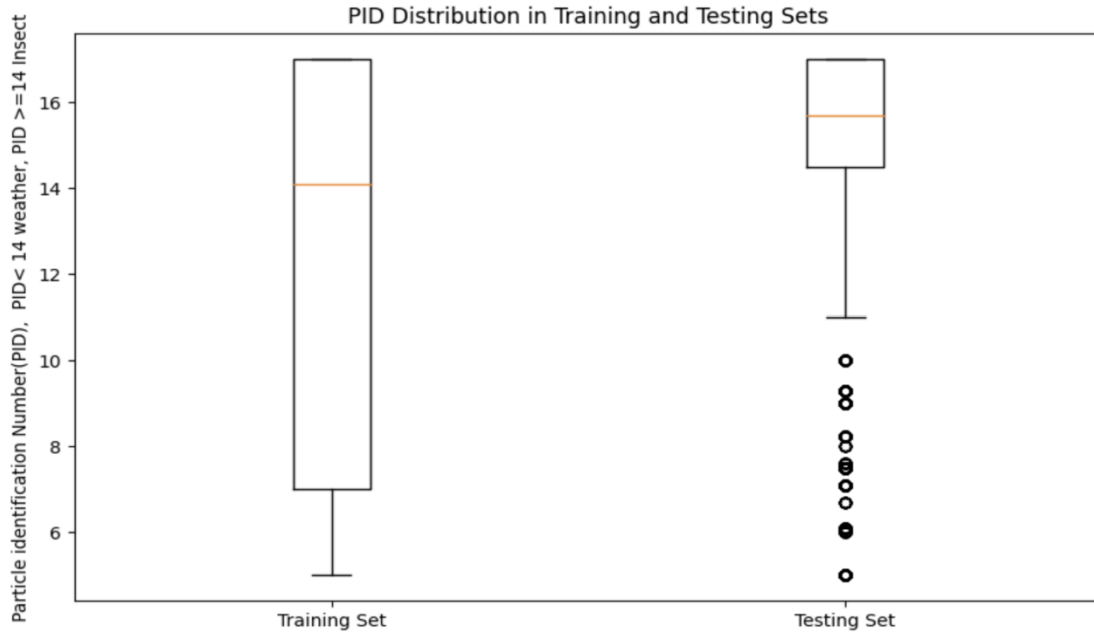


Figure 9. The distribution of radar echoes, representing weather and insect signatures, in both the training and testing datasets.

5.1.4. Membership function development

5.1.4.1. Considerations, and Assumptions

Integrated membership functions were employed to differentiate weather particles from non-weather particles like FAW. A training dataset of 1,308,956 radar echo pixels covering clear-air and non-clear-air events was collected. Sensitivity analysis was performed, using 345,239 radar echo pixels mainly from clear-air events. Training data spanned from 18 October 2020 to 29 November 2020, while testing data ranged from 15 December 2020 to 11 January 2021. Results showed 60.13% of echoes in training as weather and 39.86% as insects, while in testing, 21.23% were weather echoes and 78.77% were insects (see Figure.9).

5.1.4.2. Membership Function Identification

Radar signatures from biological scatterers, such as birds and insects, exhibit distinct polarimetric characteristics, aiding in their differentiation from meteorological targets, with insects typically displaying lower RHOHV compared to precipitation, aiding in their differentiation through polarimetric radar, as evidenced by different researchers [72], [104], [54]. The distinct shape and size differences between birds and insects result in divergent polarimetric signatures, notably with birds showing higher differential phase

and lower ZDR than insects [27], [104], [113], [65]. Leveraging algorithms such as fuzzy logic, which utilizes polarimetric variables, allows for better discrimination between birds, insects, and meteorological targets. The fuzzy logic's membership functions act as filters that enable the extraction of specific signatures from meteorological targets such as rain particles and non-meteorological targets such as birds and insects [96], [17].

This adaptability enables concurrent analysis of multiple airborne objects from a single data source. In the context of identifying FAW outbreaks in Rwandan maize plantations, the study enhances insect membership functions to refine FAW classification using radar data collected during the outbreak period. Additionally, it synthesizes existing literature sources and provides an overview of diverse methodologies in weather radar utilization for target identification, detailed in Table 4.

Table 4. A comprehensive overview of studies related to weather radar applications for target identification, utilizing a consistent key for membership functions

Citation	Parameters	Classification application	MF	Radar type
Marzano et al. 2006	DBZH and ZDR	Fuzzy Radar Algorithm for Hydrometeor Classification at C-band (FRAHCC).	Trapezoidal	C-band polarimetric radar
Kurdzo et al. 2020	Logarithm of KDP, Standard deviation of DBZ and KDP	hydrometeor classification algorithm (HCA).	Trapezoidal	WSR-88D (dual-polarization upgrade)
Mahale et al. 2014	ZH, ZDR, RHOHV,	Three-body scatter signature (TBSS) identification,	Trapezoidal	S-band
Ortega et al. 2015	DBZH, ZDR, and RHOHV	Hail size discrimination for operational polarimetric hail detection	Trapezoidal	WSR-88D
Berenguer et al. 2006	DBZH, ZDR	Identifying nonprecipitating echoes in radar scans	Pairwise function	C-band radar
Liu and Chandrasekara. 2000	DBZH, ZDR, KDP, RHOHV and Linear Depolarization Ratio (LDR)	Classification of hydrometeor type	Beta functions	S-Band

Table 5 outlines the criteria for clear-air thresholds (signatures) used to distinguish weather and non-weather particles. Input variables (DBZHC_F, ZDR_F, RHOHV_F, and KDP_F) utilize trapezoidal membership functions to define ranges for non-weather (e.g., FAW) and weather signatures. This choice is motivated by the trapezoidal function's ability to provide smooth transitions between linguistic categories, ensuring a nuanced representation of the data. The implementation of our fuzzy logic algorithm for weather classification, based on radar data, was facilitated using the scikit-fuzzy Python library ('skfuzzy') from sklearn.

Table 5. Clear air threshold (signature) consideration for weather and non-weather particles

Input	Membership Function	Insect signatures (FAW)	Weather signatures
DBZHC_F	Trapezoidal	$-10 \leq \text{DBZHC_F} \leq 37 \text{ dBZ}$	$-10 \leq \text{DBZHC_F} \leq 60 \text{ dBZ}$
ZDR_F	Trapezoidal	$-4 \leq \text{ZDR_F} \leq 4 \text{ dB}$	$-1.3 \leq \text{ZDR_F} \leq 1.7 \text{ dB}$
RHOHV_F	Trapezoidal	$0.5 \leq \text{RHOHV_F} \leq 0.87$	$0.79 \leq \text{RHOHV_F} \leq 1.0$
KDP_F	Trapezoidal	Absent $0.01 \leq \text{KDP_F} \leq 0.025$	$-0.7 \leq \text{KDP_F} \leq 1.0$

Following methodologies established by previous researchers such as Zrníc et al. [114] and Liu and Chandrasekar [60], clear-air conditions were classified into two distinct categories: non-weather and weather, each with specific linguistic interpretations. To streamline the outcomes, a singular output variable termed "output" was introduced, ranging from 0 to 100 and comprising two fuzzy sets: non-weather and weather. Fuzzy inference relies on IF-THEN rules that connect input variables to output variables, with two pivotal rules and signatures delineated: one for non-weather (Insect) output and another for weather output, based on defined signatures such as DBZHC_F, ZDR_F, RHOHV_F, and KDP_F.

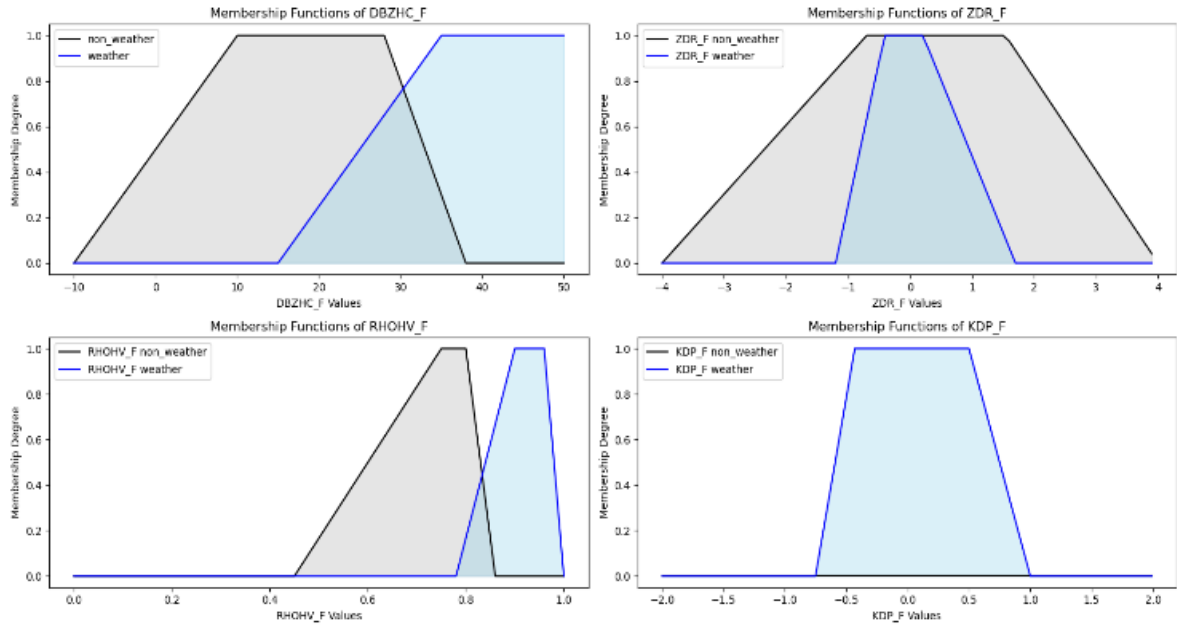


Figure 10. Optimum membership functions (trapezoidal) generated for DBZH_F, ZDR_F, RHOHV_F, and KDP_F.

These rules encapsulate intricate relationships between radar variables and weather or non-weather particles, as documented in Table 5. By utilizing a 'ControlSystemSimulation' object named "simulation," fuzzy logic rules are applied to individual data points within the established control system, facilitating the interpretation of radar data and the classification of weather and non-weather conditions.

In Figure 10, the fuzzy logic membership functions for four polarimetric input parameters utilized in the identification of FAW are presented. The corresponding signatures are detailed in Table 3. The generated membership functions include trapezoidal functions for horizontal reflectivity (DBZH_F), differential reflectivity (ZDR_F), correlation coefficient (RHOHV_F), and differential phase (KDP_F). The values that describe the trapezoidal membership functions are consistent with values from the literature for insects in contrast to other biometeors such as birds and bats [54], [104].

5.1.4.3. Membership Function Sensitivity Evaluation

The sensitivity analysis, as illustrated in Figure 11, reveals significant output changes when the Membership Degree approaches 100% or 1. Particularly for DBZH_F, sensitivity is notable within the 90%-95% range for values ranging from -10 dBZ to 7 dBZ, transitioning to consistent sensitivity for values between 7 dBZ and 15 dBZ, associated with "non-weather" output. Values at 35 dBZ and higher are predominantly

linked to weather conditions, suggesting sensitivity corresponds to shifts in DBZH_F membership functions concerning "non-weather" and "weather" output targets, as depicted in Figure's 10 and 11.

Similarly, ZDR_F consistently demonstrates sensitivity within the 90%-95% range from -0.25 to 1.2, indicating horizontal insect movement with positive ZDR_F values. Notably, a significant sensitivity shift occurs near zero, transitioning from "non-weather" to "weather" targets, aligning with small spherical weather particles associated with ZDR_F values close to zero.

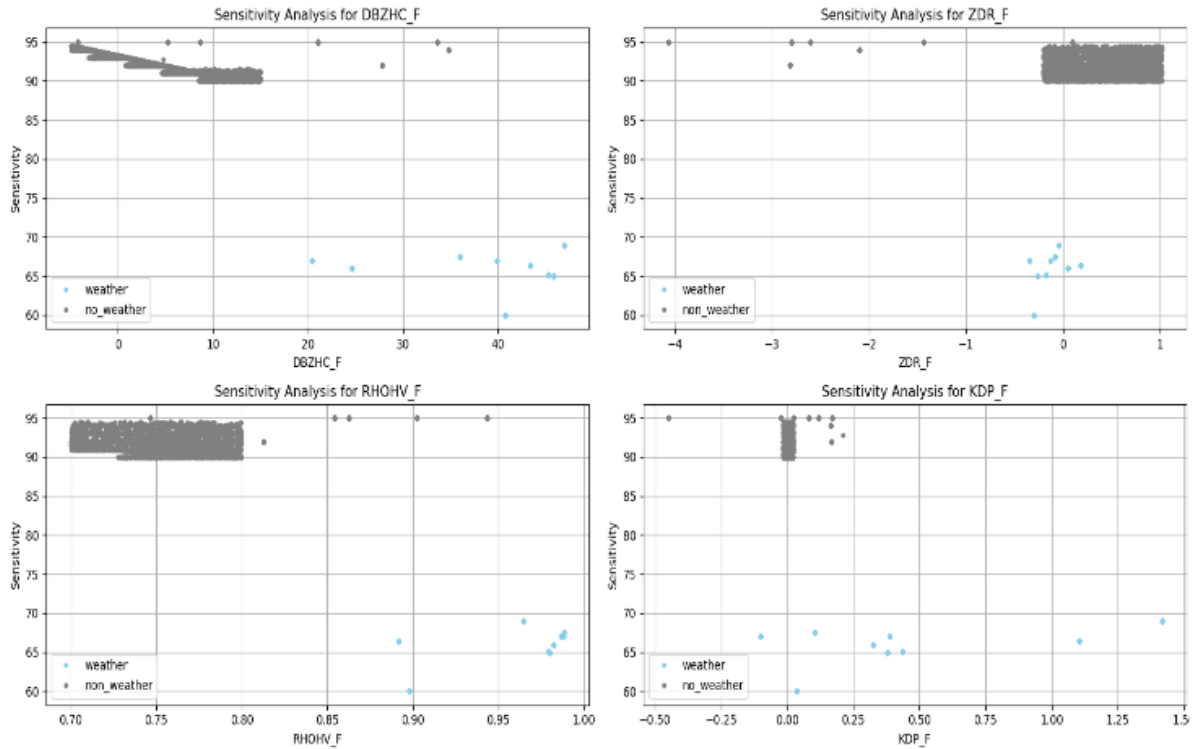


Figure 11. Sensitivity Analysis of membership function of input Parameters DBZHC_F, ZDR_F, RHOHV_F, and KDP_F on Weather and Non-Weather Targets

Regarding RHOHV_F, stable sensitivity aligns with shifts in membership degree between 0.7 and 0.86 for non-weather output and close to 1 (0.97 to 1) for weather output. Similarly, for KDP_F within the range of -0.5 to 1.5, sensitivity is noted specifically for the "weather" output target, emphasizing that KDP_F values near 0 indicate the absence of KDP_F, associated with "non-weather." These findings underscore the importance of selecting appropriate membership functions based on the sensitivity analysis of input parameters which influencing output variable performance.

5.1.5. Results and Discussion

Meteo Rwanda's weather radar uses fuzzy logic to categorize weather phenomena, identifying 13 particles ranging from 0.5 to 14.5, covering rain, hail, snow, and so on. An enhancement integrated an insect membership function into the radar's fuzzy logic, expanding the classification range to 16.5. This involved modifying TITAN's parameters files to include an insect signature, particularly for FAW detection. In visualization, all-weather particles were grouped as "weather," while nonweather particles (insects) were grouped as "nonweather."

5.1.5.1. Clear air event during the night of 12 November 2020

Validation of the neuro-fuzzy logic algorithm for classifying weather radar data involved comparing detected insect radar echoes with on-site observations of FAW in maize planted marshlands, revealing a strong alignment. This alignment suggests that observed radar echoes were primarily dominated by echoes from FAW, highlighting the radar's essential role in tracking nocturnal flying insects. Using the Meteo Rwanda TITAN system, we visualized the implemented algorithm through a customized Cartesian Interactive Data Display (CIDD). Figure 12 displays radar data from 12 November 2020, showing detected insect echoes over the Akanyaru River maize marshland in Nyanza and Gisagara districts.

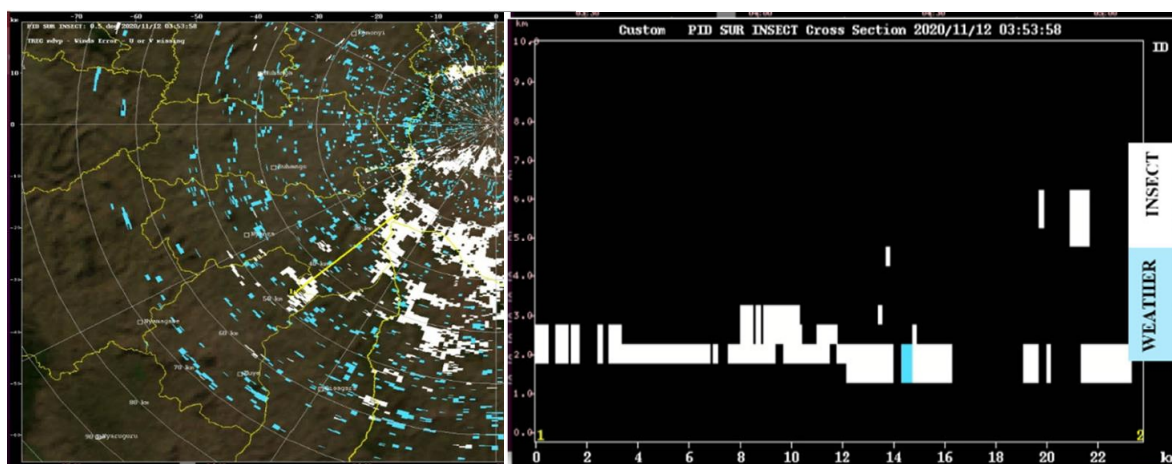


Figure 12. Weather and insect echoes on the CIDD Display. (Top) Detected instances on November 12, 2020, at 03:53:581 UTC. (Bottom) Cross section from Nyanza to Huye (24 km).

5.1.5.2. Insect activity patterns: Insights from continuous Radar monitoring on full clear-air day

Figure's. 12 and 13 reveal the radar-detected insect echoes exclusively during nighttime, contrasting with the absence radar insect of echoes during the daytime, thereby confirming the nocturnal behavior of FAW and providing detailed insights into their activity timing. The data highlight a period of heightened risk, suggesting the optimal time to focus on when employing traditional FAW monitoring methods, especially between late evening after sunset and before dawn before sunrise. This significant alignment between radar data and farmer observations not only validates reported FAW activity but also enriches our understanding of their temporal dynamics.

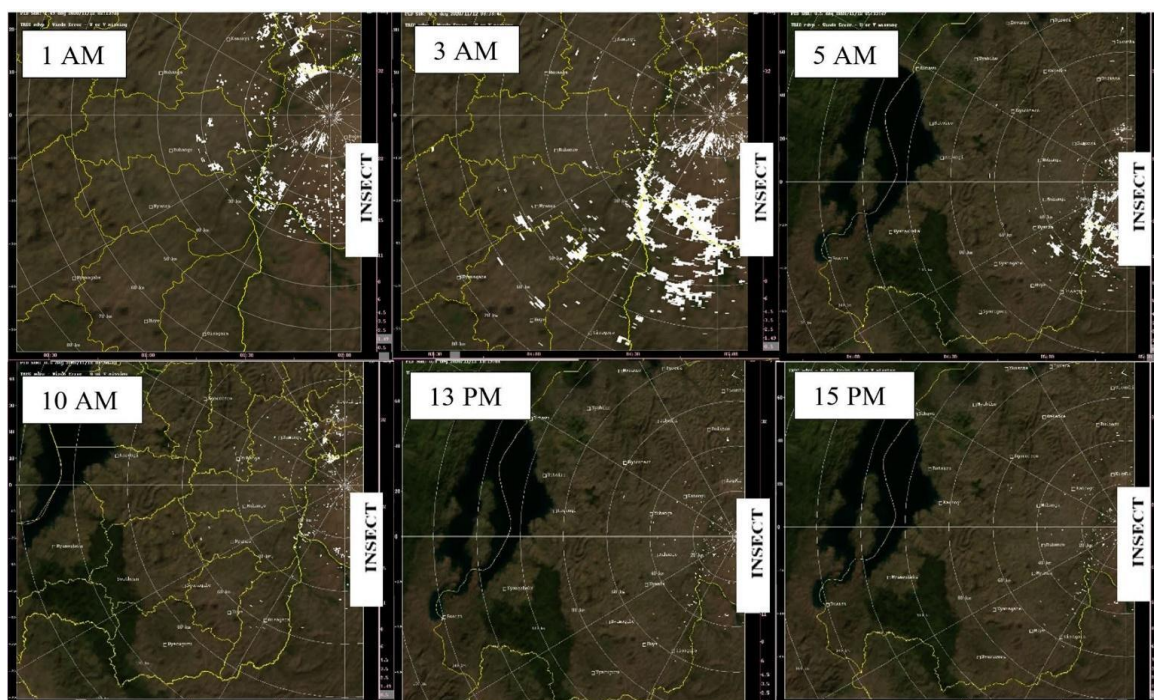


Figure 13 Monitoring of insect activity patterns throughout a continuous clear-air day using radar data recorded on November 12, 2020, utilizing the CIDD display.

5.1.6. Performance Evaluation

In the performance evaluation, 345 239 weather radar echo pixels were analyzed to capture nocturnal insect signatures between December 15, 2020, and January 11, 2021, from 120 random points in FAW-infested districts over maize marsh- lands, with a vertical sampling range of 50 m to 2.5 km above ground. Using nocturnal weather radar data at a 5-min temporal resolution, the comparison involved assessing the classification results

obtained by applying neuro-fuzzy logic to the extracted echoes and those obtained by applying insect signatures [32], [54], [115]. Evaluation metrics, such as the fraction of echoes correctly identified (FEI) and the Heidke skill score (HSS), were utilized to evaluate the algorithm's accuracy in distinguishing between weather and insect classifications under clear-air conditions. The evaluation findings, presented in a confusion matrix (Figure.14), provided detailed insights into hits, misses, false alarms, and correct rejections.

The FEI is given by the equation

$$FEI = \frac{NC * 100}{T} \quad (1)$$

While Heidke Skill Score (HSS) is given by:

$$HSS = \frac{NC - (C_{12} * C_{21} / T)}{T - (C_{12} * C_{21} / T)} \quad (2)$$

where NC is the number of echoes pixels correctly identified, T is the total number of classifications

Table 6. Performance metrics for weather and non-weather (insect) classification

S/N	Metrics	Weather	Non-Weather[Insect]
1	FEI	87.02%	98.42%
2	HSS	0.9801	
3	Hits	10803	327558
4	Misses	1612	5267
5	Correct Rejection	327558	10803
6	False Alarm	5267	1612
7	Accuracy	0.9801	0.9801
8	Precision	0.6722	0.9951
9	Recall	0.8702	0.9842
10	F1 Score	0.7585	0.9896

The neuro-fuzzy logic algorithm's performance, as depicted in Table 6, evaluates its ability to classify weather particles and insect echoes focusing on nocturnal clear air events. It achieves an 87.02% Fraction of Echoes Identified (FEI) for weather particles and a notably higher 98.42% FEI for insect echoes, showcasing strong identification capabilities. Furthermore, with a Heidke Skill Score (HSS) of 0.9801, the algorithm demonstrates overall accuracy in distinguishing between these echo types. Overall, these results emphasize the algorithm's effectiveness and reliability in echo classification tasks.

The neuro-fuzzy logic algorithm excels in classifying weather radar data during the FAW outbreak in clear air conditions, boasting 98.01% accuracy and 99.51% precision for non-weather (insect) identification.

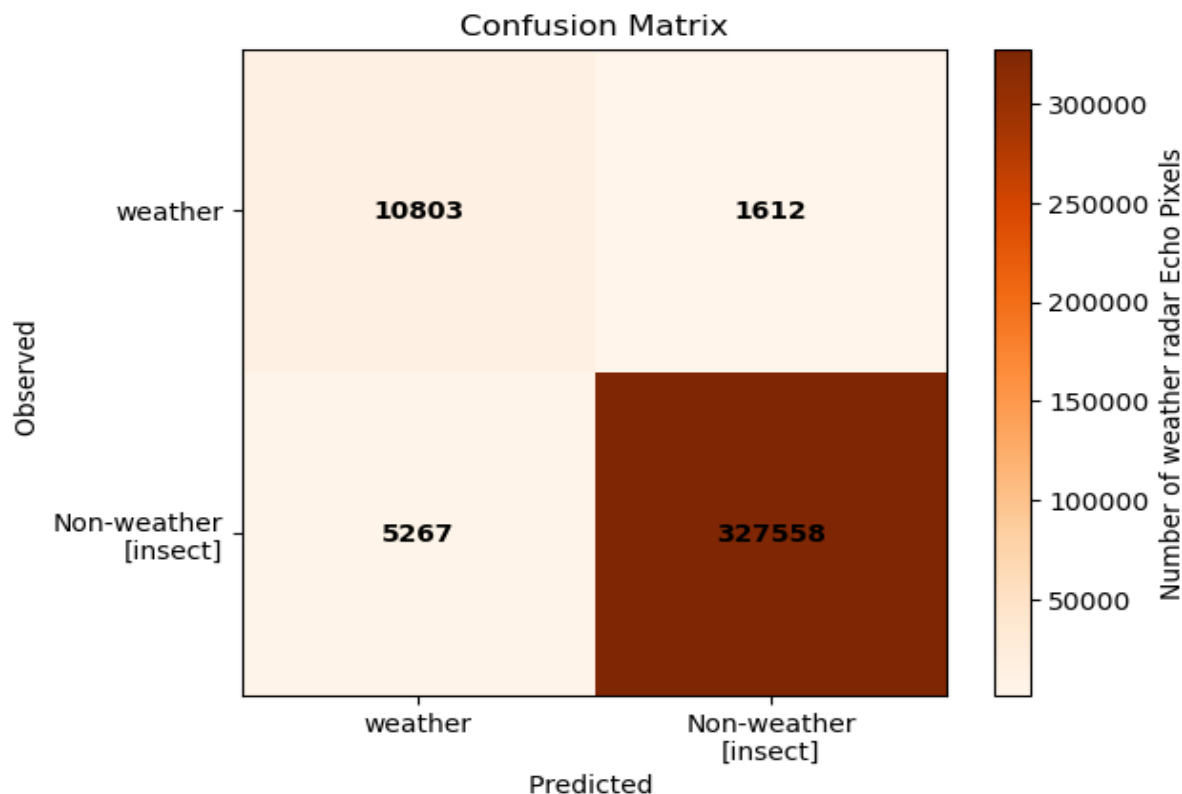


Figure 14 Confusion matrix of the performance of the neuro-fuzzy logic method for FAW Detection. The matrix from top left to top right displays the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

There is potential for improvement in non-weather (insect) classification recall. Enhancing the algorithm's strength could involve incorporating other polarimetric parameters, like depolarization radar, to consider depolarization effects for echoes originating from insect targets as they fly. This consideration is crucial for refining classification accuracy, especially in dynamic radar target such as insect.

5.1.6.1. Comprehensive comparative analysis of Radar insect echo trends before and during FAW outbreak

To refine our validation process, we compared nocturnal clear air radar insect echo trends before and during the FAW outbreak (July 12 to December 19, 2020) in the study districts. Our analysis involved aggregating all radar echoes across these districts during the

specified period, revealing a decrease in detected weather-related echoes from July to December (before outbreak to during the FAW infestation). Conversely, there was an increase in airborne insect echoes post-FAW outbreak from October to December compared to the pre-outbreak period from July to September.

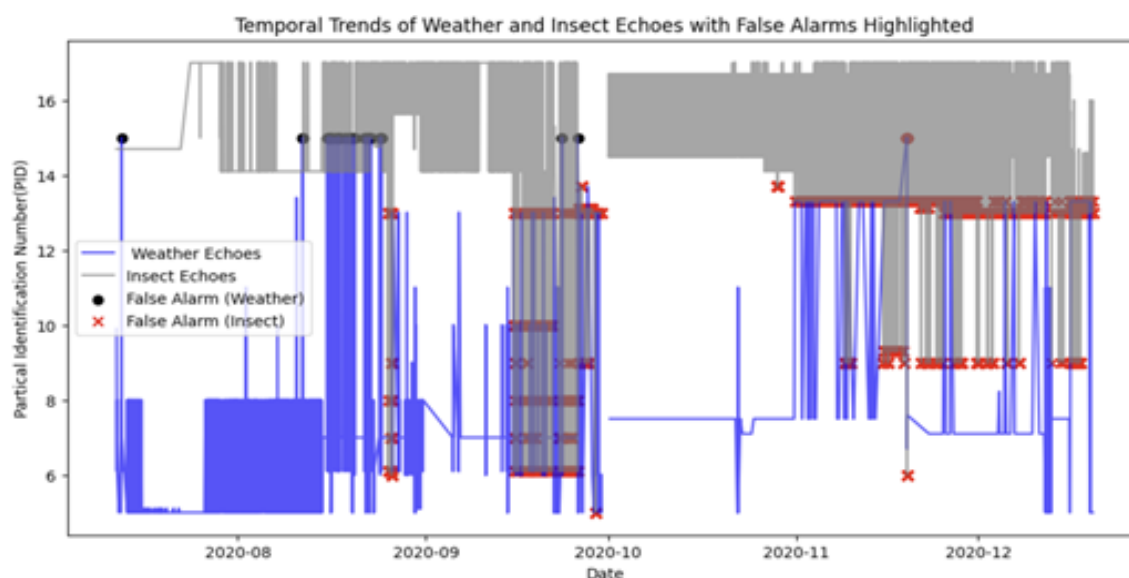


Figure 15 Temporal Trends analysis of weather (blue) and insect (gray) radar echoes with false alarms during clear air events from the Nyanza, Huye, and Gisagara districts from 12 July 2020 to 19 December 2020.

Figure 15 provides compelling insights into the shifting dynamics of radar echoes before and during the FAW outbreak. In the pre-outbreak period, spanning from 12 July 2020 to 29 September 2020, weather echoes constituted 39.86%, equivalent to 1.07440×10^9 radar echoes with weather signatures, while insect echoes contributed 60.13%, totaling 1.62065×10^9 weather radar echoes with insect signatures. However, during the outbreak (1 October to 19 December 2020), the prevalence of insect echoes grew to 96.75% of radar echoes equivalent 3.34028×10^9 radar echoes with insect signature. This substantial increase in the predominance of insect echoes highlights the heightened aerial activity of insects amidst clear air events during the outbreak, underscoring the likely impact of the FAW infestation on radar observations.

The discernible shift in radar echoes between these two periods underscores the precision and sensitivity inherent in weather radar technology. The ability to distinctly identify and track insect movements amid clear air events is a testament to the advanced capabilities of weather radar. The pronounced dominance of insect echoes during the outbreak period further emphasizes the pivotal role played by weather radar in unraveling the intricate

dynamics of insect behavior in the sky. This, in turn, contributes significantly to our comprehensive understanding of biological atmospheric phenomena, shedding light on the complex interactions between insects and the atmospheric environment.



Figure 16 Weekly radar insect echo detection counts before and during the FAW outbreak (Top). Farmers' observations of FAW in Nyanza, Huye, and Gisagara districts (Bottom)

The bottom part of Fig 16 portrays the reported FAW outbreaks by maize farmers in Nyanza, Huye, and Gisagara districts from October 2020 to January 2021. Meanwhile, the upper part of Figure 16 exhibits the weekly radar insect echo detection before and during the FAW outbreak in these areas from July 2020 to January 2021.

Figure 16 provides a comprehensive analysis of the radar echo trend during FAW outbreaks from October 2020 to January 2021 and before the FAW outbreak, particularly between July and October 2020. Radar data consistently detected insect signatures before maize farmers reported the first FAW outbreaks, indicating early FAW presence detection in the region. Throughout the FAW outbreak from October to December 2020, a notable increase in infested maize coincided with heightened radar echoes displaying insect

activity. This synchronicity suggests a pattern of adult moth arrival, mating, egg-laying, and subsequent larval feeding on maize, aligning well with the agricultural season and the maize planting period, as indicated by seasonal rainfall forecasts[116]. Furthermore, analysis of radar insect echoes alongside ground FAW infestation data suggests the early detection of FAW swarm arrival preceding initial infestation, about 3 to 4 weeks before farmers noticed FAW larvae. This underscores the radar's potential as an effective early warning system for FAW outbreaks, facilitating proactive measures such as resource allocation for pesticide application[17].

5.1.6.2. Analysis of clear air event insect echo detection before and during the FAW outbreak (August to November 2020).

Our study investigated the increase of insect echo detection during the FAW outbreak and the effectiveness of radar in identifying insect signatures. We analyzed radar data from Nyanza, Huye, and Gisagara districts, focusing on maize marshlands, comparing nocturnal insect echoes over two periods: August and September 2020 (pre-outbreak) and October and November 2020 (during the outbreak). Figure.17 highlighted a clear increase in airborne insect activity during the outbreak period, indicating a significant rise in detected insect echoes. Notably, Fig.s 17 and 18 revealed a substantial surge in insect radar echoes approximately four weeks before farmers reported FAW infestation, aligning with FAW's life cycle stages and suggesting that the majority of detected insects were likely FAW.

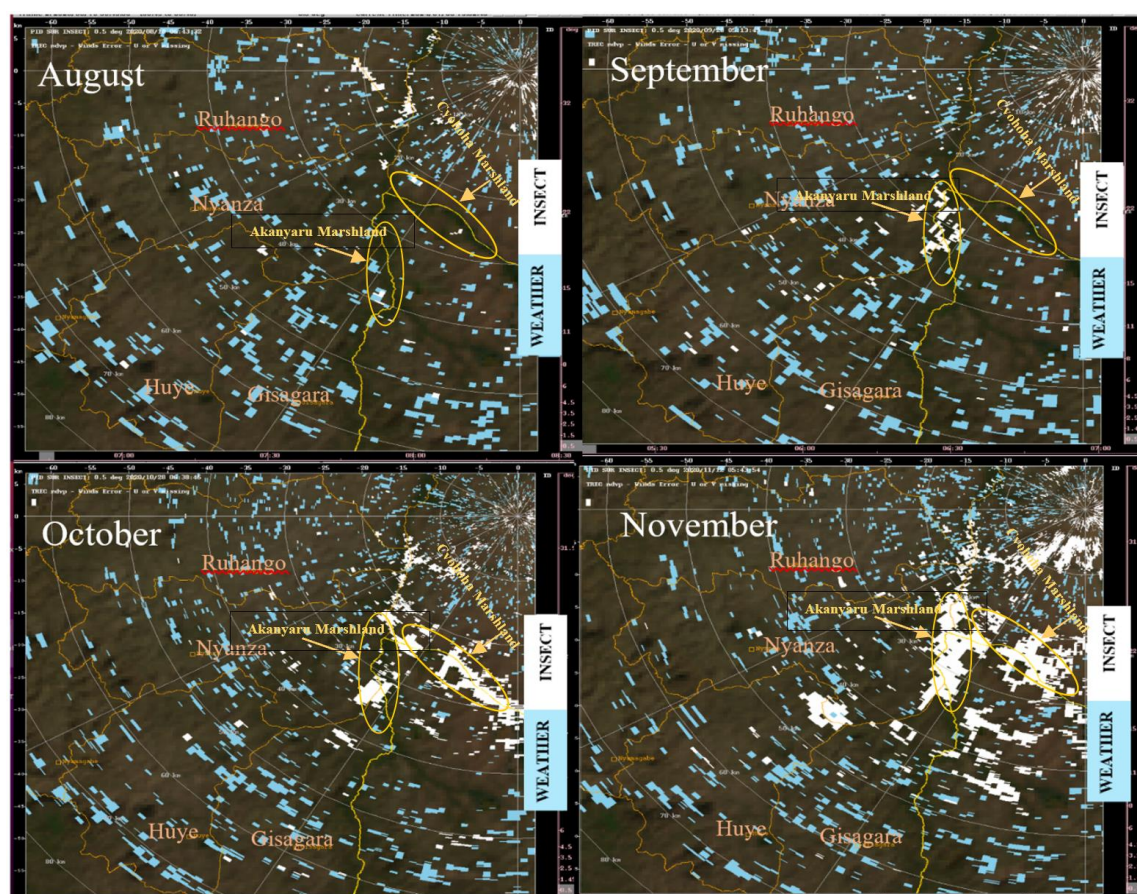


Figure 17 Weather radar echo signature analysis of clear air events before and during the FAW outbreak over and around maize marshlands adjacent to the Akanyaru River and Cyohova Lake. Radar detection image captured at 3:40 am in Nyanza, Huye, and Gisagara Districts from August to November 2020

Figure 17 presents a clear surge in clear air insect echoes detected by radar in the Nyanza, Huye, and Gisagara Districts. This finding strongly supports the evidence of increased clear air radar insect echoes during the FAW outbreak in maize fields, particularly notable over and around maize marshlands. The noticeable difference in insect echoes between the outbreak months of October and November and the months preceding the outbreak, August and September, provides robust confirmation of the reported insect outbreak. This alignment between radar data and reported insect outbreaks enhances the credibility and validity of the results, further reinforcing the connection between observed radar insect echo patterns and the occurrence of FAW infestation in these regions.

5.1.7.Conclusion

This study introduces an automated radar classification system that uses fuzzy logic and neural network algorithms initially developed for detecting hydrometeors. The system adeptly identifies and monitors the flight patterns of airborne insects, with a specific emphasis on addressing the FAW issue in Rwanda. Its groundbreaking feature lies in its ability to differentiate between weather phenomena and insect events, bringing substantial advancements to agricultural solutions. The radar's proven capability for early detection positions it as a promising early warning system for FAW outbreaks. Future initiatives involve integrating advanced deep learning techniques, exploring graph signal processing to enhance accuracy, and expanding both ground and airborne sampling methods, such as utilizing light traps for verification and incorporating additional parameters from weather radar data to improve the identification of insect signatures. The goal is to implement real-time systems and extend this technology to regions facing similar pest challenges. This contribution aims to strengthen sustainable agriculture, ensure food security, and empower farmers with timely information for effective pest outbreak management through an early warning system.

Fidele MANIRAGUHA

Reference Number: 220019513

5.2. Enhancing Identification of Meteorological and Biological Targets Using the Depolarization Ratio for Weather Radar

5.2.1. Overview

Leveraging weather radar technology for environmental monitoring, particularly the detection of biometeors like birds, bats, and insects, presents a significant challenge due to the dynamic nature of their behavior. Unlike hydrometeor targets, biometeor targets exhibit arbitrary changes in direction and position, which significantly alter radar wave polarization upon scattering. This study addresses this challenge by introducing a novel methodology utilizing Rwanda's C-Band Polarization Radar. Our approach exploits the capabilities of dual-polarization radar by analyzing parameters such as differential reflectivity (ZDR) and correlation coefficient (RHOHV) to derive the Depolarization Ratio (DR). While existing radar metrics offer valuable insights, they have limitations in fully capturing depolarization effects. To address this, we propose an advanced fuzzy logic algorithm (FL_DR) integrating the DR parameter. The FL_DR's performance was rigorously evaluated against a standard FL algorithm. Leveraging a substantial dataset comprising nocturnal clear air radar echoes collected during a Fall Armyworm (FAW) outbreak in maize fields from September 2020 to January 2021, the FL_DR demonstrated a notable improvement in accuracy compared to the existing FL algorithm. This improvement is evident in the Fraction of Echoes Correctly Identified (FEI), which increased from 98.42% to 98.93% for biological radar echoes and from 87.02% to 95.81% for meteorological radar echoes. This enhanced detection capability positions FL_DR as a valuable system for monitoring, identification, and warning of environmental phenomena in regions similar to tropical areas facing FAW outbreaks. Additionally, it could be tested and further refined for other migrating biological targets such as birds, insects, or bats.

5.2.2. Introduction

One of the key difficulties in detecting insects using radar lies in distinguishing biometeors such as birds, bats, and insects from more typical meteorological targets like raindrops, snowflakes, or hailstones [17], [83]. Biometeors are dynamic and

unpredictable, often changing direction, altitude, and speed[117]. These behaviors result in rapid fluctuations in radar wave polarization, making it difficult for conventional radar systems to accurately detect them. These traditional radar systems were primarily developed to track hydrometeors, which tend to exhibit more predictable scattering patterns due to their relatively uniform shapes and behaviors[18].

To address these detection challenges, we introduced a novel approach that leverages Rwanda's C-Band Polarization Radar. This radar system is equipped with dual-polarization capabilities, which allow it to capture additional information on the shape, size, and movement of objects by analyzing multiple radar parameters. Among the most important of these parameters are differential reflectivity (ZDR) and correlation coefficient (RHOHV). By analyzing these, we can calculate the Depolarization Ratio (DR), a key metric in distinguishing biometeors from hydrometeors[82], [18], [118], [119].

Depolarization occurs when radar waves scatter off objects that do not have a uniform shape or orientation. Insects, for example, tend to have irregular bodies and rapidly change orientation as they fly, resulting in significant depolarization. This depolarization can be captured using the DR metric, which helps differentiate biological targets from weather-related targets. Specifically, insects typically exhibit larger absolute values of ZDR, while their DR values are smaller compared to other scatterers like raindrops, which tend to be spherical and exhibit less depolarization [118].

To improve the accuracy of insect detection, we developed an advanced fuzzy logic algorithm (FL_DR) that integrates the DR parameter into the detection process [17], [18]. This algorithm allows the radar system to more effectively classify both meteorological and biological targets by considering the unique depolarization characteristics of different target types. The result is an enhanced ability to detect and monitor airborne insects, particularly during FAW outbreaks, which have a significant impact on agriculture.

One of the key advancements in weather radar technology has been the Simultaneous Transmission and Reception (SHV) mode, which allows radars to simultaneously transmit and receive horizontally and vertically polarized waves[120]. This has greatly enhanced the ability to classify atmospheric targets by providing detailed information on parameters such as ZDR and RHOHV. These parameters are crucial for understanding the shape and

behavior of objects in the atmosphere, allowing for more precise differentiation between biological and meteorological targets.

However, despite its improvements, SHV mode has limitations in fully capturing the phenomenon of depolarization [121]. Depolarization is important for understanding how various targets especially biometeors affect the polarization of radar waves as they scatter. For example, insects and birds cause far greater depolarization than raindrops, due to their complex shapes and movements. The SHV mode is not fully equipped to measure these depolarization effects, which is where the Depolarization Ratio (DR) becomes critical [122].

Before the introduction of SHV mode, weather radars used Circular Depolarization Ratio (CDR), which was especially important in aviation radars to filter out unwanted weather echoes [121], [123]. CDR was based on the scattering of circularly polarized waves, which worked well for identifying spherical particles like raindrops. These particles typically exhibited high correlation coefficients (RHOHV) and ZDR values close to 1 in linear units, making it easy to distinguish them from other objects. However, modern radars using SHV mode cannot directly measure CDR due to the nature of SHV transmission, which only involves linear polarization [60] [118], [122].

To address this issue, the Linear Depolarization Ratio (LDR) was developed [60], [119], [122]. LDR measures depolarization directly by transmitting and receiving linearly polarized waves, allowing for a more accurate understanding of how non-spherical objects, like insects, scatter radar waves. While LDR provided valuable measurements, its implementation required a dedicated polarization switch, which introduced practical limitations. These included slower data update rates and mechanical wear on the switch, reducing its widespread use in modern radar systems.

To overcome these limitations, researchers developed Depolarization Ratio (DR) as a proxy for both CDR and LDR [118]. DR can be calculated using the parameters provided by SHV mode, specifically DBZH (horizontal reflectivity) and RHOHV (correlation coefficient), without the need for a separate LDR mode [60], [119], [122], [11]. This innovation enables radars to capture depolarization effects more efficiently and provides a practical solution for distinguishing between weather-related targets and biological

targets like insects. DR offers a deeper understanding of how various objects scatter radar waves, which is especially useful in monitoring dynamic targets like airborne pests[18].

By integrating DR into our fuzzy logic algorithm, we have significantly enhanced the ability of weather radar systems to detect and classify biological targets, particularly agricultural pests like FAW. This methodology not only improves the accuracy of insect detection but also opens new possibilities for ecological research and pest management in regions where resources are limited. Our approach leverages the capabilities of existing radar technologies, such as Rwanda's C-Band Polarization Radar, to expand the scope of biological monitoring in Africa, offering a more comprehensive understanding of airborne insect movements across the continent's diverse ecosystems.

5.2.3. Materials and Methods

5.2.3.1. Derivation of the Depolarization Ratio (DR)

The Meteo Rwanda C-band dual-polarization weather radar currently lacks automatic calculation of the DR parameter, unlike other basic dual-polarization parameters. To address this, we utilized the bioRad R package (version 0.7.0.9603) [53], which offers tools for accessing, visualizing, and analyzing weather radar data for biological studies. In line with methodologies detailed in [53], we used the `calculate_param()` function within the bioRad package to compute and integrate the DR parameter using expressions outlined in previous studies. This computation was conducted within the Meteo Rwanda radar's TITAN software environment [78], facilitating easy access to radar data and updates following DR derivation. For a comprehensive understanding of the computation process, refer to the accompanying flowchart (Figure 18), which provides insight into the derivation of DR.

DR proves particularly beneficial for airborne targets like insects and birds [118]. Unlike rain or hail, the biometeors exhibit erratic movements and rapid changes in orientation while flying. Such dynamic behavior significantly impacts the polarization of the incident radar signal. By incorporating DR into radar analysis, meteorologists gain a deeper understanding of how these dynamic targets interact with radar waves [118], [124]. This enhanced understanding translates to more accurate classification and identification, not just for weather phenomena, but also for scenarios where biometeors might be present.

The ability to distinguish between these targets becomes crucial for various applications, from aviation safety to improving the accuracy of weather forecasts.

As established by various researchers [11], [24], [22],[28], [38]. the DR is mathematically expressed as:

$$DR = 10 \frac{(ZDR + 1 - 2 * \sqrt{ZDR} * RHOHV)}{(ZDR + 1 + 2 * \sqrt{ZDR} * RHOHV)} \quad (3)$$

where:

ZDR: Logarithmic ratio of horizontal to vertical reflectivity

RHOHV: Measures the similarity in polarization between transmitted and received signals

Sqrt(ZDR): represents the magnitude of depolarization caused by the scatters.

In our study, this equation is implemented utilizing the existing measurements of ZDR and RHOHV to estimate DR. This approach eliminates the need for a dedicated LDR measurement mode [118], making DR a practical and valuable tool for dual polarization weather with simultaneous transmission and reception weather radar systems like the one operated by Meteo Rwanda.

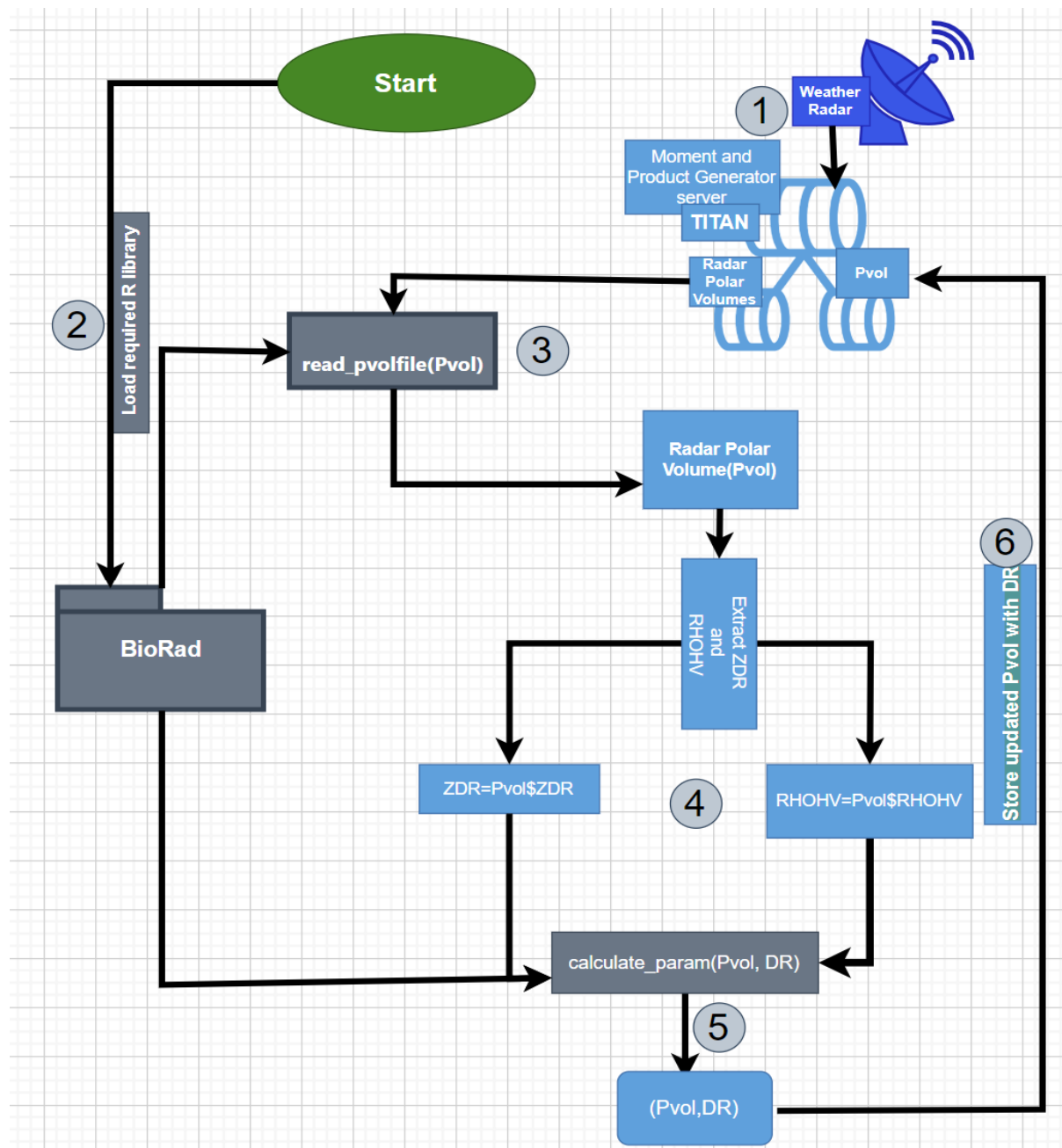


Figure 18 Flowchart for Depolarization Ratio (DR) derivation and integration into the TITAN System.

Figure 18 depicts the process of calculating and integrating the DR into the Meteo Rwanda weather radar system. Figure 18 illustrates the key steps involved.

DR derivation Process Steps:

1. Accessing Radar: Every 5 minutes, weather radar polar data volumes are received, processed, and stored by the Moment and Product Generator (MGEN/PGEN) within the TITAN environment where real-time data are accessed.

2. R Package and Library Loading: Required package and library are loaded following the methodology proposed by Kilambi et al. (2018) [118] and also using the bioRad R package (version 0.7.0.9603) developed by Dokter (Dokter et al., 2019) [53].

3. Reading Polar Volume Data: We work with low-level radar data, known as **polar volume data**, which the bioRad package interacts with. The package reads polar volumes using the read_pvolfile function, returning the volume as a pvol object (Dokter et al., 2019) [53].

4. Extracting ZDR and RHOHV: From the "pvol" object obtained in step 3, we extract the **differential reflectivity (ZDR)** and **copolar correlation coefficient (RHOHV)**, which are crucial parameters from dual-polarization radar systems.

5. DR Calculation: Using the calculate_param function on the pvol object, we compute **DR as a new parameter**. This calculation utilizes the ZDR and RHOHV values extracted in step 4 and follows Equation 3.

6. DR Integration and Storage: The calculated DR parameters are then **stored within the pvol object**, effectively updating the radar data. The updated data, including the newly integrated DR, is subsequently stored in the product Generation server (**PGEN**) server.

This integration process allows for the real-time derivation and archiving of DR alongside other weather radar parameters.

5.2.3.2. The DR Signature for Airborne biological target

Airborne biological target such as insects and birds have irregular shapes and varying orientations, leading to significant depolarization effects. Due to their irregular shapes, biological targets tend to exhibit larger absolute values of ZDR ($|ZDR|$) compared to hydrometeors which are more spherical in shape and typically have similar reflectivity in both horizontal and vertical polarization. The depolarization term, represented by $|ZDR|$, dominates the numerator in the DR equation (3) for biological targets. As a result, the DR values for biological targets are typically significant than those for hydrometeors.

However, weather echoes with higher depolarization, such as those from hail and possibly melting graupel, are exceptions. As we're focusing on clear air events, these exceptions

are not included. Since hail generally isn't observed during clear air periods and has reflectivities never seen in biological echoes (> 35 dBZ), applying a reflectivity threshold helps recognize them as weather. This filtering out of weather particles enhances data cleaning and preparation.

Insect Targets:

For insect targets, which exhibit significant depolarization due to their irregular shapes, we expect $|ZDR_{insect}|$ to be high $|ZDR| \gg 1$, and low values of $RHOHV_{insect} < 0.88$ indicate less similarity in polarization between transmitted and received signal,

$$DR_{insect} = \frac{ZDR_{insect} + 1 - 2 * \sqrt{ZDR_{insect} * RHOHV_{insect}}}{ZDR_{insect} + 1 + 2 * \sqrt{ZDR_{insect} * RHOHV_{insect}}} \quad (4)$$

5.2.3.3. Integrating depolarization ratio (DR) in fuzzy logic

The precision of weather radar target classification can be greatly improved by incorporating multiple parameters. For example, the research by Wang et al. [56] demonstrates that a comprehensive use of polarimetric measurements derived from dual-polarization Doppler weather radar data enhances the accuracy of identifying various types of hydrometeors. Differences in the shape, size, and spatial orientation of different hydrometeors generate distinct polarization parameters, which can significantly advance hydro meteorological classification using these polarization measurements.

To tackle these challenges, integrating demoralization ration (DR) into fuzzy logic weather radar data classification is pivotal. This integration enhances the ability to accurately discern and classify biological targets, especially given their dynamic flight nature. The objective is to advance the accuracy of target identification and classification in weather radar applications, with a specific focus on FAW detection and identification.

The simplified proposed fuzzy logic integrating DR (FL_DR) is illustrated in Figure 19 below:

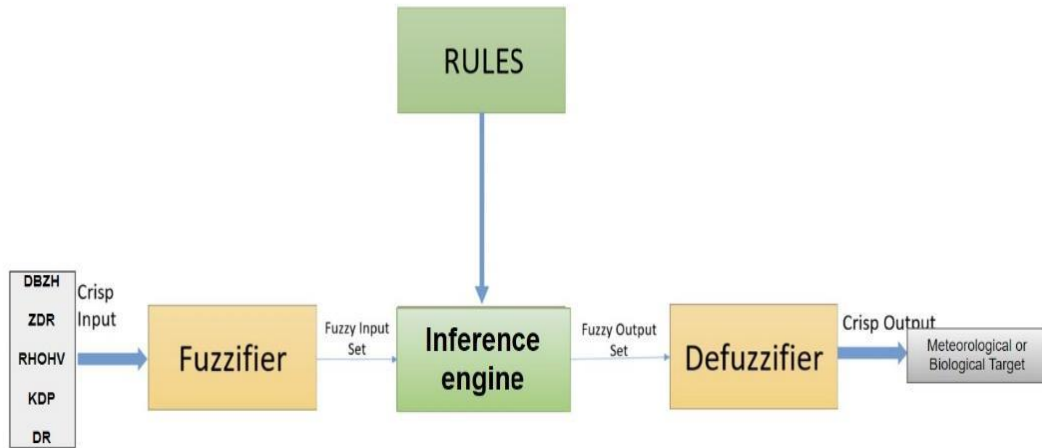


Figure 19. A simplified Fuzzy Logic architecture comprising four key components and utilizing five crisp inputs (DBZH, ZDR, RHOHV, KDP, and DR) for the classification of weather radar echoes in Rwanda as either meteorological or biological.

The FL_DR classification method is used to classify radar pixels into either as meteorological or biological category, relying on our predefined membership rules[17] which was adopted following a method proposed by Liu and Chandrasekar [60] using fuzzy logic to class hydrometeors.

Essentially, each radar pixel is classified based on a set of its values for parameters including DBZH, ZDR, KDP, RHOHV, and DR. If all of these parameter values fall within the range of a single class, the pixel is straightforwardly classified into that class. However, when there are overlaps in parameter values classification is still possible. In this case, the membership degree to which each pixel belongs to a particular class can vary. This means that while some parameters might lean towards one class, others might lean towards the other. In such cases, the determination of a pixel's class hinges on the collective degree of membership across all parameters. This collective membership degree serves as the deciding factor.

Yet, there are scenarios where there is no overlap in one or more parameters. In these instances, the dominant class is determined not only by the presence of membership but also by the number of membership degrees. This approach allows FL and FL_DR for a flexible and nuanced classification process that accounts for the varying degrees of certainty in categorizing radar pixels.

5.2.4. Results and Discussion

Understanding the pairwise relationship between ZDR and RHOHV is pivotal as they discern meteorological from non-meteorological targets, underlining the importance of target density analysis. The derivation of the depolarization ratio from these metrics notably enhances target classification precision, as evidenced by in chapter 4 [118], [120].

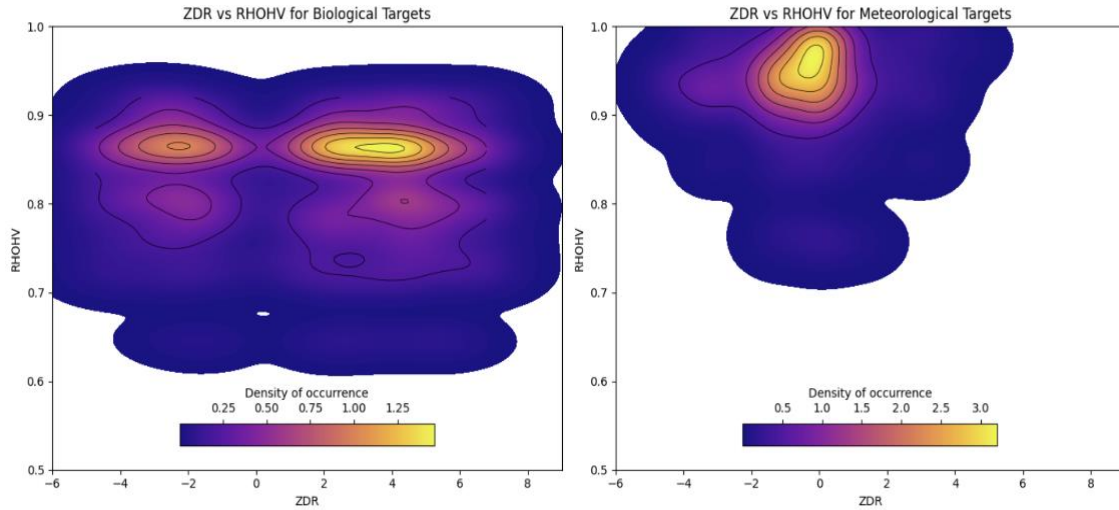


Figure 20 Spatial distribution of biological and meteorological targets in ZDR-RHOHV Space

Figure 20 provides a detailed exploration of both biological and meteorological targets within the ZDR-RHOHV space, leveraging our comprehensive training dataset consisting of 1,308,956 nocturnal clear air radar echo pixels. On the left side of the figure 20, we delve into the density of biological targets, predominantly represented by Fall Armyworm (FAW). Here, we observe 850,821 clear air radar echoes categorized as biological targets, along with 458,135 echoes classified as meteorological targets. Conversely, the right side of Figure 20 focuses on the density of meteorological targets, based on 458,135 clear air radar echoes.

The contour lines within the plot delineate areas of equal probability density, shedding light on variations in the density of biological targets (insects) or meteorological targets (weather phenomena) across the ZDR-RHOHV space. Thicker contour lines highlight regions of higher density, while thinner lines indicate areas of lower density. This visualization aids in understanding the spatial distribution of targets, enabling the identification of prevalent target categories for specific ZDR-RHOHV value pairs.

Specifically, for biological targets, higher densities are observed within the ZDR range of -6dB to +6dB and RHOHV range of 0.68 to 0.91. Notably, the highest density regions occur between -4dB to -2dB and +2dB to +6dB for ZDR, and 0.8 to 0.9 for RHOHV. Conversely, for meteorological targets, the highest density regions are typically observed near ZDR values close to 0dB and RHOHV values greater than 0.9.

5.2.4.1. Implementation of Depolarization Rate (DR) Derivation

Since the Meteo Rwanda C-band Doppler polarimetric weather radar doesn't automatically compute DR, we derived it directly from the radar data using the parameters of differential reflectivity and correlation coefficient. Following the methodology and procedural steps outlined in the flow chart shown in Figure 18, we obtained DR. To illustrate this process, we present an example demonstrating the computed DR for a clear air event on November 12, 2020, at 5:20:11 (Kigali Time, UCT+2).

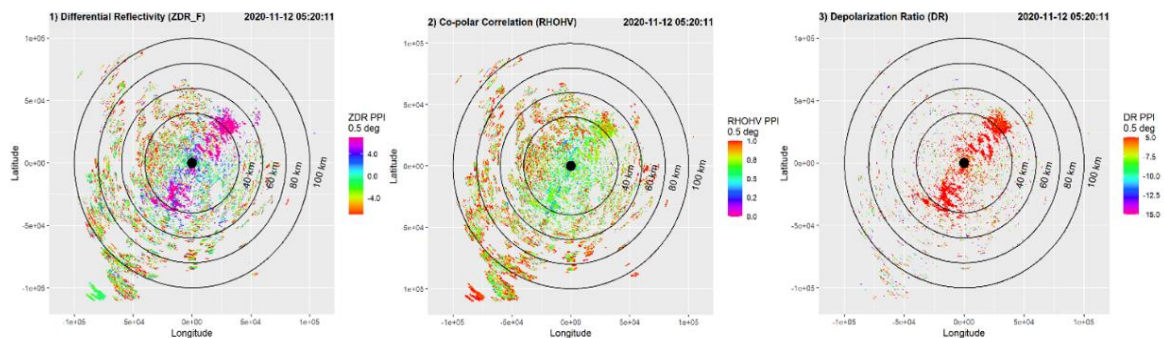


Figure 21 Meteo Rwanda Radar captured a clear air event on November 12, 2020, at 5:20 AM, displaying ZDR, RHOHV, and DR during a FAW outbreak

Figure 21 depicts data from a clear air event on November 12, 2020, at 5:20:11 am (Kigali, Time, UCT+2), showing Differential Reflectivity and Correlation Coefficient alongside the newly derived DR. This observation, conducted at a 0.5-degree elevation angle amidst the FAW outbreak in maize fields, reveals that insect signatures typically exhibit DR values exceeding -13 dB, ZDR values between 2 dB and 7 dB, reflectivity (DBZH) under 30 dBZ, and correlation coefficient (RHOHV) below 0.88, often associated with biological phenomena. Evaluating the FL_DR algorithm's accuracy compared to the standard FL involves analyzing on-site observations of adult FAW moths in maize fields. This includes examining the classification output of radar echoes produced by both FL_DR and FL algorithms, applied to radar data collected over infested maize areas and

maize marshlands during FAW outbreaks spanning from September 2020 to January 2021.

5.2.4.2. Integrating DR in fuzzy logic (FL_DR)

5.2.4.2.1. Clear air event case for FAW radar echoes detection on November 12, 2020

Our research aimed to improve the detection of airborne biological particles, focusing specifically on FAW outbreaks between October 2020 and January 2021. We sought to enhance existing fuzzy logic (FL) systems by integrating DR, a polarimetric radar parameter. Using the TITAN software from Meteo Rwanda to visualize and gain more insight of the output of a standard FL system and an upgraded version that incorporated DR alongside additional parameters (FL_DR).

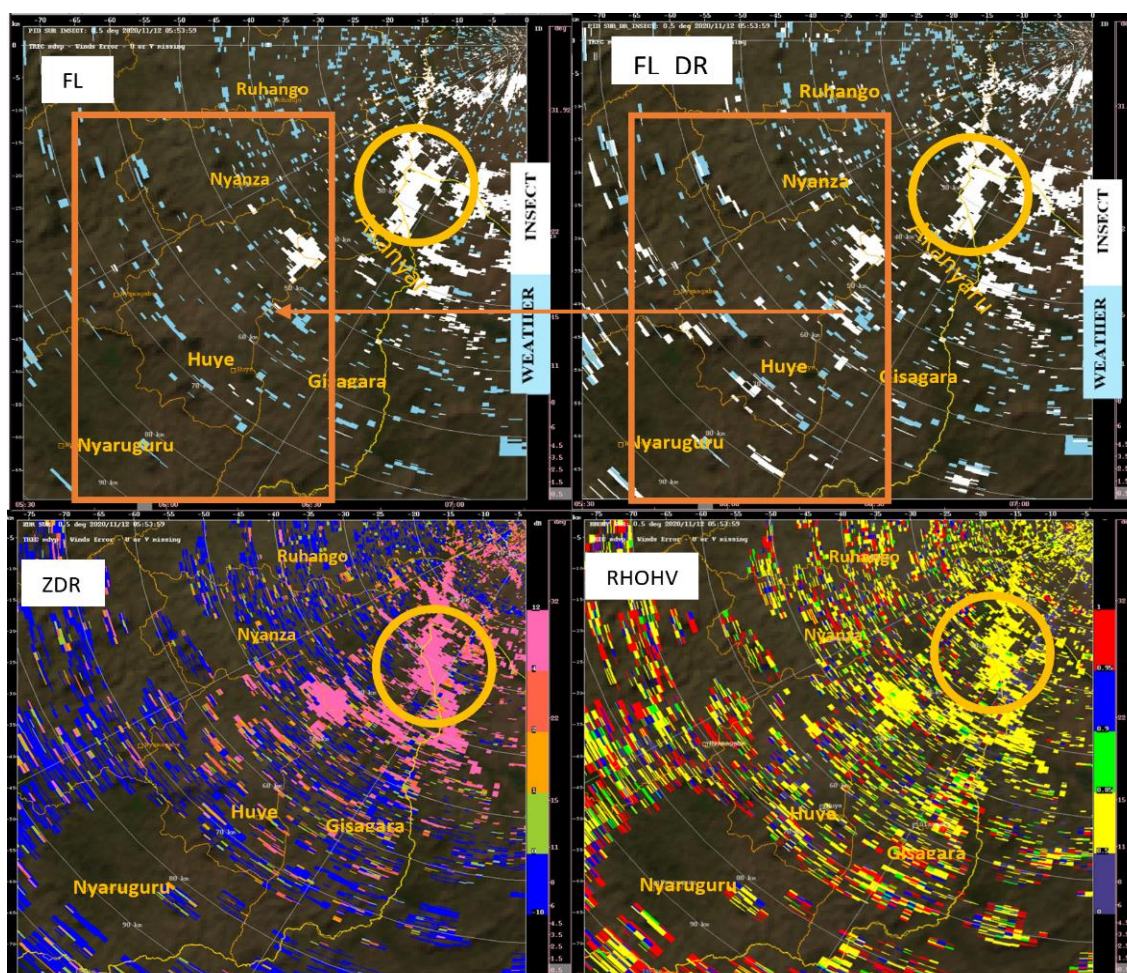


Figure 22 Comparison of FL and FL_DR weather radar detecting FAW adult moths, an example of November 12, 2020, 20-40 minutes before sunrise. Lower panels show differential reflectivity (left) and correlation coefficient (right).

The data in Figure 22 upper panel demonstrates that the FL_DR algorithm outperforms FL in detection capabilities, particularly beyond a 50 km range from the radar site, attributed to consideration of depolarization effects from the target. Within a 50 km radius, both algorithms perform similarly, as observed over maize fields around the Akanyaru River in Gisagara and Nyanza districts. However, beyond this range, FL_DR excels in detecting biological echoes at significant distances, highlighting its potential for improving the monitoring of airborne agricultural pests. The lower panel shows corresponding ZDR and RHOHV values, where FL and FL_DR algorithms detect more insects correspond with ZDR values between 2 and 7 dB and RHOHV between 0.7 and 0.88, typical for insect signatures. However, due to the tropical weather and climate in Rwanda, it is common to encounter hydrometeors in the sky, often caused by cloud formations such as stratocumulus and altocumulus clouds. These clouds form when a layer of air is lifted and cooled, often by a weak frontal system, and usually indicate stable weather but can bring drizzle [38]. Under these weather conditions, insects can fly, which explains why Figure 22 shows the possibility of seeing weather particle echoes. This is naturally related to the tropical weather conditions.

5.2.5. Performance Evaluation

A comparative assessment was conducted between a novel fuzzy logic algorithm incorporating depolarization ratio (FL_DR) and the standard fuzzy logic (FL), which utilizes only four standard polarimetric parameters. The training dataset consisted of 1,308,956 radar echo pixels collected from October 18, 2020, to November 29, 2020, covering both nocturnal clear-air and non-clear-air events. The analysis compared the results FL with the results of FL_DR, which incorporate DR.

Both FL and FL_DR classify radar pixels as either meteorological or biological targets based on specific logic and rules. If all parameter values (DBZH, ZDR, KDP, RHOHV, and DR) belong to one class, the classification is straightforward. However, overlaps exist where parameter values have varying degrees of membership in each class. In cases where values overlap across all parameters, the membership degree determines the pixel's classification. If there is overlap in one or more parameters, the dominant class is determined by the number of membership degrees. This method offers flexibility in accounting for uncertainties in classifying radar pixels.

For the testing dataset, comprising 1,045,102 Weather radar nocturnal Echo pixels sampled during clear air events amidst a Fall Armyworm outbreak in the Nyanza, Huye, and Gisagara districts from November 30, 2020, to January 2021, over maize fields and marshland, FL with four parameters and FL_DR with five input parameters, including DR, were trained and tested on these samples.

The resulting classification outputs were compared using the Fraction of Echoes Correctly Identified (FEI) and Heidke Skill Score (HSS). FEI measures accuracy as a percentage, while HSS assesses the algorithm's skill, with values ranging from -1 to 1, where 1 signifies perfect skill and 0 indicates no skill or random performance. Table 8 presents the comparative performance analysis of FL_DR against FL.

$$FEI = \frac{NC*100}{T} \quad (5)$$

While Heidke Skill Score (HSS) is given by:

$$HSS = \frac{NC - (C_{12} * C_{21} / T)}{T - (C_{12} * C_{21} / T)} \quad (6)$$

- NC is the number of correctly identified echoes.
- T is the total number of classifications attempted.
- C12 is the number of cases where a meteorological echo was incorrectly classified as a biological echo.
- C21 is the number of cases where a biological echo was incorrectly classified as a meteorological echo.

Table 7. presents the performance metrics of Fuzzy Logic (FL) and Fuzzy Logic with Depolarization Ratio (FL_DR) for identifying meteorological targets (M.T) and biological targets (B.T). It also includes a comparison with similar work by Kilambi et al. (2018) using the DR threshold method.

Perform ance Metrics	FL [11]		FL_DR		Kilambi et al. [11]			
	DR>-13Db				DR>-12dB		With RHOHV and ZDR	
	M.T	B.T	M.T	B.T	M.T	B.T	M.T	B.T
FEI	87.02%	98.42%	95.81%	98.93%	97.1%	95.8%	95.1%	97.4%
HSS	0.98	0.98	0.96	0.98	0.93	0.97	0.89	
Hits	336398	611506	359707	662480	-	-	-	-
Misses	39038	58160	15729	7186	-	-	-	-
False Alarm	58160	39038	7186	15729	-	-	-	-

Table 7 compares the performance metrics of three methods: Fuzzy Logic (FL), Fuzzy Logic with Depolarization Ratio (DR) integration (FL_DR), and a threshold method by Kilambi et al. [118]. The analysis shows significant improvements in identifying biological and meteorological targets from weather radar data using FL_DR. This method enhances the Fraction of Echoes Correctly Identified (FEI), achieving 95.81% accuracy for weather and 98.93% for non-weather targets, surpassing conventional FL. Additionally, the Heidke Skill Score (HSS) supports FL_DR's superior performance, with scores of 0.96 for weather and 0.98 for non-weather echoes, indicating high proficiency in distinguishing between event types.

Figure 23 presents a comparative analysis of confusion matrices for FL and FL_DR during the Fall Armyworm (FAW) outbreak from October 2020 to January 2021 in the Nyanza, Huye, and Gisagara districts. The integration of DR in FL_DR led to significant improvements in classification accuracy. For meteorological radar echoes, FL_DR increased classification accuracy from 87.02% to 95.81%, reducing incorrect classifications from 12.98% to 4.19%. For biological targets, classification accuracy increased from 98% to 98.93%, with incorrect classifications decreasing from 1.58% to 1.07%. Notably, FL_DR demonstrated lower false positive rates compared to FL. The DR threshold method for biological and meteorological targets at DR > -12 dB showed a FEI of 97.1% and an HSS of 0.9257 for meteorological targets, and a FEI of 95.8% and an HSS of 0.8939 for biological targets.

The integration of Depolarization Ratio (DR) into Fuzzy Logic significantly enhances precision, reliability, and overall performance in radar-based target identification for both weather and non-weather events. This improvement highlights the effectiveness of FL_DR in distinguishing between meteorological and biological echoes, especially during events such as the FAW outbreak. The strong correlation observed between radar predictions and ground observations further solidifies FL_DR as a robust tool for accurately identifying and classifying various types of radar echoes, thereby aiding in effective decision-making processes.

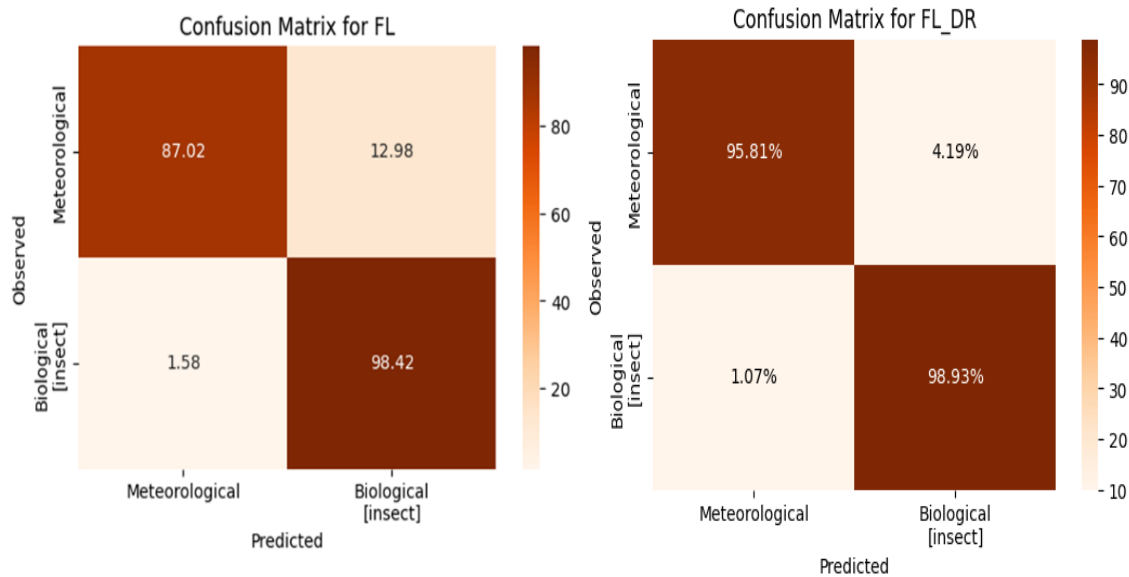


Figure 23. Confusion matrices depicting the alignment between radar-based target identification using Fuzzy Logic (FL) and Fuzzy Logic integrated with Depolarization Ratio (FL_DR), validated against Fall FAW outbreak observations data and a heavy rain event.

To refine our performance evaluation, we conducted a comprehensive Precision-Recall (PR) analysis, using PR curves and associated Area Under the Curve (AUC-PR) values to assess the effectiveness of our proposed fuzzy logic algorithm, FL_DR, compared to FL. The PR curve demonstrates the balance between precision (correctly identified positive cases) and recall (true positive cases correctly identified) for different classification thresholds. A higher AUC-PR value indicates better overall performance. Our focus was on detecting and classifying meteorological (weather) and biological (insect) radar echoes (see Figure 24). For this analysis, we utilized the Python programming language and the sci-kit-learn library, employing the `precision_recall_curve` and `average_precision_score`

functions from the sklearn metrics module to compute the PR curve and AUC-PR for each classification output from FL_DR and FL. The curves in Figure 24 illustrate the precision-recall performance of FL_DR compared to FL, showcasing their ability to distinguish between weather and insect radar echoes. Higher AUC-PR values indicate superior performance in both precision and recall.

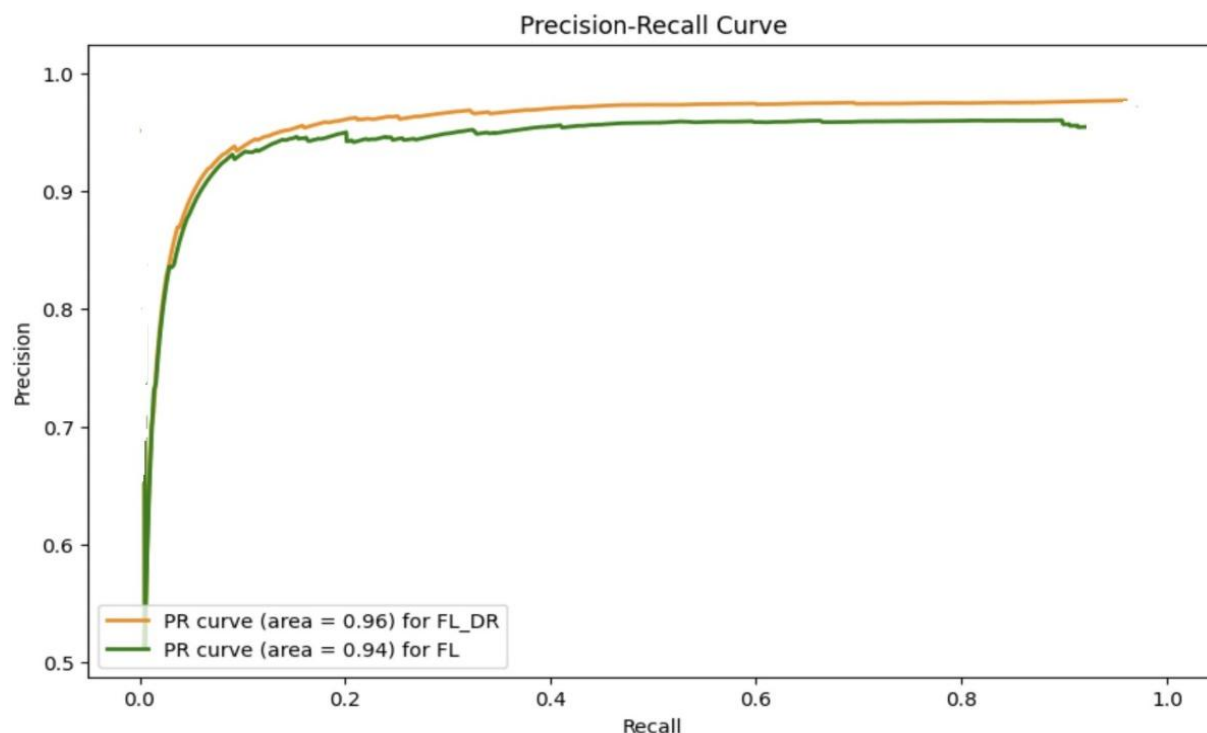


Figure 24 Precision-Recall analysis of FL_DR and FL for meteorological and biological radar echoe detection and classification.

Our analysis drew from a dataset of 1,045,102 weather radar echoes pixel comprising 843,237 nocturnal clear air radar echoes extracted over FAW-infested fields and maize marshlands. These radar echo pixels were collected and extracted from 30 randomly points (location with infested maize fields and marshland) across Nyanza, Gisagara, and Huye Districts during September and October 2020, covering altitudes ranging from 200m to 2000m, with a 200m sampling vertical resolution.

In this comparison, the PR curve for FL_DR showcased a marginally larger Area Under the Curve (AUC) of 0.96 compared to FL, which achieved an AUC of 0.94. These notable AUC-PR values indicate good performance in distinguishing between weather (meteorological) and biological (insect) radar echoes. AUC-PR values nearing 1 demonstrate high precision and recall across various threshold values, highlighting the

fuzzy logic algorithm's proficiency in achieving both a low false positive rate and a low false negative rate.

Moreover, these results underscore the remarkable performance of both classifiers in distinguishing between weather and insect radar echoes, with FL_DR demonstrating a slight advantage over FL based on the AUC-PR values. It's essential to highlight the significance of FL_DR's capability to leverage DR data alongside other radar variables and consider integrating depolarization effects from radar targets, especially bio meteors, which often exhibit changing directions and positions, unlike weather targets.

5.2.6. Conclusion

The challenge of distinguishing insect swarms from weather patterns poses a significant obstacle to the effective utilization of weather radar applications. Our study addresses this challenge by leveraging Meteo Rwanda's weather radar data collected during a FAW outbreak and infestation of maize crop fields in three districts of Rwanda's southern province from September 2020 to January 2021.

We adopted a method that analyzes ZDR and RHOHV to estimate DR, a crucial parameter for understanding how objects modify radar signals. While existing metrics provide valuable insights, they also possess limitations. To overcome these limitations, we developed FL_DR, an advanced fuzzy logic algorithm integrating DR. Our findings demonstrate that FL_DR significantly enhances accuracy in identifying both insects (from 98.42% to 98.93%) and weather phenomena (from 87.03% to 95.82%) compared to a standard FL algorithm. This enhanced detection capability positions FL_DR as a valuable system for monitoring, identification, and warning of environmental phenomena in regions similar to tropical areas facing FAW outbreaks. Additionally, it could be tested and further refined for other migrating biological targets such as birds, insects, or bats.

In future research, it would be essential to explore the integration of advanced techniques such as aerial light traps and camera drones to enhance validation and refinement processes. These methodologies offer significant promise in providing real-time sampling of bio-scatters from the atmosphere, allowing for correlation with radar-detected echoes. Additionally, there is considerable potential in incorporating DR into other machine learning algorithms, such as Random Forest, XGBoost, and SVM, to improve the identification of hydrometeors and diverse airborne biological targets.

Chapter 6. Quantification of Insect Migration and Distribution from Weather Radar Data: FAW Outbreak in Rwanda.

6.1. Overview

For over a decade, various studies have aimed to identify airborne biological targets, such as insects, using weather radar. However, few studies have focused on quantifying and tracking crop pests like the Fall Armyworm (FAW) to provide real-time warnings for farmers, hindering proactive pest management. This study addresses this gap by exploring the potential of weather radar data, analyzed with the bioRad R package, to quantify FAW activity during an outbreak in Rwanda from September 2020 to January 2021. By leveraging bioRad's capabilities in extracting biological information from vertical profile analysis, we obtained insights into insect abundance using quantities like Vertically Integrated Reflectivity (VIR) and Vertically Integrated Density (VID). We further utilized Migration Traffic Rate (MTR), and Vertically Integrated Reflectivity (VIR) incorporating FAW radar cross-section (RCS), to quantify and estimate insect movement more accurately. Our findings revealed significant nighttime activity during the FAW outbreak, aligning with the moths' nocturnal behavior. Furthermore, we examined insect vertical distribution and activity patterns using KMeans clustering on radar data from FAW-infested maize farms (November 7th-12th, 2020). This analysis identified three distinct layers of insect abundance: a lower layer (1693m to 2043m altitude) with the highest density, a middle layer (2043m to 2750m altitude) with moderate density, and an upper layer (above 2750m altitude) with the lowest density. Daytime activity was concentrated below 700 meters, while nighttime activity surged and extended up to 1200 meters. Comparing insect echo characteristics during both day and night demonstrates the potential for improved understanding of FAW behavior and its radar manifestations. This study highlights the effectiveness of bioRad in elucidating insect movement patterns using weather radar data, offering valuable insights for developing pest management strategies that may benefit agriculture and the environment in regions facing FAW outbreaks.

6.2. Introduction

Africa has lagged behind developed regions in adopting weather radar technology for weather forecasting, biological, and environmental monitoring applications [55], [65], [21], [125]. While North America and Europe have extensively used this technology to study airborne animal movements and ecological patterns, its application in Africa remains limited. This discrepancy is evident in the scarcity of operational weather radar systems across the continent, which hampers african researchers' ability to leverage these tools for ecological studies [126].

Radar technology has evolved since the mid-20th century to better exploit its potential for tracking organisms. In 1965, Doppler radar identified clear-air echoes, pinpointing discrete targets [31]. Hardy et al. in 1969 associated these echoes with insects and birds [67]. Weather radar has become indispensable for monitoring airborne biological entities such as insects, birds, and bats, with applications in epidemic control, environmental preservation, flight safety, and crop disaster prediction [68].

Over the past decade, significant progress has been made globally in extracting biologically relevant information from low-level radar data [15], [17], [32], [53], [55]. These advancements align with a growing ecological need to understand and predict the movements of airborne animals. Consequently, the use of weather radar in ecological research has surged, particularly in developed nations where it has become crucial for monitoring bird migrations and insect movements [68], [69], [70], [71].

Gauthreaux et al. [68] used reflectivity data from weather radar to establish a quantitative model for bird migration. The introduction of dual-polarised radar by Zrníc enabled detailed measurements of insects and birds [36], [72]. Cui et al. quantified insect migration across the Bohai Strait [127], while Nussbaumer et al. [74] used European radar networks to estimate nocturnal bird migration densities. These efforts have laid the groundwork for large-scale phenology research and improved the separation of birds and insects in radar data. For example, insect migration often takes place at significant heights, commonly hundreds of meters above the ground. They harness the power of strong winds to facilitate their long-distance journeys. This phenomenon is characterized by the concentration of migrating insects within specific altitude bands, typically between 40 and 290 meters above ground level. The range of altitudes for insect migration varies widely, spanning

from 150 to 1200 meters, with a notable preference for medium-sized migrants weighing between 10 and 70 milligrams[75], [77].

A key factor contributing to the widespread adoption of weather radar in these regions is the development of user-friendly software packages. A good example is the bioRad package for the R programming language, developed by Dokter et al. [53], which provides researchers with accessible tools for biological analysis of weather radar data. This package lowers the barrier to entry by offering functionalities that simplify the analysis of biological information within radar data.

However, while the bioRad package provides robust tools for analyzing biological data from weather radar, it has certain limitations. The package primarily focuses on extracting biological information and quantifying insect activity, but may not fully account for all environmental factors influencing insect behavior. Additionally, bioRad's reliance on radar cross-section (RCS) data might not always provide the most accurate estimates of insect movement due to variations in insect size and orientation[128]. Further refinement and integration with other data sources could enhance its accuracy and applicability in various ecological contexts[128].

While some African countries like Rwanda possess advanced weather radar systems such as the Meteo Rwanda C-band polarimetric Doppler radar, their utilization has primarily been restricted to tracking weather patterns and precipitation[32], [17]. This study in Rwanda aims to broaden the scope by exploring the potential of weather radar for environmental monitoring, specifically focusing on quantifying insect migration patterns. By harnessing the bioRad R package alongside the Meteo Rwanda C-band Doppler radar, this work strives to attain a more comprehensive understanding of insect movement across the country. This encompasses analyzing seasonal variations, preferred flight altitudes, and geographical distribution of different insect populations. This approach fills a critical gap in African ecological research by providing insight on insect migration and lays the groundwork for a new era of ecological studies within the African continent.

By leveraging bioRad with weather radar data, the aim is to generate real-time insights into Fall Armyworm (FAW) movement patterns[17], [53] enabling farmers to prioritize scouting efforts and optimize resource allocation for more effective pest control. This approach focuses on assessing the ability of weather radar systems, particularly those

operated by Meteo Rwanda, to detect and quantify FAW movement and density across affected agricultural regions.

Using bioRad, an open-source tool designed for analyzing biological scatterers in radar data, helps differentiate between biological targets like insects and other meteorological phenomena. This allows for a more accurate tracking of FAW populations. By extending the analysis over time, the study examines FAW movement across various seasons and weather conditions, mapping their trajectories and estimating population densities.

The insights gained contribute to better understanding migratory patterns and outbreak zones, which can inform more precise pest management strategies. This provides essential data for early warning systems, allowing farmers to implement preventive measures in high-risk areas, reducing crop losses and minimizing the environmental impact of pest control.

6.2.1. Radar Cross Section in Quantifying Biometeors: A Comprehensive Overview.

Radar Cross Section (RCS) values are essential for evaluating how effectively radar systems can detect insects, which is crucial for applications ranging from agricultural pest monitoring to environmental meteorology [94]. RCS values depend heavily on the physical characteristics of insects, such as their size, shape, orientation, and composition. Variability in RCS across different insect species and age groups arises from these morphological and compositional differences, influencing how radar waves interact with their bodies. Recent studies have explored this variability, revealing how factors like body length, orientation, and incident angles impact RCS values[129], [130].

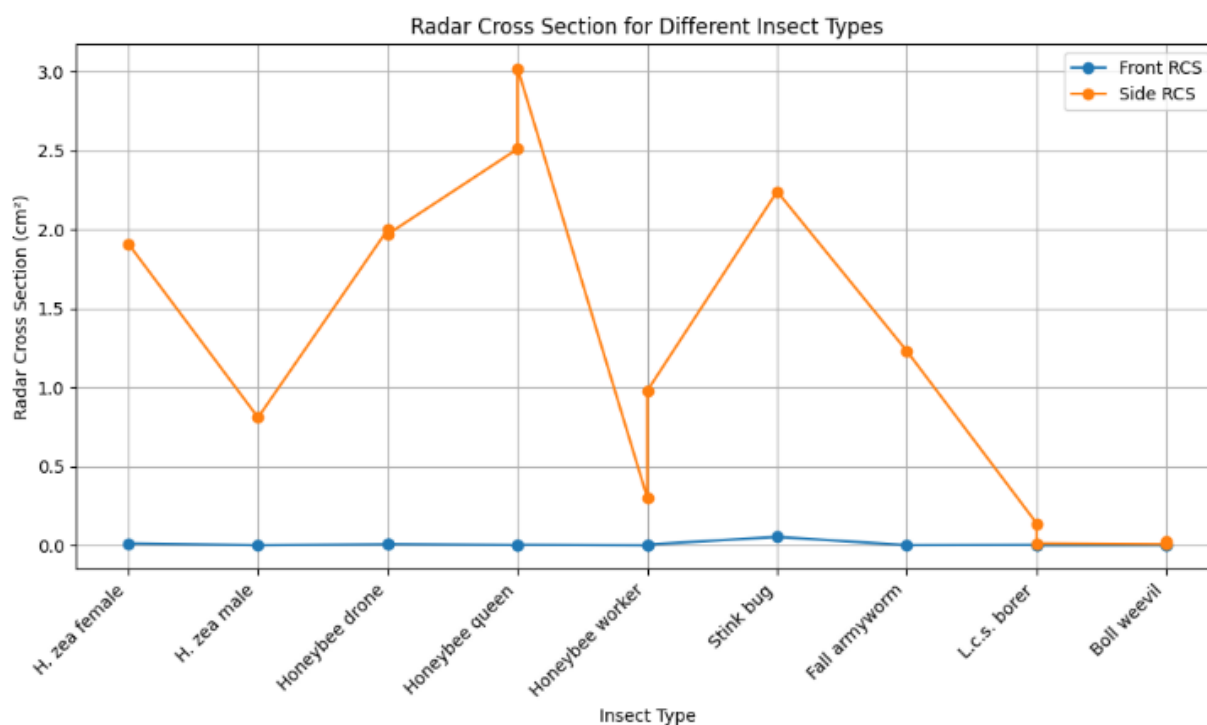


Figure 25. Radar cross section for six different adult insect species including FAW

Wolf et al. [128] conducted an extensive study to measure the RCS of six insect species using high-resolution radar (Figure 25). They analyzed insects from different angles (aspect angles, which refer to the angle at which radar waves strike the insect) and varied the polarization angles (the orientation of the radar wave's electric field) to gain insights into how insects reflect radar signals under varying conditions. The study found significant differences in RCS values, ranging from as high as 3 cm² to as low as 5 x 10⁻⁴ cm². For example, the honey bee (*Apis mellifera*) and the lesser cornstalk borer (*Elasmopalpus lignosellus*) exhibited distinct RCS values that corresponded to their unique physical features, such as body shape, size, and composition [128].

The study also provided important findings on the Fall Armyworm (FAW), a significant agricultural pest. When observed from the front, the FAW displayed an average RCS of 0.0022 cm², indicating relatively low radar reflectivity when viewed head-on. However, when viewed from the side, the FAW's RCS increased significantly to 1.23 cm², suggesting a much larger radar signature. These differences highlight how the insect's orientation in relation to the radar affects its detectability. By averaging these measurements, the radar cross-section for the Fall Armyworm (σ_{FAW}) is calculated at

0.6161 cm², offering a representative value of its radar signature across different viewing angles.

This averaged RCS value for the FAW is a critical metric for understanding how radar systems detect this pest in the field, especially in environmental radar applications aimed at monitoring and managing pest outbreaks [26], [125], [128], [129], [131], [132]. These findings provide valuable insights into the radar detectability of insect species, facilitating the development of more accurate pest monitoring tools and improving the precision of agricultural interventions.

6.3. Materials and Methods

6.3.1. Weather Radar Data and Corresponding Ground Reference Data of FAW Maize Infestation Events.

To prepare the data for analysis, a multi-step preprocessing procedure was implemented (Figure 26) [78], [32]. This involved cleaning the raw radar data, removing clutter (non-insect signals), extracting echoes specifically from insects, and converting the data into a format compatible with the bioRad R package (HDF5).

Following preprocessing, the bioRad package's suite of tools was applied to the radar data. This analysis aimed to assess both daytime and nighttime insect activity and abundance. Time series of vertical profiles were generated and analyzed. These profiles included key parameters such as insect ground speed (both west-to-east and south-to-north components), vertical and horizontal speeds, flight direction, reflectivity factors (indicating insect size and density), and total radar reflectivity.

Since the FAW outbreak primarily occurred at night, a specialized nighttime analysis was conducted. This analysis considered local sunrise and sunset times at each radar location to precisely examine insect migration patterns throughout the entire day-night cycle.

6.3.2. Screening Non-Insect Echoes

Screening out non-insect echoes from weather radar data is crucial for accurately assessing insect populations, but it is challenging because airborne insects can be

misidentified as precipitation. To filter out clutter echoes, we first employed a ground clutter method for data cleaning to extract biological weak echoes is described in our previous study [32]. Then we use thresholds for the correlation coefficient ($\text{RHOHV} > 0.95$) parameter and the depolarization ratio ($\text{DR} > -13$ dB) to filter out weather echoes from our radar data. The correlation coefficient and depolarization ratio thresholds are a straightforward and reliable method for distinguishing between weather and biological echoes when dual-polarization data is available[32], [118]. By setting an RHOHV threshold value above 0.95, we ensure that only data with a strong correlation between horizontal and vertical polarizations are retained. This reduces the inclusion of weather phenomena, which typically have higher RHOHV values, and maximizes the capture of biological scatterers with lower RHOHV values. Even though our radar data was collected during clear air nocturnal events, particularly during the Fall Armyworm (FAW) outbreak, we prioritize eliminating any potential weather interference by screening out reflectivity areas with $\text{RHOHV} > 0.95$ (see Figure 26).

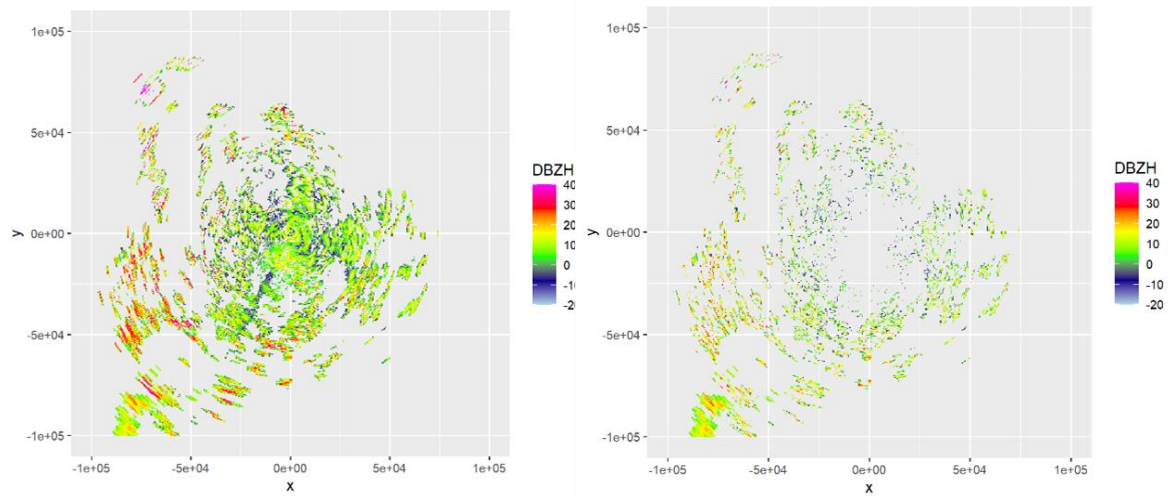


Figure 26. Uncleaned reflectivity (left) and cleaned reflectivity (right), after screening out non-insect echoes from weather radar data.

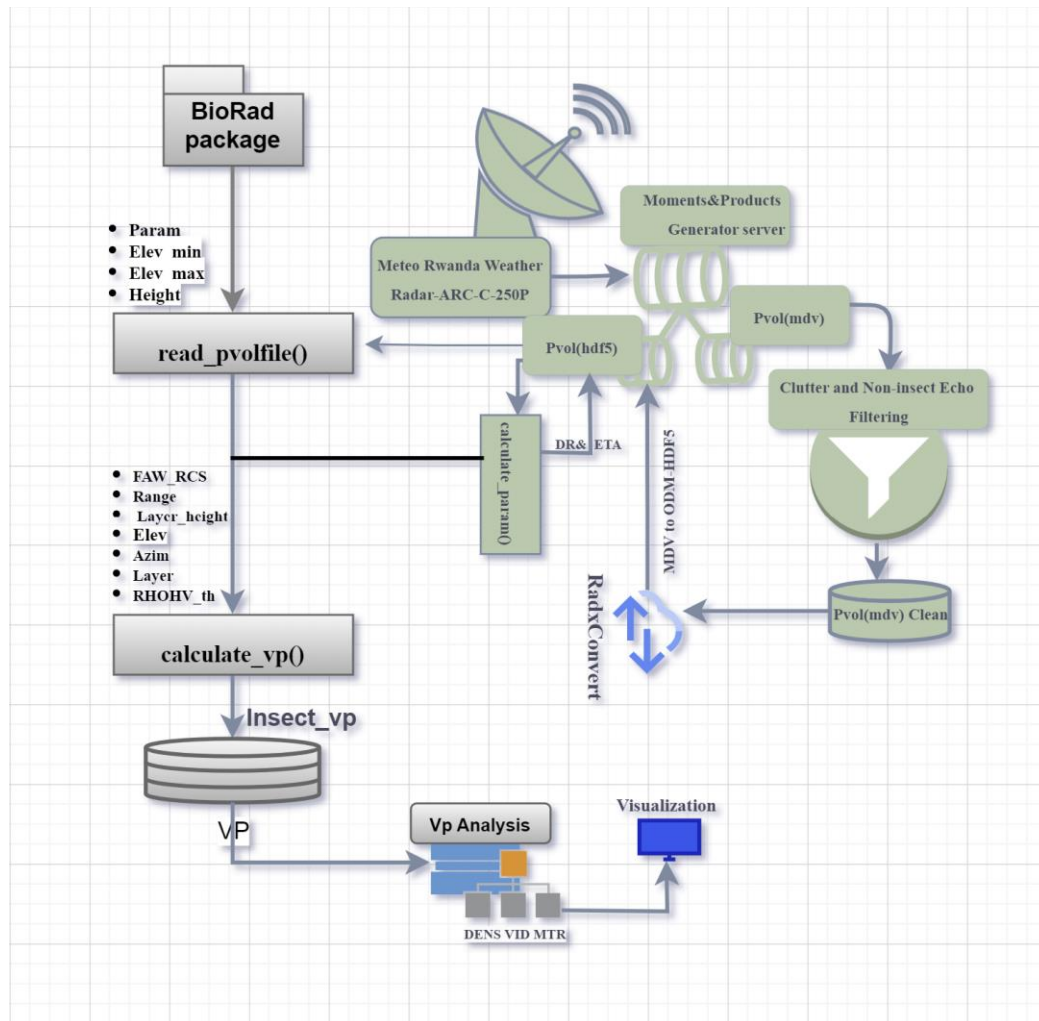


Figure 27. Flow chart showing the analysis steps for quantifying vertical insect distribution in time. Green is preprocessing with TITAN and gray is analysis with bioRad.

Our study focuses on analyzing the movement patterns of insects, specifically the Fall Armyworm (FAW), during its outbreak in Rwanda from September 2020 to January 2021. To conduct this analysis, we used the bioRad R package (version 0.7.0.9603). We tailored the functions within the bioRad package to suit the specific parameters and requirements of our study. The steps we took in pre-processing with TITAN and adapting bioRad to our problem are detailed in Figure 27 and listed below, to highlight the key algorithm parameters and their preferred settings.

Radar Data Access, Cleaning, and Formatting:

1. The Moment and Product Generator (MGEN/PGEN) system is responsible for receiving large amounts of raw radar data (called "polar data volumes") every 5 minutes.

2. This data is then processed and stored within the TITAN environment
3. We used archived data collected during the FAW outbreak in Nyanza, Huye and Gisagara districts.
4. From TITAN, quality checks are performed to ensure its accuracy this consist clutter remover as well as significant weather echoes filtering.
5. The RadxConvert function is used to format the data into HDF5, a form compatible with the bioRad package.

BioRad analysis process:

1. Polar Volume Data Reading: Working with low-level radar data, known as polar volume data, the bioRad package interacts with these data using the read_pvolfile function, returning the volume as a pvol object[53].
2. New Parameter Calculation: From the "pvol in hdf5 format," the Calculate_parm() function computes DR and ETA, and then updates the dataset with these new computed parameters for all scans.
3. Setting Parameters with Read_pvolfile: Crucial parameters such as DBZH, VRADH, WRADH, RHOHV, and ZDR are set using the Read_pvolfile function. Additionally, we specify the minimum and maximum scan elevation angles, as well as the height of the antenna's center above sea level in meters. This function also offers the flexibility to override the stored height value if necessary.
4. Computing Vertical Profile: The calculate_vp() function is used to compute the vertical profile, allowing for the definition of insect cross-section characteristics:
 - i) RCS: The radar cross-section (RCS) value for individual insects is defined, with the average RCS used of 0.6161 cm² used for FAW.
 - ii) Altitude and height layers: Altitude and height layers are set, taking into account the topography of Rwanda, with altitudes up to 4500m considered.
 - iii) RHOHV: A lower threshold in correlation coefficient (RHOHV) is set to filter out non-insect scattering, with a value of 0.95 chosen to discard precipitation, as precipitation typically exhibits higher correlation coefficient values. Additionally, the function allows for the definition of minimum and maximum azimuth angles, as well as minimum and maximum range distances from the radar.

- iv) Azimuth Min and Max: The function also enables the definition of the minimum and maximum azimuth angles to include, measured in degrees clockwise from north. The minimum angle is set to 0 degrees, indicating north, while the maximum angle is set to 360 degrees, representing a full circle.
- v) Range Min, Range Max: We establish the minimum and maximum range, indicating the distance from the radar, for the inclusion of data. We set the minimum range to 2 km to take advantage of the radar's clear view and exclude the closest ranges that often contain significant ground clutter. The maximum range is set to 120 km to encompass a broad area of interest.

6.3.3. 2. Estimating Insect Density with bioRad and C-band Doppler Weather Radar

To assess insect populations using weather radar, insect density is derived from radar reflectivity measurements [97], [69], [74], [133], [134].

Radar reflectivity (η) measures the sum of backscattered cross-sections per unit volume. Under Rayleigh scattering, reflectivity (η), reflectivity factor (**DBZH**), radar cross-section (σ_{insect}), and insect density (ρ_{insect}) are related by:

$$\eta = \frac{10^3 \pi^5}{\lambda^4} |K|^2 DBZH = \rho_{insect} \sigma_{insect} \quad (7)$$

where:

- η is the reflectivity in $\text{cm}^2 \text{ km}^{-3}$,
- **DBZ** is the equivalent reflectivity factor in $\text{mm}^6 \text{ m}^{-3}$,
- K is a constant related to the refractive index of the scatterers, typically $\sqrt{0.93}$ for water,
- λ is the radar wavelength in cm,
- ρ_{insect} is the insect density in insects per km^3 ,
- σ_{insect} is the radar cross section of an insect in cm^2 .

The factor $\frac{10^3 \pi^5}{\lambda^4} |K|^2$ changes with the wavelength of the radar specifically:

For C-band radars ($\lambda = 5.3$ cm), the factor is 361, so:

$$\eta = 361 * DBZH \quad (8)$$

For example, during a fall armyworm migration, if a C-band radar measures a reflectivity factor of 20 dBZ ($100 \text{ mm}^6 \text{ m}^{-3}$), the reflectivity (η) is:

$$\eta = 361 \times 100 = 36,100 \text{ cm}^2 \text{ km}^{-3}$$

Assuming an average radar cross-section of 0.6161 cm^2 for Fall armyworms [22], the insect density (ρ_{FAW}) is:

$$\rho_{FAW} = \frac{\eta}{\sigma_{FAW}} = \frac{36100}{0.6161} = 58,594 \text{ insects per km}^3$$

This method converts radar reflectivity measurements into insect density estimates, aiding studies on insect migration and ecological phenomena.

6.4. Results and Discussion

6.4.1. Insect Vertical Distribution and Abundance

Many insects migrate at high altitudes (150-1200 meters) using air currents for long journeys. They often concentrate in specific altitude bands, a behavior known as layering [135], [133], [81], [136], [20]. This study investigated both day and night insect activity in Rwanda to understand layering patterns and abundance variations during the known FAW infestation.

With the objective of assessing whether the surge in insect detections during nighttime, as illustrated in Figure 28 (indicating higher density during nighttime compared to daytime), could be linked to FAW activity, we conducted KMeans clustering analysis on radar data obtained from maize farms afflicted by FAW infestations in the Nyanza, Huye,

and Gisagara Districts, using data collected from November 7th to 12th, 2020, as outlined in our prior research [17].

This data used encompassed both clear air daytime and nighttime periods. By combining data on altitude, wind components, aerial insect reflectivity, and insect density, with average radar cross-section of 0.6161 cm^2 for FAW, our analysis identified three distinct layers of high insect abundance and activity, as illustrated in Figure 28.

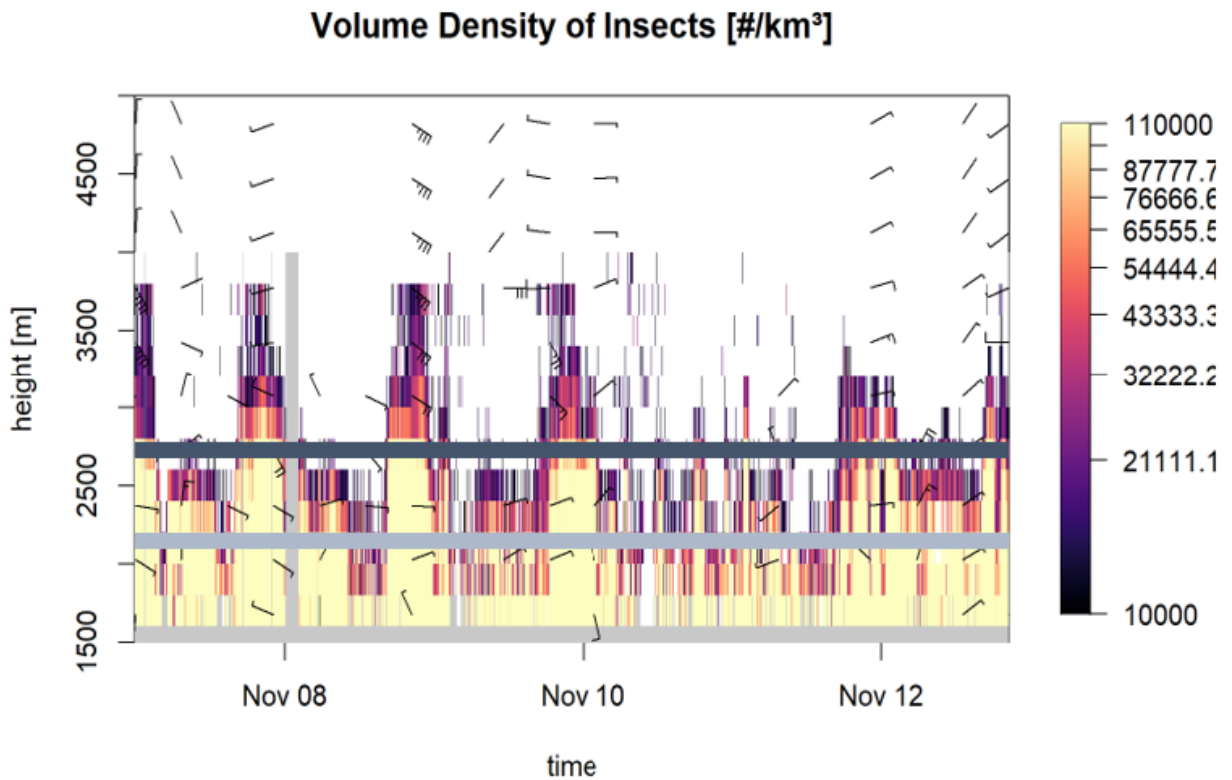


Figure 28 Daily variation in insect density ($\#/\text{km}^3$) across three height layers.

- Cluster 0:** This cluster represents the lowest average height, ranging approximately from 77m to 350m above ground level, corresponding to an altitude between 1693m to 2043m. The wind components in this cluster are nearly neutral, with u at -0.26 m/s and v at -0.74 m/s . The reflectivity is high, measuring at 9.47 dBZ . Cluster 0 exhibits the highest insect density among the clusters, averaging at $1,438,982$ insects per km^3 .
- Cluster 1:** This cluster features a moderate average height, spanning approximately from 350m to 707m above ground level, corresponding to an altitude between 2043m to 2750m. The wind components in this cluster are slightly negative, with u at -0.96 m/s and v at -1.10 m/s . The reflectivity is moderate, measuring at 6.09 dBZ .

Cluster 1 displays an intermediate insect density, with an average of 681,610 insects per km³.

- **Cluster 2:** Characterized by a higher average height of 700m above ground level, corresponding to an altitude higher than 2750m. The u wind component in this cluster is moderately negative, measured at -2.45 m/s, and the reflectivity is low, recorded at 1.55 dBZ. Cluster 2 exhibits a relatively low insect density, averaging at 46,724.7 insects per km³.

Daytime activity is concentrated below 700 meters, likely due to strong winds from tropical convection. Conversely, nighttime sees a surge in insect abundance and activity, extending up to 1200 meters. This knowledge can inform pest management strategies and contribute to understanding insect behavior and ecology.

In addition to the preferred height layer of insects during the day and night as presented in Figure 28, Figure 29 offers a detailed depiction of the daily hourly mean reflectivity factor for unfiltered reflectivity (bio + meteo). This provides more insight into how both biological and meteorological echoes behave during the sample period from November 7 to 12, 2020. By presenting the mean filtered reflectivity factor, which isolates biological targets by filtering out weather-related echoes, the figure allows for a clearer understanding of biological activity across different hours of the day. This analysis includes hourly averages of vertical insect density estimates, utilizing radar data collected over the infested regions of Nyanza, Huye, and Gisagara. The data were meticulously averaged vertically to reveal the spatial and temporal dynamics of insect populations within the studied areas.

The analysis highlights periods of higher and lower insect activity throughout the day, providing valuable insights into insect behavior. This information is crucial for confirming the presence of specific insect types based on their activity patterns. For example, the Fall Armyworm (FAW) is known to be more active during the night. On 11th November 2020, there was a notable reduction in detected insect density both during the day and night. This decrease can be attributed to enhanced convective activities that resulted in high winds and the creation of clouds, which are unfavorable for the dynamic movement of insects.

However, it is important to note that weather conditions in tropical regions do not typically prevent insect flight for the entire day. After periods of rain, the sky often clears, allowing insects and other airborne biological targets to resume flying. This implies that the reduced number of detected insect echoes, especially during the night hours of 11th November 2020, compared to previous data such as from 8th November 2020, is likely due to transient weather conditions rather than a complete cessation of insect activity.

By understanding these activity patterns, we can better target pest control measures and improve the accuracy of insect population monitoring. This comprehensive approach offers a robust framework for studying insect behavior in relation to both biological and meteorological factors, contributing to more effective pest management strategies in the affected regions.

This deeper insight into insect activity and its correlation with weather conditions can aid in developing timely and precise pest control interventions, ultimately leading to improved crop protection and agricultural productivity.

6.4.2. Diurnal and Nocturnal Insect Activity Analysis

To gain insights into the periods when FAW are most active, we analyze weather radar data collected both during the day and at night. We then constructed time series by organizing multiple vertical profiles of reflectivity and radial velocity data collected during these nighttime periods. This time series approach allows us to track changes in insect echo characteristics over time, aiding in the detection of FAW outbreaks.

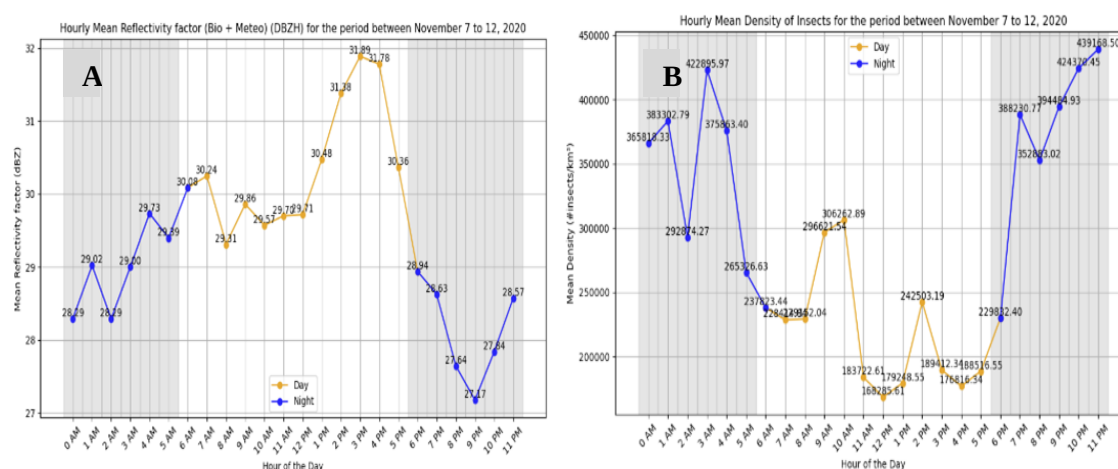


Figure 29 Diurnal and nocturnal hourly reflectivity patterns and density analysis during a critical period of maize infestation (Nov 7-12, 2024). The gray shaded areas represent nighttime periods.

Figure 29 provides a comprehensive analysis of insect activity patterns during a crucial timeframe, specifically from November 7th to 8th, 2024. This analysis incorporates both diurnal and nocturnal data, offering valuable insights into the behavior of insects during this period. The data is segmented into three quantities, each highlighting different aspects of insect activity and environmental influences.

The vertically integrated factor for both biological and meteorological reflectivity factors is shown in Figure 29A examines the average hourly detection reflectivity factor (dBZ), encompassing both biological and meteorological targets. A clear diurnal pattern emerges, with higher average reflectivity during the day. Minimum reflectivity (29.81 dBZ) occurs at 8:00 AM, while the peak (31.89 dBZ) hits at 3:00 PM. Interestingly, the night shows an opposite trend, with a maximum of 29.73 dBZ at 4:00 AM and a minimum of 27.17 dBZ at 9:00 PM.

In Figure 29B Insect Densities takes the analysis a step further. The biological reflectivity factor by inversely related to the estimated insect cross-section as per Equation 1, we can calculate the density of detected insects per cubic kilometer. This confirms the nocturnal trend observed earlier. The highest density is found at 10:00 PM, with an impressive average of 439,168 insects detected per cubic kilometer. Conversely, the minimum density (168,285 insects per cubic kilometer) occurs during the day at midday.

The notable contrast in insect density between day and night implies that the majority of insects exhibit heightened activity during nocturnal hours. This observation seamlessly aligns with the well-documented nocturnal tendencies of the Fall Armyworm (FAW) moth, a significant agricultural pest. The surge in insect density during nighttime can thus be attributed, at least partially, to the presence of adult FAW moths linked to the prevalent maize infestation in the Nyanza, Huye, and Gisagara districts.

The significant difference in hourly mean reflectivity factor, characterized by higher values during the day and lower insect density, can be ascribed to tropical convection weather patterns, which are more prevalent during daylight hours. These weather phenomena often induce increased wind speeds, which are unfavorable for insect movements, and the formation of scattered clouds. Consequently, this leads to a temporary accumulation of dispersed cloud particles, thereby elevating the mean reflectivity factor. As a result, there is a rise in vertical integrated mean reflectivity.

In contrast, during the night, convection activity typically diminishes, resulting in lower mean reflectivity primarily attributed to echoes from biological targets, including insects such as the Fall Armyworm (FAW), known for its nocturnal behavior. This nocturnal activity is likely associated with the movements of adult FAW moths, particularly following the infestation of FAW in the study area during this period[17].

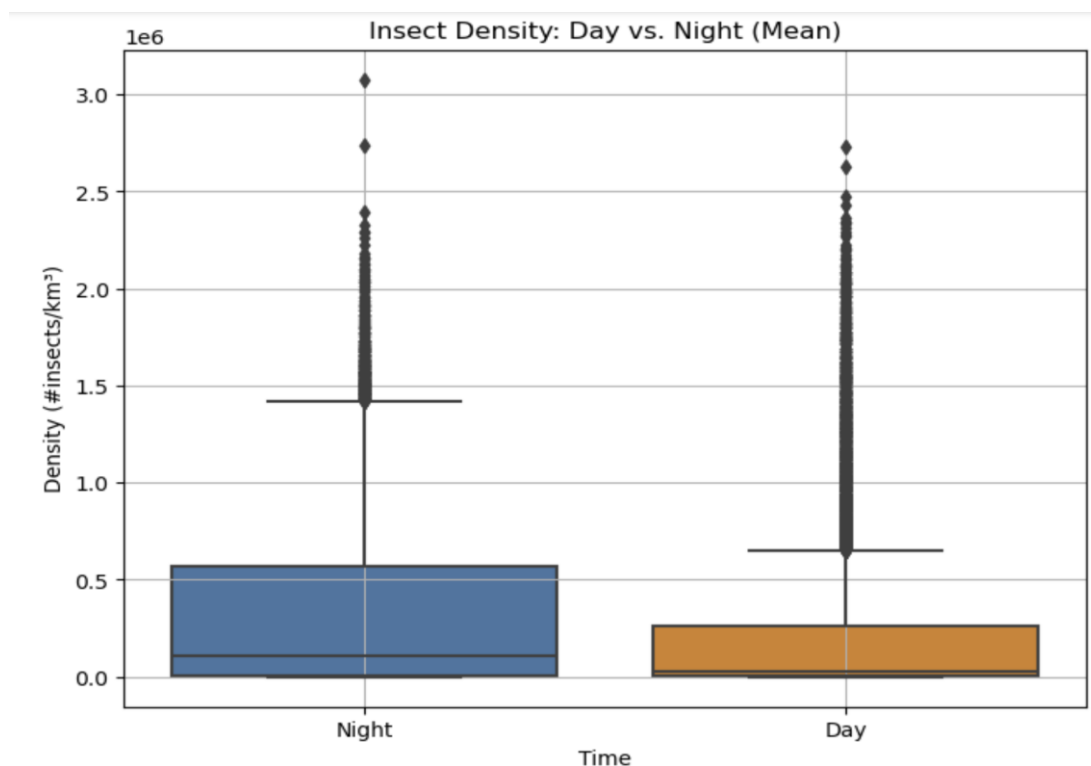


Figure 30. Summarized insect density between day and night, showing diurnal variations in Fall Armyworm (FAW) activity in the Huye, Nyanza, and Gisagara districts of Rwanda from November 7th to 12th, 2020.

The boxplot Figure 30 illustrates the comparison of summarized insect density between day and night, providing insights into variations of insect activity over areas infested by the Fall Armyworm (FAW) in the Huye, Nyanza, and Gisagara districts of the Southern Province of Rwanda.

The data depicted in this Figure 30 pertains to insect density within vertically integrated insects per cubic kilometer over areas infested by the Fall Armyworm (FAW) in the Huye, Nyanza, and Gisagara districts of the Southern Province of Rwanda. The analysis covers the period from September 2020 to January 2021. The boxplot illustrates a clear distinction between day and night in terms of summarized density during November 7 to

November 12, 2020. The visual representation highlights the notable differences between the two time periods. This suggests varying levels of insect activity between day and night.

Understanding these patterns is crucial for effective pest management and agricultural planning in FAW-infested regions. By recognizing when insect activity is highest, particularly during nocturnal hours, strategies can be developed to mitigate the impact of pests like the FAW moth on crops.

6.4.2.1. Vertically integrated reflectivity (VIR) versus vertically integrated density of insects

Airborne biological studies often leverage weather radar technology to track insect populations, particularly during migrations or outbreaks. However, differentiating insect echoes from background noise necessitates analyzing clear sky data from both day and night. This section explores two key metrics derived from weather radar data using the bioRad package [53]: Vertically Integrated Reflectivity (VIR) and Vertically Integrated Density (VID), which quantify insect abundance.

VIR offers a rapid assessment of overall insect activity. It measures the total radar signal strength returned by insects within a specific scanned surface (cm^2/km^2). Imagine a flashlight beam pointed upwards at night; the reflected light indicates the presence and size of objects but not their exact number. Similarly, a high VIR suggests a large or dense insect population, but not the precise quantity.

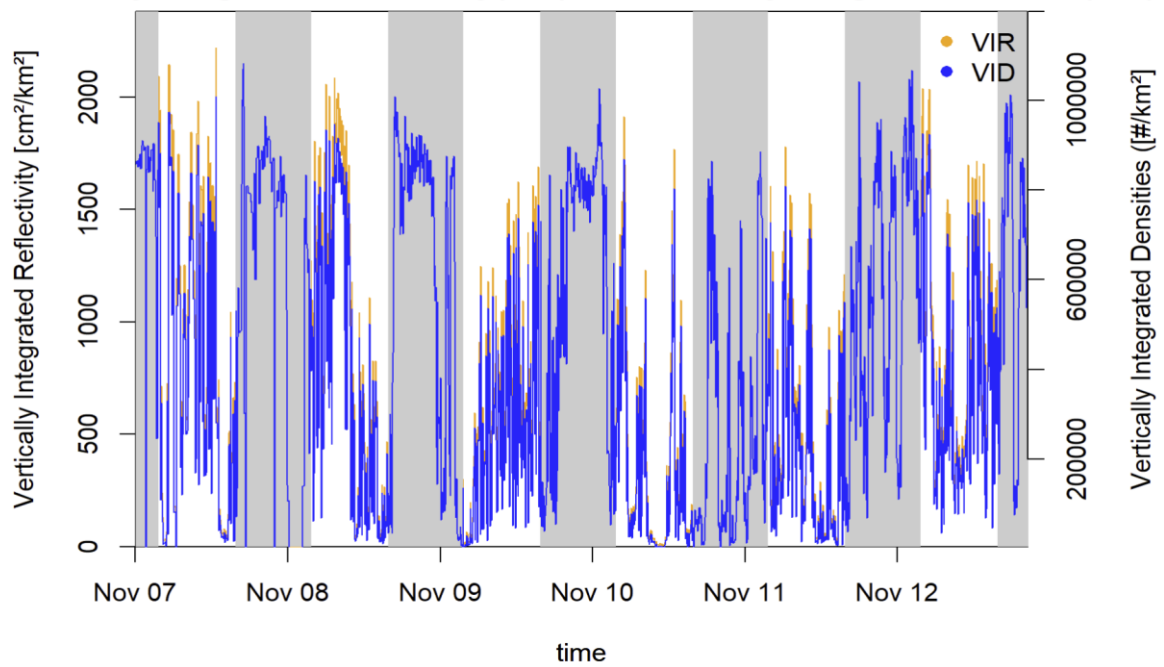
Vertically Integrated Reflectivity(VIR) vs. Vertically Integrated Density(VID)

Figure 31. Comparison of vertically integrated reflectivity (VIR) in cm^2/km^2 and vertically integrated Density (VID) in ($\#/\text{km}^2$)

VID strives for a more precise estimate of insect numbers. However, it requires an additional parameter – the radar cross section (RCS) of the target insects. RCS essentially represents an insect's "radar signature" how effectively it reflects radar waves. With known RCS, VID can convert the total reflected signal (VIR) into an estimated insect density using the formula $\text{VIR} = \text{VID} / \sigma_{\text{insect}}$ (σ_{insect} represents RCS per insect). Vertically Integrated Density (VID) is expressed in individuals per square kilometer ($\text{individuals}/\text{km}^2$). VID represents the surface density of insects, providing a measure of the number of individuals present within a given area.

Our study, focusing on the nocturnal Fall Armyworm (FAW) moth, highlights the value of using both VIR and VID. By comparing day and night data (when FAW moths are inactive), we confirmed their dominance in nighttime radar echoes. However, VIR alone wouldn't provide the exact population. Here, VID, with its ability to estimate insect numbers based on a known RCS for FAW moths, becomes crucial. Notably, the correlation between VIR and VID (shown in Figure 31) signifies that both metrics offer a consistent picture of insect abundance, albeit in different dimensions. VIR provides a quick overview, while VID delivers a more detailed estimate (given the RCS). This

combined approach allows us to not only detect insect presence but also gain insights into population fluctuations and behavior, even for unidentified species.

6.4.2.2. Reflectivity traffic rate (RTR) versus migration traffic rate (MTR)

While the bioRad package provides functionalities for basic analysis of insect abundance (VIR and VID)[53], it offers a much richer toolkit to understand insect movement patterns. It includes functions specifically designed to extract biological information relevant to insect behavior. This allows US to move beyond just presence or density and delve into aspects like migration patterns and flight characteristics. The bioRad package proves instrumental in differentiating and comprehending the patterns between Fall Armyworm (FAW) echoes during day and night. This analysis strengthens our initial assumption that the majority of nighttime echoes are indeed associated with FAW activity, particularly during the outbreak period of September 2020 to January 2021.

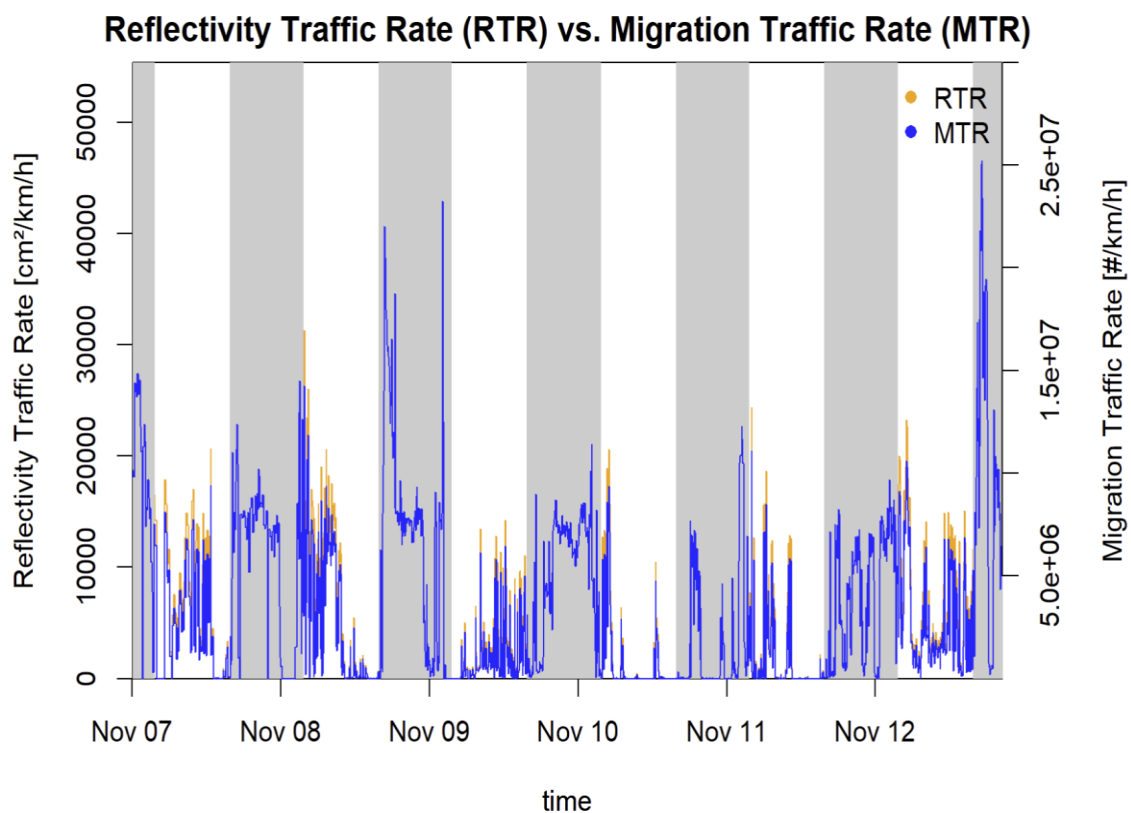


Figure 32. Comparison of migration traffic rate (MTR) and reflectivity traffic rate (RTR) during FAW outbreak

Figure 32 showcases this phenomenon by depicting both Migration Traffic Rate (MTR) and Reflectivity Traffic Rate (RTR). As observed, significantly higher traffic is evident during nighttime compared to daytime. This aligns perfectly with the findings from our previous study [17], where we observed a similar trend. While both MTR and RTR offer valuable insights, they provide information on different aspects of insect movement. RTR acts like a quick indicator of overall insect activity. A high RTR suggests a larger or denser insect population traffic, but not the exact number. MTR takes the analysis a step further by incorporating the concept of radar cross section (RCS), essentially an insect's "radar signature." This allows MTR to provide a more precise estimate of the actual number of insects migrating through a specific airspace per unit time.

In the context of our study, the nighttime dominance in both MTR and RTR strongly suggests that the majority of nighttime echoes originated from FAW moths, confirming their nocturnal activity patterns during the outbreak period, understanding the outbreak period and nocturnal activity of FAW moths, authorities can allocate resources strategically. This could involve prioritizing nighttime scouting efforts, to validate the radar observation.

6.5. CONCLUSION

In chapter 6 we explored the potential of weather radar data, analyzed using the bioRad R package, to quantify and understand Fall Armyworm (FAW) activity during an outbreak in Rwanda (September 2020 – January 2021). The study successfully differentiated areas with varying insect densities and movement patterns through clustering analysis, revealing a strong correlation between radar reflectivity and insect presence. Notably, nighttime data analysis demonstrated a stronger correlation between insect density and radar signals, confirming the nocturnal activity of FAW moths and their dominant contribution to radar echoes during these periods.

By leveraging the functionalities of bioRad, this research delved deeper into FAW behavior, examining and quantifying the vertical distribution and temporal integration of insect activity. These insights provided a detailed understanding of FAW movement patterns and dispersion within the study area, highlighting the significant potential of radar technology for nocturnal insect population monitoring.

This study underscores the importance of understanding environmental influences on insect behavior, which is crucial for developing effective pest management and mitigation strategies. Building upon these findings, future research should focus on species-specific identification using radar data, real-time monitoring systems to validate weather radar observation for early warnings development, improved vertical profiling for migration insights, and ecological modeling for proactive pest management strategies. Additionally, fostering collaboration between researchers, data specialists, and agricultural extension services is vital to ensure effective communication and development of practical tools for farmers to utilize radar technology in their fight against FAW infestations.

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Chapter 7. Conclusion, Recommendations, and Future Research

This research study aimed to improve the detection, identification, and understanding of the Fall Armyworm (FAW) outbreak in Rwanda using dual-polarization weather radar technology. The research was structured around three central questions, each addressing the core challenges of enhancing radar-based pest detection, optimizing algorithms, and analyzing insect migration patterns. By investigating these challenges, the study aligned with the broader objective of developing radar-based insect detection algorithms for better pest management.

First, the research explored how ground clutter and beam blockage, two significant obstacles in radar data interpretation, could be mitigated to improve the detection of FAW. By implementing advanced ground clutter mitigation techniques and beam blockage correction using Digital Elevation Models (DEM), this objective was successfully achieved. These techniques significantly improved the radar's ability to filter out unwanted noise and focus on insect echoes, enhancing detection capabilities and providing clearer insights into FAW movements. This improvement was crucial for obtaining reliable radar data with complex terrain, as seen in the study area.

Second, the research addressed how to optimize insect detection and identification algorithms to improve FAW classification accuracy. The use of polarimetric radar parameters such as Reflectivity (DBZ), Correlation Coefficient (RHOHV), and Differential Reflectivity (ZDR) proved effective in distinguishing FAW from other meteorological targets. By optimizing fuzzy logic algorithms and integrating the Depolarization Ratio (DR) into the classification process, the accuracy of FAW detection was enhanced. This achievement demonstrates the utility of radar technology in pest monitoring, showing that advanced signal processing techniques can help improve the precision of pest identification compared to traditional ground-based methods.

The third research question focused on how radar data could be utilized to quantify the spatial and vertical distribution of FAW during an outbreak. The study achieved this objective by using

radar data to map the migration and activity patterns of FAW, particularly at night when their activity peaks. The results provided insights into the altitudes, times, and regions where FAW was most active, which can help improve pest management strategies. This quantification offers valuable data for predicting future outbreaks and designing targeted pest control interventions.

The thesis also made significant contributions to the field. A comprehensive literature review provided context for radar-based pest monitoring, identifying gaps that the research addressed. The development of novel ground clutter mitigation techniques and the optimization of neuro-fuzzy logic algorithms for FAW classification pushed the boundaries of current methodologies. Furthermore, the quantification of FAW migration and distribution patterns laid the groundwork for integrating radar data into real-time pest management systems.

In conclusion, this study demonstrated the feasibility and potential of using dual-polarization weather radar for agricultural pest monitoring, particularly for FAW. It addressed all three research questions effectively, showing that radar technology can be a powerful tool for detecting, classifying, and understanding pest insect behavior.

Moving forward, several recommendations and future research directions can enhance the impact of this work. First, it is recommended that real-time radar monitoring systems for agricultural pests like FAW be established to provide farmers with actionable insights into pest outbreaks. Additionally, the integration of radar data with ground-based monitoring methods, such as light traps and drones, can further improve insect identification and provide a more holistic understanding of pest movements.

Future research should focus on developing species-specific identification algorithms using radar data. While this study successfully classified FAW, refining algorithms to differentiate between various pest species would improve targeted pest control. Moreover, incorporating advanced machine learning techniques, such as Random Forest or XGBoost, could further optimize the classification process, enhancing the detection of insect swarms and migration patterns.

Additionally, the exploration of Machine learning and signal processing techniques to improve radar data clustering and tracking of insect movement patterns presents a promising future research avenue. Extending the geographical scope of the research to include other regions

affected by FAW or similar pests will also allow for comparative studies, providing insights into how environmental factors influence pest infestations in different contexts.

Lastly, the use of multi-radar networks to monitor larger-scale pest migrations across regions offers potential for more coordinated pest management strategies. By leveraging a network of weather radars, it would be possible to track insect movements over larger areas, providing a more comprehensive view of pest activity and enabling more effective interventions on a national or regional scale.

This research contributes to sustainable agriculture by improving the ability to monitor and manage pest outbreaks, enhancing food security through innovative use of radar technology.

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Reference Number: 220019513

APPENDICES

LIST OF PUBLICATIONS

1. **F. Maniraguha**, A. Vodacek, E. Ndashimye and G. Rushingabigwi, "**Ground Clutter Mitigation and Insect Signature Detection for Polarimetric C-Band Doppler Weather Radar**," 2021 IEEE Global Humanitarian Technology Conference (GHTC), Seattle, WA, USA, 2021, pp. 289-296, doi: 10.1109/GHTC53159.2021.9612449.

Journal Metrics

Journal Name	IEEE Explore
Publisher	IEEE
Indexing	Science citation Index(SCI)

2. **F. Maniraguha**, A. Vodacek, K. S. Kim, E. Ndashimye and G. Rushingabigwi, "Adopting a Neuro-Fuzzy Logic Method for Fall Armyworm Detection and Monitoring Using C-Band Polarimetric Doppler Weather Radar With Field Verification," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-10, 2024, Art no. 5105910, doi: 10.1109/TGRS.2024.3395281.

Journal Metrics

Journal Name	IEEE Transactions on Geoscience and Remote Sensing
Publisher	IEEE
Indexing	Science Citation Index Expanded(SCIE)

3. **F. Maniraguha**, A. Vodacek, K. S. Kim, E. Ndashimye and G. Rushingabigwi, "Enhancing Identification of Meteorological and Biological Targets Using the Depolarization Ratio for Weather Radar: A Case Study of FAW Outbreak in Rwanda," *Remote Sens.* 2024, 16, 2509. <https://doi.org/10.3390/rs16142509>

Journal Metrics

Journal Name	Remote Sensing
Publisher	MDPI
Indexing	Science Citation Index Expanded(SCIE)

4. **F. Maniraguha**, A. Vodacek, K. S. Kim, E. Ndashimye, and G. Rushingabigwi, "Quantifying Insect Migration with Weather Radar: Case Study on Fall Armyworm Outbreak in Rwanda," *Submitted for publication* (under review).