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Edited by Girma Gebresenbet and Techane Bosona



Technologies and Innovations in Agriculture

*Edited by Girma Gebresenbet
and Techane Bosona*

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Aims and Scope of the Series

The importance of agriculture cannot be overstated. It helps sustain life, as it gives us the food we need to survive and provides opportunities for economic well-being. Agriculture helps people prosper around the world and combines the creativity, imagination, and skill involved in planting crops and raising animals with modern production methods and new technologies. This series includes two main topics: Agronomy and Horticulture, and Animal Farming. This series will help readers better understand the intricacies of production agriculture and provide the new knowledge that is required to be successful. The success of a farmer in modern agriculture requires knowledge of events happening locally as well as globally that impact input decisions and ultimately determine net profit.

Meet the Series Editor



W. James Grichar has been employed with Texas A&M AgriLife Research for over 45 years with an emphasis on research in agronomy, plant pathology, and weed science. He obtained his BS from Texas A&M in 1972 and his Masters of Plant Protection in 1975. He has published 195 journal articles, over 330 research reports and briefs, 11 book chapters, and over 300 abstracts of profession meetings. He also directs research in many crops including corn, grain sorghum, peanuts, and sesame. He has held various positions in different professional societies including the American Peanut Research and Education Society, Southern Weed Science Society, and Texas Plant Protection Conference in addition to being Associate Editor for Peanut Science and Weed Technology. Significant accomplishments have included spearheading efforts to determine the optimum planting time for soybean production along the upper Texas Gulf Coast. These efforts have shown growers that soybean yields can be improved by 10 to 20% by following a late March to early April plant date. He also has been instrumental in developing a herbicide program for peanut production in the south Texas growing region. Through the development and use of herbicides that are effective against major weed problems in the south Texas region, peanut yields have increased by 25 to 30%.

Meet the Volume Editors



Girma Gebresenbet, Ph.D., is a Professor and Head of the Division of Automation and Logistics at the Department of Energy and Technology, Swedish University of Agricultural Sciences. He also holds an honorary academic position at Ambo University in Ethiopia. He earned his MSc in Mechanical Engineering with honors and completed his Ph.D. in Agricultural Engineering. His doctoral dissertation was recognized with a special award from the

Swedish Academy of Forestry and Agriculture as the outstanding dissertation of the year. Professor Gebresenbet has held a full professorship since 2000. His research and teaching focus on automation, mechatronics, robotics, and digitalization in the food production and supply chain sectors. He is also deeply involved in logistics and supply chain management, with a particular interest in city logistics, food supply systems, and value chain management as they relate to quality, safety, animal welfare, and environmental impact. He is a founding member and current president of the Oromo Society of Science and Technology. Throughout his career, he has authored 137 scientific papers, 70 conference papers, 27 reports, and 5 book chapters.



Techane Bosona (Ph.D.) is a Senior Researcher at the Swedish University of Agricultural Sciences (SLU), Department of Energy and Technology. He studied for a Ph.D. in technology, focusing on freight logistics and supply chains at SLU. His MSc degree is in Hydraulics and Hydropower Engineering from Arbaminch University, Ethiopia. He has research experience at the national and international levels. His current research focuses on logistics

network design, green logistics and supply chain management, traceability, system analysis and modelling, life cycle analysis, life cycle cost analysis, value chain analysis, resources management (e. g. water, renewable energy), and smart logistics systems. Dr. Techane Bosona has authored or co-authored 31 scientific journal papers, 2 book chapters, and 17 conference and other popular papers.

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Preface

The global challenges in the entire food production and supply chain include (a) an ever-increasing population that demands food security and safety, (b) high postharvest losses and food waste, and (c) significant environmental impact in the agricultural and food sectors. The objectives of this book are to contribute to the solutions to the aforementioned challenges, and its focus is on utilizing emerging technologies and innovations in agriculture to increase productivity.

The book covers important aspects of technology in agriculture. It includes a wide range of conventional and digital technologies to enhance efficiency, productivity, food safety, food security, and environmental sustainability. It focused on mechanization and postharvest technologies (tillage, weeding, irrigation, harvesting, and postharvest handling), as well as digital technologies such as artificial intelligence, automation, mechatronics, robotics, drones, sensors, and machine vision, along with the Internet of Things (IoT). The book integrates fundamental theories and the latest research results on the applications of emerging technologies to meet the demand for efficient and sustainable food production and supply while also enhancing food safety and security. Researchers can use the book as a reference and for educational purposes in agricultural engineering.

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Section 1

Modeling and Decision Support System for the Advancement of Agriculture

Alfalfa Crop Irrigation Modeling in Salamiyya, Syria

Tammam Kheder Yaghi and Hussam Saeed

Abstract

The study was carried out during three successive growing seasons from 2015 to 2017 at Salamiyya Research Center, Syria. That was to study the alfalfa crop water requirement and how we can improve its water crop productivity. Three treatments: drip method (A_1), sprinkler method (A_2), and surface one (A_3) were designed and implemented using complete randomized block design (CRBD) with three replicators as well as surface irrigation treatment (A_4) as the area's farmer does. All these programs: WEAP₂₁ (SPAW and MABIA), NewLoc-Clim1.10, and ET₀Calc had been used. The simulation results for SPAW and MABIA programs after calibration were approximately identical. Alfalfa response coefficient reached 0.78 in the modern irrigation methods and 0.91 in the surface irrigation method in this type of soil. The water saving has been reached at 29% for drip irrigation and 22% for sprinkler irrigation compared with the surface irrigation method. There were tangible significant differences at the Water Use Efficiency (WUE), whereas treatment A_1 excelled all the rest treatments, and the order of this excellence was as follows: $A_1 > A_2 > A_3 > A_4$. Finally, the integrated program (MABIA) and other programs can be considered very modern and sophisticated tools, making the water expert save time, effort, and costs in addition to obtaining very accurate results.

Keywords: alfalfa crop, simulation, calibration, water use efficiency, integrated program (MABIA)

1. Introduction

Although the area of irrigated land in the world does not exceed 16% of the area of cultivated land, it provides more than 40% of crop production. Water is a limiting factor for production, especially in arid and semi-arid areas [1]. The total volume of water in the world was estimated at about 1386 million km³, while the fresh water reservoir was about 35 million km³ (97% of the total volume of water that is in the seas and oceans), which is equivalent to 1338 million km³, while the tank of fresh water on land constitutes about 25% of the reservoir [2]. The total freshwater resources in the Arab world have reached 363.5 km³ [3]. Considering that water uses for irrigation exceed human uses about at least ten times [4], Syria faces a severe and direct water shortage, as it extracts approximately about 3.5 km³ of groundwater being pumped from wells, and another 2.1 km³ from natural springs, groundwater is now being pumped from the upper layers [5].

As a result of the current situation in the field of using water resources for agricultural irrigation purposes in the Syrian Arab Republic, the overall effectiveness of the use of these resources in the agricultural sector is still below the acceptable technical and economic limits between 35 and 45%. Therefore, rationalizing the use of water, improving its performance, and building human capabilities in all parties involved in production processes, the awareness of beneficiaries and decision makers and their participation in the management of water resources in their various sources has become an urgent necessity in improving the use of groundwater and human resources in the agricultural sector to become an absolute priority [6].

Thus, the thinking of officials in Syria and most other Arab countries has turned seriously toward applying modern irrigation systems such as sprinkler and drip irrigation. In light of the growing population and competition for available water, in addition to the large number of other uses, irrigated agriculture has had to produce more food with less water to achieve food security [7–9].

Any serious vision that aims to expand irrigated areas and increase the economic returns of various crops cannot be isolated from developing and rationalizing the technical and economic efficiency of water use in agriculture [10], as various efforts have been made in this field and most of them were futile. Addressing the difficult problems facing irrigation management requires a better understanding of the water budget within the irrigation project through non-conventional water reuse, especially in water deficit areas [11–13].

Familiarity with climate data, soil characteristics, the type of plant grown, and the efficiency of irrigation applied. The complexity of irrigation projects at the water basin level requires advanced mathematical models through which water can be reallocated according to priorities at the level of the farm, the irrigation project, and the entire basin [14]. In order to operate the program correctly, it must be calibrated, and this requires knowledge of the water reality, the demand at the farm level, the applied irrigation system, and finally the basin studied. The MABIA program was developed to link with the WEAP program in order to schedule and manage irrigation projects at the farm level and thus the basin as a whole. It is based on a set of advanced, precise scientific technological features and characteristics to determine water productivity in agriculture, as it relies on climate inputs on a daily basis in order to calculate the evaporation-transpiration reference. (ET_0), which takes into account the relationship between the type of plant grown, the type of soil, and the efficiency of irrigation applied, in addition to the productivity and price of the crop within the cultivated area per unit of water.

The importance of alfalfa comes first through the presence of a type of bacteria in its roots that absorb nitrogen from the atmosphere. The plant benefits from a small part of it and keeps the rest. Therefore, alfalfa can be used as a natural fertilizer for the soil. It helps improve the natural and chemical properties of the soil. Secondly, alfalfa is considered a complete food or fodder for animals because it contains protein and amino acids that increase milk production. It is also rich in mineral salts (calcium and phosphorus) and vitamins (D, E, and K) and is used as green fodder or dried fodder [15].

Due to the expansion of the genetic improvement program for sheep (Awass) at the Scientific Agricultural Research Center in Salamiyya, there was an urgent need to grow this crop, which is a major feed source after strategic grain crops such as barley. It is used either as green fodder or as a dry material that is mixed with the rest of the fodder mixtures and presented to the animal. Since the target area includes arid and semi-arid areas, it is necessary, with water scarcity at the present time, to estimate the

water needs of this crop and develop an optimal irrigation program to conserve the greatest amount of water and improve its effectiveness.

This research aims to study the water needs of the alfalfa crop and develop a mathematical model that simulates the climatic reality of the region and improves the crop's water productivity by using advanced programs and mathematical modeling to reach the best irrigation method that can be applied.

2. Materials and methods

2.1 The site

The study was conducted at Al-Karim village in Salamiyya Research Center, General Commission for Scientific Agricultural Research (GCSAR). It is located 25 km from Hama city toward the east and 6 km west of Salamiyya, at a longitude of 36° E, a latitude of 34.20° N, and a height of 435 m above sea level. It enfolds in the third climatic zone (**Figure 1**).

This experiment was designed in three irrigation treatments, each treatment having three replicates distributed randomly in addition to the surface irrigation treatment (as irrigated by the farmer), as shown in **Figure 2**, which shows that the surface irrigation replicates (A4) cannot distribute them through the rest of the treatments in the sectors. They were placed next to each other in one sector due to the difficulty of distributing them within the drip and the sprinkler irrigation treatments (A1 + A2) according to the dimensions of the field designated for this experiment. Each treatment included three lines spaced 0.8 m apart for drip irrigation and 12 m for sprinkler

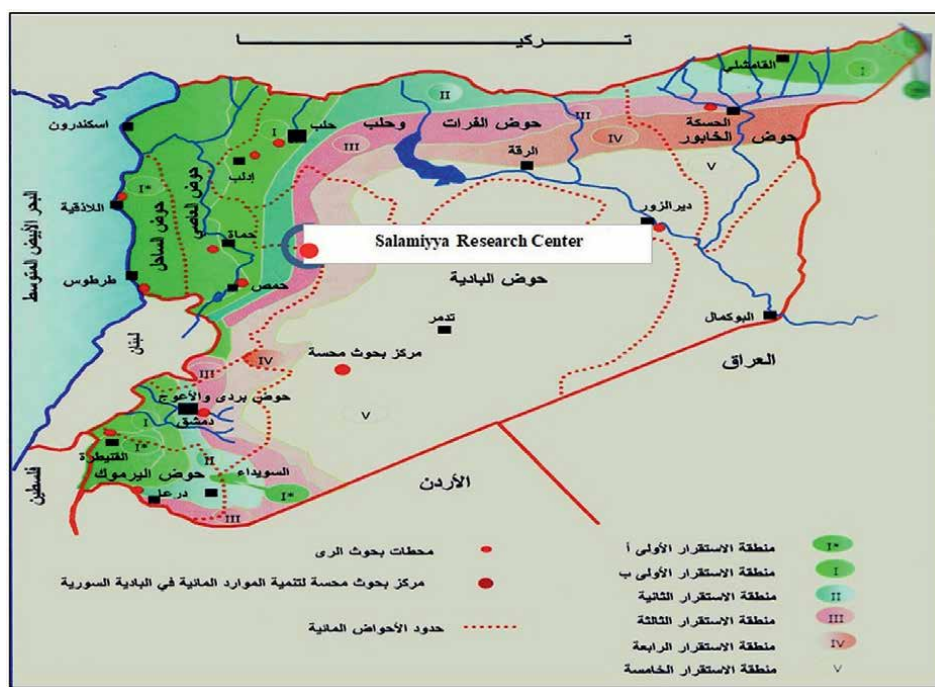


Figure 1.
 The climatic zones of the study area.

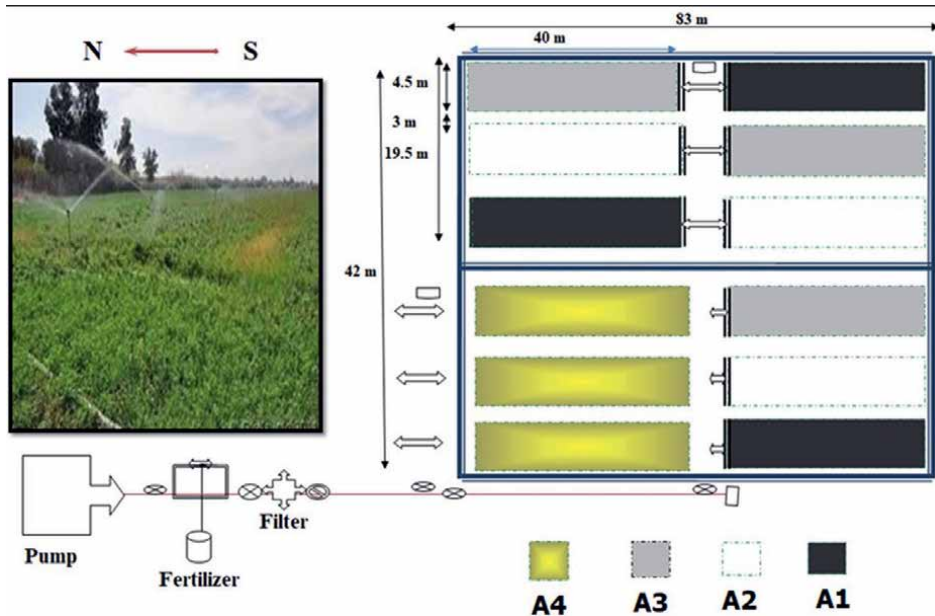


Figure 2.
Layout of implementing the alfalfa crop experiment.

irrigation. A distance of 3 m was left between the treatments in one replicate, so the entire experimental area was approximately 3500 m².

Soil analysis samples were taken before implementing the experiment, and the results are represented in **Table 1**. After that, the experimental land was prepared, and the crop was planted scattered on 10 November 2015.

Climatic factors were also monitored, including rainfall, as shown in **Table 2**. The data recorded in the table showed the amount of rainfall that falls during the growing seasons. It was noted that rainfall was concentrated in the months of December and January. The rainfall rate gradually decreased until it reached its lowest point in April and May. It is clear to us that the rainfall rate decreased during the first and third

Soil properties	Average soil depth (0–105 cm)
Sand (%)	14
Celt (%)	52
Clay (%)	34
Texture	Silty Clay Loam
Organic matter content (%)	1.4
Porosity (%)	56.9
Mineral N (mg/kg)	4.8
Available P (mg/kg)	7.0
Available K (mg/kg)	580.5

Table 1.
Some physical and chemical properties of the soil of the experiment.

The month	Rainfall amount (mm)			Notices
	2014/2015	2015/2016	2016/2017	
Sep	13	10	7	Decreasing rainfall in the first and third seasons.
Oct	13	11	8	
Nov	23	0	6	
Dec	42.5	23	33	
Jan	51.5	76	68	Frost on March 6–12, 2015–2016
Feb	30	57	39	
Mar	5.5	41	20	
Apr	5	12	14	
May	0	10	4	
Total	183.5	240	119	

Table 2.
Average rainfall during growth seasons.

growing seasons, and this led to adding two supplementary irrigations compared to the second growing season results.

In addition, most of the other climatic factors, including temperature, wind speed, evaporation, and others, were collected on a daily and monthly basis from the climate stations surrounding the center, and the following software was used for modeling:

- ET₀Calc: To calculate evapotranspiration on a daily basis in a watershed [16].
- NewLoc-Clim1.10: For extracting agro-climatic maps, filling gaps (absent data), and correcting errors [17].
- SPAW: To characterize the soil and estimate the available water in each soil type and each watershed in order to determine the irrigation rate for each crop.
- WEAP-MABIA: To calculate crop productivity and its response factor to water, simulate and verify with extreme accuracy and save effort and costs [18].

Each program was calibrated at 75% probability (dry years), especially the programs for calculating water consumption, such as MABIA, and the required data was entered. The following equations were used to explain how the program works:

$$\text{Crop water consumption (mm / day)} : ET (\text{Crop / day}) = ET_0 \times K_c. \quad (1)$$

$$\begin{aligned} \text{Water consumption during each growth stage : } ET (\text{Crop / stage}) (\text{mm}) = \\ \text{Crop water consumption } ET (\text{Crop / day}) \times \text{Length of growth stage T.} \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Available water depth (mm)} = (\text{Volumetric field capacity} - \text{Volumetric wilting limit}) \\ \times \text{Root depth (m)} \times 10. \end{aligned} \quad (3)$$

$$\text{Net irrigation depth } D(\text{net})(\text{mm}) = \frac{\text{Total available water depth}(\text{mm}) \times \text{Maximum permissible moisture depletion factor}(P)}{\quad} \quad (4)$$

$$\begin{aligned} \text{Number of irrigations to be provided} &= \frac{\text{Water consumption during the entire growth stage } ET(\text{Crop / stage})(\text{mm})}{\text{Net irrigation depth } (D_{\text{net}})(\text{mm})}. \end{aligned} \quad (5)$$

$$\begin{aligned} \text{Actual or real net irrigation depth } D(\text{net-actual})(\text{mm}) &= \frac{\text{Water consumption during the entire growth stage } ET(\text{Crop/stage})(\text{mm})}{\text{Number of irrigations adjusted after rotation}}. \end{aligned} \quad (6)$$

$$\begin{aligned} \text{Gross irrigation depth, } D_{\text{gross}}(\text{mm}) &= \frac{\text{Actual or real net irrigation depth } D(\text{net-actual})(\text{mm})}{\text{Water addition efficiency}(\%)}. \end{aligned} \quad (7)$$

$$\begin{aligned} \text{The amount of water to be provided during each growth stage} &= \text{Total irrigation depth } (D_{\text{gross}}) \times \text{Number of irrigations adjusted}. \end{aligned} \quad (8)$$

Calculating irrigation water use efficiency: Water use efficiency (WUE) means measuring the productivity of water consumed by the crop [19] and is calculated according to the following equation [20]:

$$\begin{aligned} \text{Total water use efficiency provided } (\text{kg/m}^3) &= \frac{\text{Yield}(\text{kg/ha})}{\text{Total amount of water supplied}(\text{m}^3/\text{ha})}. \end{aligned} \quad (9)$$

The results were analyzed according to a completely randomized block design using a computer, using the GenStat v7 program and the Excel system, and the coefficients were compared using the least significant difference (L.S.D) at the 0.05 level and applying the Duncan test.

3. Results and discussion

3.1 The climate water balance calculated programmatically using the programs ET₀Calc and NewLoc-Clim 1.10

After calculating the reference evaporation-transpiration using the program ET₀Calc and correcting errors between the experiment site and the electronic climate station, the results were formulated in the form of charts, considering the dry climate condition that prevails in the study area and comparing the rainfall rate for the probability of a dry year (75%) with the maximum evaporation-transpiration. Determining the periods for benefiting from rainfall in irrigating the planted crops, which begin to be planted in the fall, winter, and spring months, and applying water harvesting and supplementary irrigation techniques, based on the intersection of the (PET) curve with the (P) curve, and this concurred with the results of Yaghi et al. [21] in Erbil, Iraq, which manually calculated the water increase and decrease using

mathematical equations, where the results showed that the rainfall rate for a 75% probability (dry year) will reach about 1.8 mm/day during the period extending from November 19 to March 5 (the growth period colored in blue, winter months), while it will decrease to 1.7 mm/day during the period from 6 to March 27 and from 8 to November 18 (the growth period colored in green, which is the spring and autumn months). Thus, rainfall will continue to decrease until it does not exist during the summer months in this watershed, which has an area of 200 ha (Salamiyya Research Center), as in **Figure 3**.

The water increase appears at a rate of 103 mm during the winter months, where the maximum evapotranspiration is equal to the true evapotranspiration, and the greatest benefit from rainwater in irrigating crops ends during the last two-thirds of March and begins in mid-November, when the rate of rainfall is greater than half of the maximum evaporation-transpiration rate. Here, supplementary irrigation plays an important role in increasing agricultural water productivity, especially for the alfalfa crop, which requires large amounts of water compared to other crops, as its need reaches 20,000 m³/ha in dry and semi-arid areas. As for the water decrease, it amounted to about 1170 mm during the dry period extending from the end of March to the first 10 days of November (colored in yellow), where half of the maximum evaporation-transpiration rate is greater than the rainfall rate.

3.2 Water balance for soil and plant systems using the program (SPAW)

The program described the experiment's soil as a yellow-brown, medium-fertile structure with an increased percentage of silt to 52%, and its texture became silty

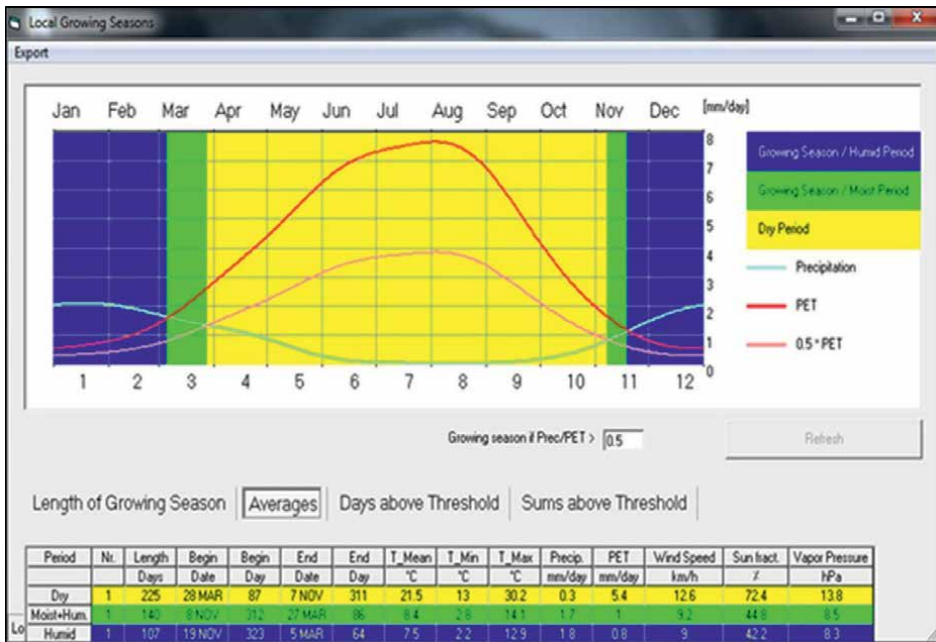


Figure 3.
Results of calculating an evapotranspiration ET_0 and critical periods during growth stages.

clay. The water available to the plant was about 160 mm/m, and the infiltration rate was about 4.57 mm/h. Accordingly, the value of the depletion coefficient was raised. The maximum permissible amount (MAD) is more than in other types of soils in the center, and the spacing between irrigations is reduced to ensure the appropriate needs of the crop. This is consistent with the results of Doorenbos and Kassam [22], as shown in **Figure 4**.

The results showed an extra of 19,100 m³/ha using the surface irrigation method (A3), with a number of irrigations of 24 ones, 15,700 m³/ha using the sprinkler irrigation method (A2), with a number of irrigations of 23 ones, and 14,644 m³/ha using the drip irrigation method (A1), with a number of irrigations of approximately 22 ones. This was an average for 3 years, which is considered one of the driest years that has passed over the target area. Accordingly, the actual water saving rate for (A1) and (A2) treatments in comparison with (A3) was approximately 23 and 18%, and these results are also in agreement with those of Thomas et al. [23].

3.3 Mathematical model of alfalfa crop in Salamiyya using MABIA program

The importance of using the MABIA program appears in calculating the amount of actual water consumption of the alfalfa crop during the growing months daily (**Figure 5**). This is because the program contains all the climatic data, soil specifications, root depth of the crop, and phenological phases and performs the calculations daily. The monthly cumulative water consumption reached 1339 and 1475 mm/ha for the modern drip and sprinkler irrigation treatments, respectively, while it was 1893 mm/ha for the traditional surface irrigation treatment (watersheds). The water saving rate was approximately 29.3% for drip irrigation and 22% for sprinkler irrigation compared to surface irrigation (watersheds). The average daily water

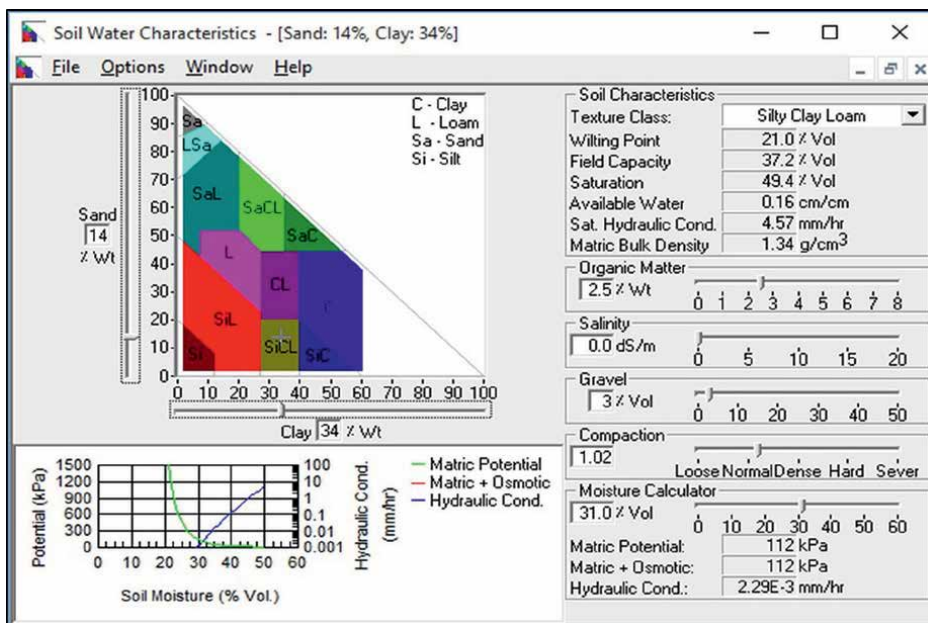


Figure 4.
Modeling of experiment soil hydrophysical specifications.

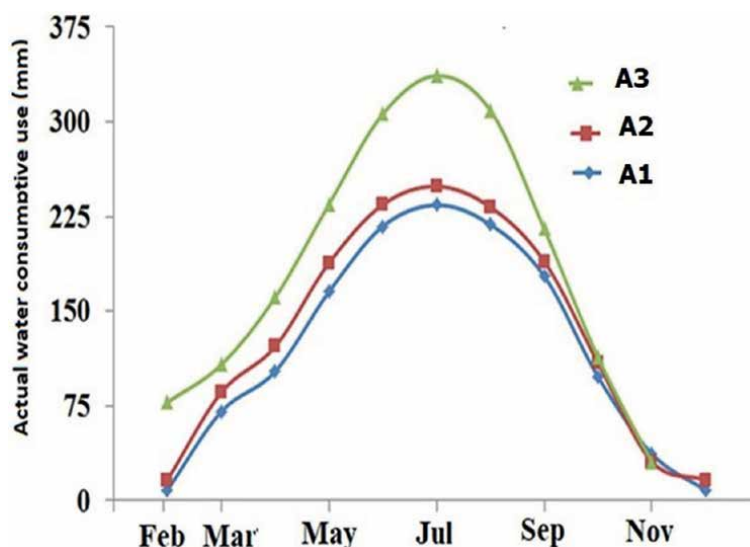


Figure 5.
 The program simulates the average monthly actual crop water consumption for three successive years.

consumption during the peak month of July was 7.8 and 8.3 mm for the two modern irrigation treatments, respectively, while it was 11.2 mm for traditional surface irrigation.

3.4 Water productivity (alfalfa crop water use efficiency)

After calibration, the simulation results of the two integrated programs SPAW and MABIA linked to the global program WEAP21 showed a convergence of about 99.2% at (A3), 99.5% at (A2), and 99.78% at (A1) according to the alfalfa crop response coefficient. This factor reached about 0.78 in modern irrigation methods (A1 + A2) and 0.91 in (A3). Similar data were reported by [24]. The results of the statistical analysis showed that there were significant differences between the treatments regarding water use efficiency (kg/m^{-3}), as shown in **Figure 6**, where the least significant difference ($\text{LSD}_{0.05}$) was approximately 0.12. The drip irrigation treatment excelled the rest of the treatments and recorded 6.2 kg/m^3 as green fodder and 2.1 kg/m^3 as dry fodder (hay), followed by the sprinkler irrigation treatment, which in turn significantly excelled the surface irrigation treatment: 4.5 kg/m^3 as green fodder and 1.5 kg/m^3 as hay. These results are also in agreement with those of growing the crop in the same place in 2008. However, when we compared with the farmer results (A4), there is a huge difference in terms of biological and water productivity, which decreased to 0.47 kg/m^3 . So we excluded them as a reference in that comparison. If these results have been generalized to all the irrigated area implemented according to the percentage of the crop grown in Salamiyya and after implementing the modern irrigation transition project, it is concluded that in addition to raising production in quantity and quality, it is possible to save and keep approximately 7.1 MCM annually when following the irrigation programming. This quantity will be sufficient to cover the deficit in drinking water supplies and domestic use as a first priority in the study area, especially in very dry years.

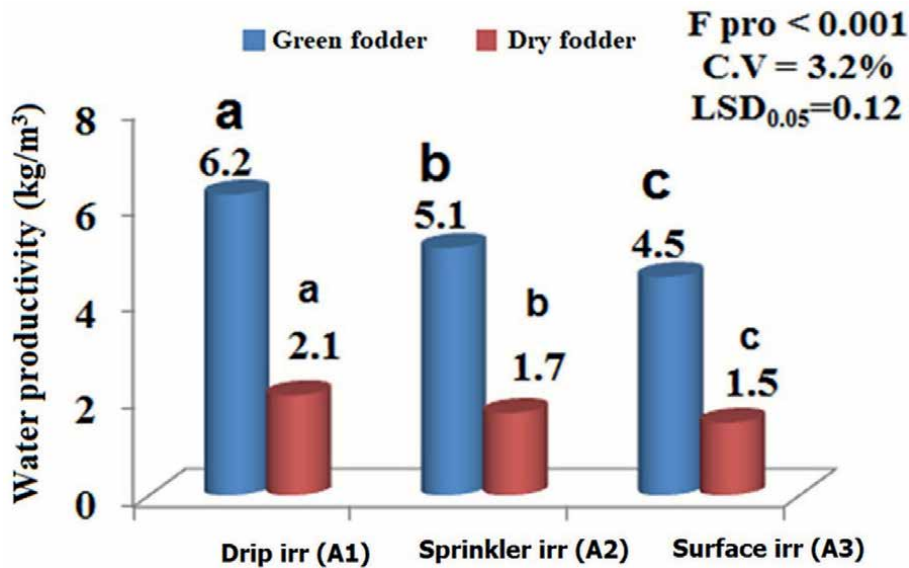


Figure 6.
Average alfalfa crop water use efficiency in Salamiyya.

4. Conclusions and suggestions

It has been found that using the MABIA program, proposals can be made to increase water productivity by obtaining the largest production with the least amount of water provided because it takes into account the relationship between climate, soil, and the cultivated plant, the applied irrigation efficiency, and the stages of crop growth, unlike the farmer's method, which relies on field observations and inherited personal experience. The texture of the soil affects irrigation scheduling. As the softness of the soil increases, its ability to absorb moisture increases (the value of available water increases), and this result is consistent with the results of [25]. Consequently, the provided amount of water increases, and the number of irrigations decreases as the period between irrigations increases during the season, and vice versa.

Despite the importance of this crop in terms of fodder, especially for Awassi sheep in the center, its water requirement is high in the conditions of the dry region, so it is recommended to replace it with crops that have a higher nutritional value and are resistant to drought.

We recommend that if the crop must be grown in the targeted area, avoid the surface irrigation method as much as possible. Although the drip irrigation treatment was superior in the study, it is only suitable for small areas, while the sprinkler irrigation method is better from a technical, service, and cost standpoint when cultivating large crop areas. Here, it is recommended to use marginal water (drainage returns) after treatment in irrigation in order to provide the largest amount of fresh water for crops with a higher economic return.

Advanced mathematical programs such as MABIA, SPAW, and others are considered effective tools for calculating and raising water productivity. They also enable the water expert to dispense with many measuring tools and save a lot of time and effort, not to mention saving the costs resulting from the analyses that must be performed.

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Decision Support Geospatial Analysis: Multi-Criteria Evaluation Suitability Assessments for Agrifood Systems Interventions

Nelson Rosas Ribeiro Filho

Abstract

The chapter details with geospatial analysis as part of the FAO Hand-in-Hand Initiative, which aims to accelerate agricultural transformation and sustainable rural development to eradicate poverty, end hunger and malnutrition, and reduce inequalities. The research uses integrated geospatial analysis to identify opportunities to improve rural incomes and reduce vulnerabilities. Suitability assessments for agrifood systems infrastructure interventions are conducted for over 60 countries, covering crops, livestock, and fish farming. The methodology includes literature reviews and GIS Multi-criteria Evaluation (MCE) using weighted factors to combine geospatial data and decision criteria. GIS-MCE enhances decision-making by structuring problems, designing, evaluating, and prioritizing alternatives. Geospatial modeling is developed for different farming system, considering socioeconomic and biophysical factors to determine location suitability. Transportation networks are modeled using raster-based travel time/cost analysis, and market accessibility is assessed based on population size and purchasing power. Final recommendations use criteria like proximity to roads and access to technology and finance. GIS-MCE provides a replicable model that improves communication among stakeholders and helps refine decision criteria. While GIS modeling supports evidence-based decision-making, complex socioeconomic and political factors many times prevail. The quality and reliability of input data are crucial for trustworthy conclusions.

Keywords: geographic information systems, GIS, multi-criteria evaluation, multi-criteria decision analysis, site suitability analysis

1. Introduction

This chapter was created as an expanded version of a conference paper, originally published in the proceedings of the 12th International Conference on Agro-Geoinformatics 2024, titled ‘Geospatial Analysis for Decision Support: Suitability Assessment for Value Chain Infrastructure Interventions’ [1]. The paper was itself

descendent of a series of technical reports documenting methodology for the different agrifood systems and interventions pilot case analyses.

In this chapter, we try to summarize the Geographic Information Systems Multi-Criteria Evaluation (GIS-MCE) desk research, conducted under the scope of the Hand-in-Hand Initiative (HiHI) flagship program of the Food and Agricultural Organization launched in 2019, to accelerate agricultural and rural development through targeted investments and partnerships. The Initiative supports nationally led programs to transform agrifood systems, aiming to eradicate poverty (SDG1), end hunger (SDG2), and reduce inequalities (SDG10).

Using advanced geospatial analytics and a partnership-driven approach, the HiHI prioritizes poverty- and hunger-affected areas to drive market-based agrifood transformation. Its focus includes value chain development, agro-industries, water management, digital services, precision agriculture, food waste reduction, and climate resilience.

This territorial approach leverages geospatial (biophysical and socioeconomic) data to identify high-impact intervention zones, ensuring economic growth, social inclusion, and sustainable resource use. The HiHI promotes an integrated investment planning framework, facilitating donor engagement and resource mobilization to align national strategies with investment plans.

National ownership is key, with strong government integration, leadership, and transparency and accountability achieved through shared monitoring and evaluation.

While writing this chapter for ‘Technologies and Innovations in Agriculture,’ we reflect not only on the challenge of summarizing years of work by a team of geospatial analysts, but also on how we could measure the future impact of this work: not only directly on actual interventions in the target countries, but also on the contribution to the adoption of geospatial data evidence and geographic information systems-based analysis in agrifood systems decision support, planning, approaches, and interventions.

Geographic information systems (GIS) have seen spectacular development in the last three decades. Advancements in processing power, communication networks, storage capacity, microelectronics, and the massification of GPS-enabled devices have combined with a growing abundance of open-access remote sensing satellite data, transitioning from data scarcity to a (big) data-rich environment. The maturity of cloud storage and processing, as well as the growing availability of open-source software tools, has allowed previously costly and highly technical scientific analysis to become mainstream in information systems. This has enabled GIS to penetrate into diverse fields of knowledge, from earth sciences to every discipline where location on the globe’s surface is relevant.

Social and economic geography focuses on examining the spatial aspects of social and economic processes, and how resources, industries, urban forms, social patterns, and life forms are distributed and interact within different geographical environments. The subject matter involves analyzing the physical, economic, and social processes that create and reshape society’s spatial patterns. Food systems are an obvious object for social and economic geography and a perfect fit for geospatial analysis technology. Not only do they depend on biophysical geographical factors, but they also encompass the diversity of actors and interconnected activities that add value to food products. These systems incorporate flows from supply to demand, from production and aggregation to processing, distribution, consumption, and disposal. Food systems cover products from crop and livestock, forestry, fisheries, and aquaculture within the broader economic, societal, and natural environments where these systems

operate. They also include the provision of inputs and services in the extended value chain, which impact the flow of goods through the various stages of the core value chain.

1.1 Knowledge gap

There is a current boom in the use of geospatial technologies in AgroInformatics, driven by the rapid development of information systems and technologies based on remote sensing data abundance, cloud computing, AI, and machine learning. However, there is a significant knowledge gap in the field. Most studies, algorithms, and publications focus primarily on machine learning remote sensing applications for classification or identification and measurement of biophysical aspects affecting agrifood system production components, such as crop type mapping, plastic mulch detection, climate-related factors, vegetation health, or plant growth. There is a lack of research and development aimed at enhancing decision support systems on a macro-, holistic, and socioeconomic basis, which includes other data dimensions relevant to agrifood systems from an economic geography perspective. Even less attention is given to using these technologies to support agrifood systems transformation/development targeting sustainable development goals through an integrated territorial approach based on evidence.

To bridge this knowledge gap, significant effort is needed to integrate the different data dimensions required to support informed decision-making. Additionally, it is crucial to engage different stakeholders within the development community, country governments, and donors. Analyses conducted under an evidence-based and clear territorial or spatial approach can facilitate this engagement, contributing to informed and transparent decision processes. This is fundamental for both donor engagement and for opening new paths in project and intervention monitoring and evaluation.

1.2 Objective

This book chapter examines how the FAO's HiHI leverages geographic information systems (GIS) and multi-criteria evaluation (MCE) methodologies to pinpoint optimal locations for agrifood system interventions and guide evidence-based investment strategies. By highlighting the practical applications of these tools, the chapter underscores their role in enhancing precision and efficiency in resource allocation. Its broader objective is to advocate for the integration of geospatial data and GIS-driven analytics into agrifood decision-making frameworks, strategic planning processes, and targeted interventions, thereby fostering data-informed policies and scalable solutions.

The chapter outlines tailored approaches based on literature review and geospatial GIS-MCE modeling techniques for various applications, including crop warehousing, storage, or aggregation centers; livestock dairy processing or slaughterhouses; and suitability assessments for different fish farming systems.

The expected outcome is to enhance the adoption of GIS-MCE in decision support frameworks, refining criteria and approaches. This will increase support and engagement with recipient country teams and governments, facilitating effective spatial collaborative decision-making and planning. The goal set is to make ways for the process to encompass both the deliberative dimension (consensus building) and the analytical dimension (generating a collective solution) in spatial planning and decision-making.

1.3 Research questions

The GIS-MCE suitability assessments analysis research departure questions can be exemplified by the following:

- *Where are the best sites for a specific crop storage facility?*
- *What would be the best site to locate a dairy processing unit (UHT and milk powder)?*
- *What are the provinces and districts where fish farming should be promoted for poverty alleviation, improving nutrition, and food security?*
- *Where are the best sites for intensive commercial fish farming open systems?*

Simply put, what are we trying to locate? This leads to the questions: ‘What are the business rules?’ and ‘What are the factors that influence location?’

One of the most obvious features of GIS tools is data integration by location. The self-explanatory concept of data integration by location refers to the process of combining data from multiple sources based on geographical or spatial attributes. This process effectively enables the extraction of data from diverse sources into a standardized format within a unified system, connecting datasets through their spatial references. It also facilitates the use of analytical software tools and spatial database management systems for location-based or location-aware queries.

In this framework, performed by the FAO’s CSI Agro-Informatics geospatial analysis team, the GIS multi-criteria evaluation (MCE) suitability assessments aim to propose and demonstrate evidence-based, participatory processes to identify opportunities and support planning agrifood system interventions. The GIS-MCE suitability assessments use a well-reported standard approach for suitability mapping. They employ a multi-criterion decision model that combines indicators into a single measure across the decision-making process objectives, considering biophysical and socioeconomic factors such as supply, demand, and infrastructure/accessibility.

Each project applies the same GIS-MCE approach—a geospatial site suitability analysis—that identifies an objective, sets criteria, and scores and weights the factors in an additive model applied to different agrifood system challenges, with Boolean¹ logic final constraints to recommend the potential sites. Spatial decision problems typically imply a set of alternatives and multiple (sometimes opposing) assessment criteria, frequently evaluated by many participants. In GIS-MCE, GIS capabilities are enhanced by multi-criteria decision analysis procedures, techniques, and algorithms for structuring decision problems, designing, evaluating, and prioritizing alternatives [2–4].

The analysis produced data products for near 70 HiHI participating countries, covering various agrifood systems in crops, livestock, and fish farming. The results are published as Digital Public Goods on the FAO AgroInformatics Platform (AIP), cataloged with standard metadata, and accessible for download or *via* Open

¹ Boolean logic is a branch of algebra that deals with true or false values, often represented as 1 and 0. It is used in computer science, mathematics, and logic to perform operations like AND, OR, and NOT, which helps in decision-making and problem-solving processes.

Geospatial Consortium web map services. The FAO AIP data infrastructure supports map services, metadata, and tabular/database frameworks, enabling integration with other applications and data management systems.

2. Methodology

Apologies to the less technical reader (from an information system perspective). We will try to avoid complex technical language and jargon, but from this sub-chapter on, we will use some specific terms, explaining them when possible.

2.1 General methodology

To answer those questions, we can say that the general methodology comprises a literature review on agrifood system and country context and background, which will support theory and assumptions, and help define the modeling business rules.

The geospatial modeling assumes a GIS-MCE methodology using weighted factors [2–4]. The modeling is developed for distinct agrifood systems or different farming systems, playing with criteria combination and weighting, and differently combining sets of constraints. The business rules define the utilization and combination of criteria coming from a set of sub-models, the criteria weighting, and the spatial constraints, all characterizing socioeconomic and biophysical factors that affect the suitability for a specific use of space/territory.

The accessibility criterion (transportation network infrastructure modeling) is of high relevance, and it is modeled as raster²-based travel time/cost analysis [5]. A market/demand factor is particularly weighted for commercial production systems, and it relates to accessibility, processed for large urban areas, weighting Atlas AI population size and purchasing power (asset wealth index (AWI)) [6, 7]. Constraints are added as final steps using Boolean logic, for example, minimum distance to major roads, access to information and communication technologies, and access to finance (minimum distance to bank agency), to identify and recommend optimal locations.

The GIS-MCE approach follows a structured workflow that begins with defining the research objective or problem, supported by a literature review to identify relevant criteria, constraints, and business rules, followed by data collection to address the research question. Subsequent steps involve developing sub-models through geoprocessing, where input data layers are edited, selected, and transformed into standardized formats, and then normalized to a common scale to ensure comparability. Criteria are ranked based on their relative importance, after which a suitability index map is generated by applying a weighted sum of the normalized criteria, assigning scores to geographic areas that reflect their alignment with the defined objectives. The most suitable sites or regions are pinpointed by applying additional constraints using Boolean logic to filter results. Finally, outcomes are disseminated through geospatial platform publishing, metadata documentation, and stakeholder presentations to enable knowledge transfer. The process incorporates iterative feedback loops for

² *Raster Data*: Represents space as a grid of cells (pixels), each with a value representing information. As opposed to *Vector Data*, representing features on the earth surface by using points, lines, and polygons, with data values associated with each feature.

model refinement, followed by strategic applications such as investment planning and matchmaking to translate analytical insights into actionable decisions.

3. Transversal sub-models

The accessibility criterion (transportation network infrastructures) is used across all the analyses, employing OpenStreetMap data to produce the raster-based travel time/cost analysis [5].

The market/demand factor is also important for commercial production systems. It relates to accessibility and is processed to large urban areas, weighting Atlas AI population size and purchasing power (AWI) [6, 7].

3.1 Sub-models: Accessibility - Infrastructure/market

Figure 1 shows a diagram with the general steps for the accessibility calculations.

The workflow begins with *preprocessing*, where raw geospatial data undergoes extraction, attribute-based filtering, and editing to refine relevance and accuracy before being organized and loaded into a centralized database repository. Next, *rasterization* transforms vector-based transportation networks (e.g., roads, railways, pedestrian pathways, waterways) into raster grids, with each cell assigned a value representing the average time (in minutes) required to traverse it, depending on the transportation mode (walking, driving, train travel, or navigation). *Cost/friction processing* then overlays these rasterized layers to propagate the minimum traversal time (or “cost”) value across overlapping cells, prioritizing the most efficient path or barrier-free routes. This sets the stage for *cumulative cost processing*, which calculates accessibility by generating service areas around the selected points (e.g., demand centers), modeling the total accumulated time/cost to reach surrounding areas and producing maps that highlight zones within specific time or resource thresholds. Finally, *normalization* standardizes the output units by scaling values to a uniform range (e.g., 0–100), enabling the integration of these metrics into a composite suitability index.

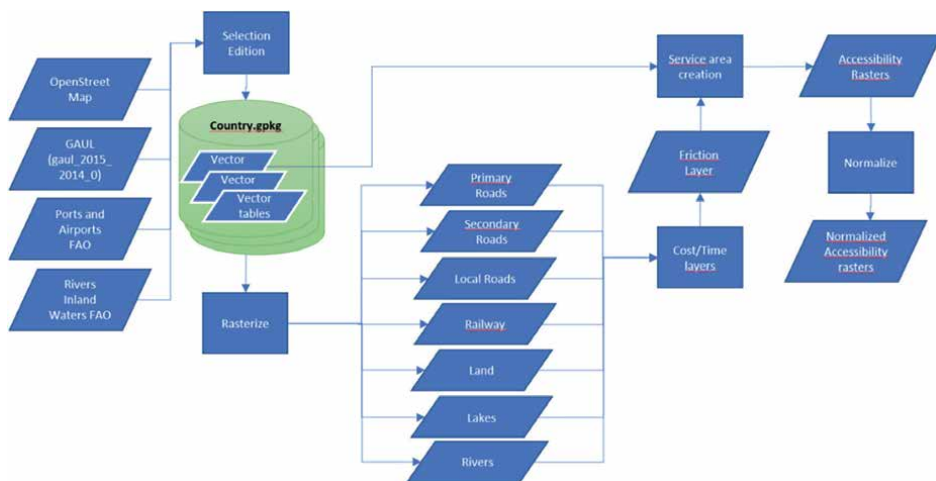


Figure 1.
Accessibility general workflow.

This standardized index supports comparative analysis and decision-making by translating multidimensional spatial and temporal factors into a unified, interpretable framework.

Accessibility to major urban areas is determined by population density and area thresholds (e.g., areas with more than 1500 inhabitants/km² and an area greater than 25 km²), and calculated to major urban places points, or road network and urban polygon intersection points.

The ‘thresholds’ can be adapted to specific country context and dimension of urban centers, as also to specific interventions, commodities, or value chains. For example, large-scale production and processing will most likely need good connectivity to the largest urban centers, while small-scale production can target farmgate sales or small city and village markets.

Cross-border trade demand can be also considered, adding accessibility to large regional cities as a criterion. Here, the differentiating factor can be whether the intervention is planned for import substitution commodities or targeting export markets.

Accessibility to major maritime ports is used in some of the modeling to input a measure of access to both agrifood systems input and output markets.

3.2 Sub-models: Market demand

The market demand criterion is modeled using accessibility to large urban areas weighted by population size and purchase power (Atlas AI AWI). This measure is introduced utilizing the population density and the AWI zonal statistics³ to add pull weight to large urban markets with the highest purchase power, following the steps:

The process begins by *extracting population density zonal statistics* (summed values) for urban polygon features, which quantify total population within the boundaries. Next, a *population-weighted AWI average* is computed for these urban polygons using the formula:

$$\frac{\sum_{i=1}^n awi_i * population_i}{\sum_{i=1}^n population_i} \quad (1)$$

and ensuring the result is normalized to positive values. The population of each urban polygon is then multiplied by its corresponding normalized AWI value, and a *percentage share* is calculated relative to the total urban population to reflect each area’s proportional economic influence. *Individual accessibility raster layers* are generated for each urban polygon, representing travel time or cost to reach these markets. Finally, a *weighted sum* of all accessibility layers is performed, using the percentage share (from the population-AWI product) as the weighting factor. This synthesizes a composite suitability index that prioritizes urban markets with high accessibility, dense populations, and higher purchasing power (**Figure 2**).

³ Raster zonal statistics is a geospatial analysis technique that computes statistical metrics (e.g., mean, sum, standard deviation) of raster data within specific zones defined by vector polygons.

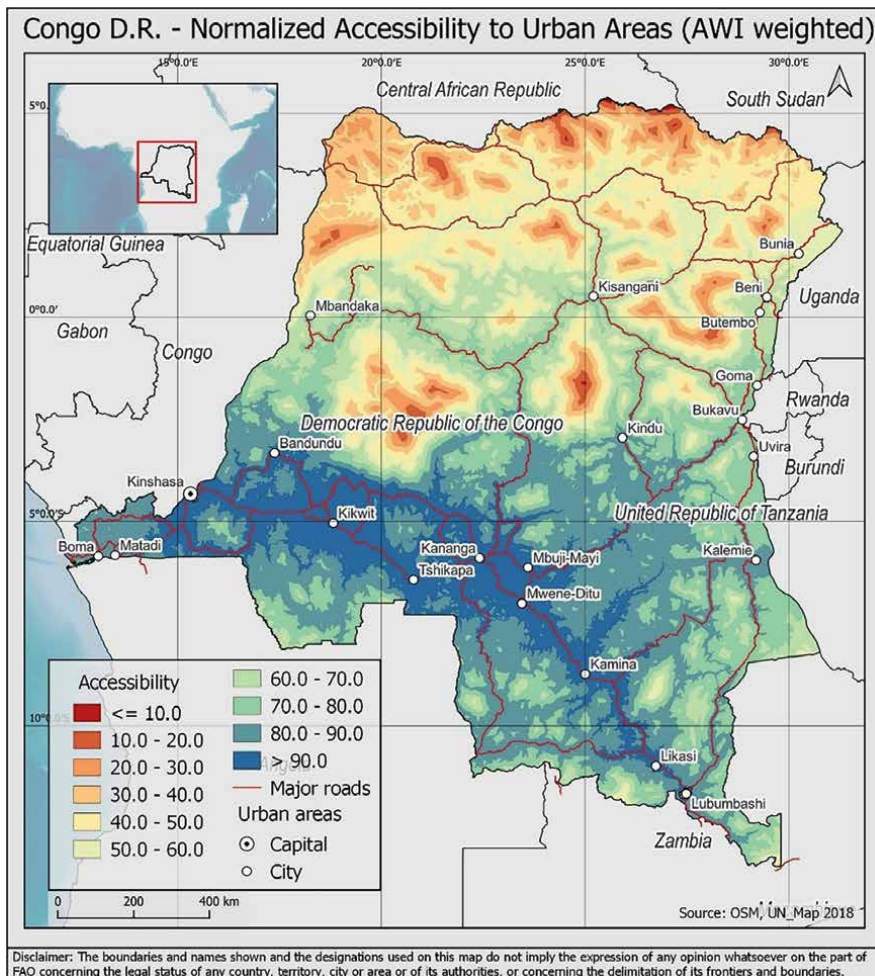


Figure 2.
Demand map—normalized weighted accessibility to urban areas.

4. Crop storage/warehouse suitability assessment

The modeling for crop storage or warehousing is applied with various requirements, such as grain storage, milling, processing, old cold storage, and aggregation centers for fruits and vegetables, thus utilizing distinct criteria and weighting of these location factors.

For production (supply) data input, the storage/warehousing location analysis utilizes IFPRI's Spatial Production Allocation Model (MapSPAM) or FAO Global Agro-Ecological Zone (GAEZ) models [8, 9]. In the case of cold storage, processing or aggregation centers also account for electrification (Atlas AI) [6, 7].

Crops are selected using FAOSTAT⁴ main food staples and exports or following the specification of the HiHI country team (governmental stakeholders and FAO country office) (Figures 3 and 4).

⁴ <https://www.fao.org/faostat/en/#data/QCL>

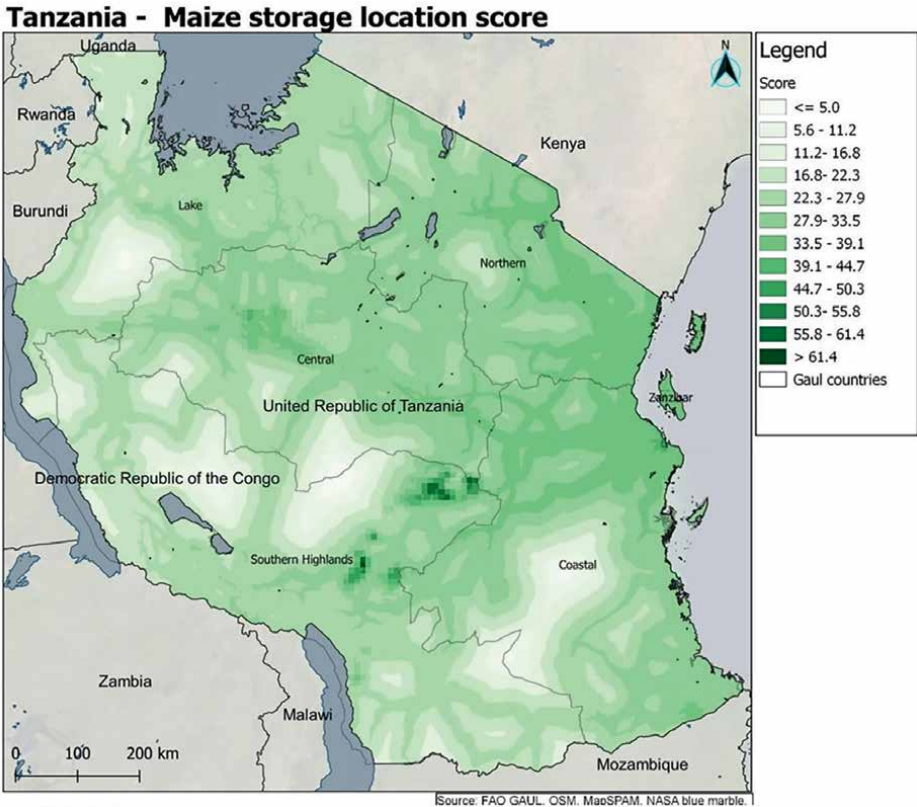


Figure 3.
Storage suitability index.

A suitability index is created through an arithmetic weighted sum of the normalized/scaled input grids (map layers representing criteria). The weightings can vary depending on the specificity of the agrifood system, such as export or import substitution crops, or the country context. For example:

$$\begin{aligned}
 & \left(\text{"Crop Production"} * 0.4 \right) + \left(\text{"Human Population Density"} * 0.2 \right) \\
 & + \left(\text{"Port Accessibility"} * 0.2 \right) \\
 & + \left(\text{"Major Cities Accessibility"} * 0.1 \right) \\
 & + \left(\text{"Regional Cities Accessibility"} * 0.1 \right)
 \end{aligned} \tag{2}$$

Final recommended locations are obtained by filtering the suitability index mapping using constraints such as access to finance (distance to bank agencies), proximity to major roads, and access to ICT (mobile broadband coverage). Coverage maps are processed from the Collins Bartholomew mobile coverage explorer database [10] into a derived raster map (1/0 for coverage/no coverage). This map results from the aggregation of 3G (strong signal), 4G, and 5G grids, originally obtained from operators' submissions and OpenCellID cell tower location datasets (Table 1).

In the Tanzanian pilot case, validation of recommended locations was sought through visual map inspection, to identify logistics and industrial districts, port and railway station proximity, availability of space in urban areas, and avoiding

Tanzania Maize Storage Final Locations

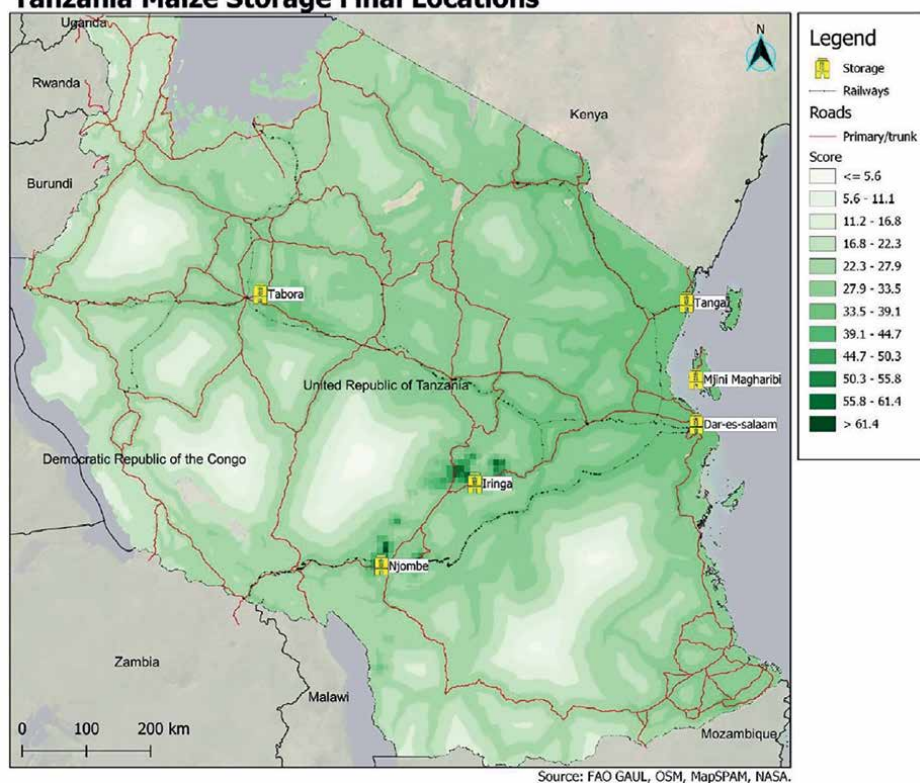


Figure 4.
Recommend locations.

Region	District	Zones	Location
Tabora	Uyui DC	Central	T8 Rd., Mayombo
Dar-es-salaam	Ilala MC	Coastal	Nelson Mandela Rd., Tabata Mwananchi, logistics district
Tanga	Tanga CC	Northern	T13, Monbassa Rd., Tanga
Njombe	Wanging'ombe DC	Southern Highlands	T1 Rd., Wanging'ombe-Makambako
Iringa	Kilolo DC	Southern Highlands	T1, Iringa Rd., Ilula/Masukanzi
Mjini Magharibi	Mjini	Zanzibar	Zanzibar City

Table 1.
Recommended location details.

residential or touristic areas or districts. Although value judgment is present when pinpointing suggested sites, the exercise evaluates the return from modeling abstraction to field reality, while also reducing the number of proposed sites by aggregating close locations.

5. Livestock dairy processing suitability assessment

For the pilot case analysis, suitability assessment for ultra-high temperature (UHT), and milk powder processing, the requirement was defined based on necessities assessed by the national plan, *Tanzania Livestock Master Plan* [11], and justified by the country's large cattle population and livestock keeping traditions, while being a large importer of UHT and powder milk.

The theoretical framework for locating large-scale dairy processing facilities (UHT and milk powder) is grounded in key economic and logistical assumptions. First, it posits that small-scale operations for such processing are economically unviable, necessitating industrial-scale infrastructure to achieve profitability. *Supply-side considerations* prioritize regions with high raw milk production potential, modeled using crop and livestock density data to identify areas where feed availability (for intensified feedlot systems) is sufficient, crossbred dairy cattle can thrive, or existing dairy herd densities are already elevated. This reflects the premise that milk volume sustainability hinges on proximity to agroecological zones capable of supporting intensive dairy farming. *Demand-side criteria* emphasize proximity to high-consumption markets, with facility placement optimized near large urban centers or regions with dense populations to minimize distribution costs and align with consumer access. *Logistical requirements* further narrow site selection by prioritizing accessibility to robust transportation networks (roads, railways) and infrastructure, ensuring efficient connectivity to both supply chains and output markets. Together, these criteria balance production capacity, market reach, and operational efficiency, framing location suitability as a function of integrated agricultural, demographic, and infrastructural synergies.

5.1 Dairy production

The analysis is centred on the dairy production intensification potential, targeting large-scale processing (UHT, powder). Modeling uses crop, livestock production systems, and dairy herd density:

- IFPRI MapSPAM crop data (aggregated production).
- Livestock production systems [12] high length of growing period (LGP)—n° of days per year during which crop growth is possible.
- Density of dairy herd based on:
 - Cattle distribution: Gridded Livestock of the World (GLW) [13] 2.0, 1 km res.
 - Cows number—[14].
 - Administrative Divisions: (GAUL_Level1).

5.2 Global livestock production systems

FAO Global Livestock Production Systems [12] uses a livestock-oriented classification developed by Seré and Steinfeld [15] and is the methodology for input data and classification of production systems in the Tanzania Livestock Sector Analysis [16].

The Seré and Steinfeld scheme classifies livestock systems into four major types:

1. Landless livestock production systems (LL, which may be monogastric or ruminant).
2. Grassland-based system (LG, in which crop-based agriculture is minimal).
3. Mixed rainfed systems (MR, mostly rainfed cropping combined with livestock).
4. Mixed irrigated systems (MI, in which a considerable proportion of cropping uses irrigation and is interspersed with livestock).

The livestock-only and mixed farming systems are further characterized in agro-climatic terms, based on temperature and Length of Growing Period. The agroclimatic categories were defined as:

- Arid and semi-arid: LGP $\leq$ 180 days.
- Humid and sub-humid: LGP $>$ 180 days.
- Tropical highlands or temperate. Temperate: +1 -month daily mean temp $< 5^{\circ}\text{C}$. Tropical highlands daily mean during the growing period of $5\text{--}20^{\circ}\text{C}$.

This classification system includes then 11 types: livestock only, grassland based (LG), which may be arid/semi-arid (LGA), humid/sub-humid (LGH), or tropical high-land/temperate (LGT); landless monogastric-based (LLM), and landless ruminant-based (LLR); mixed, rainfed systems (MR) by the three agro-ecological zones, and mixed, irrigated systems (MI), also by the three agro-ecological zones.

The Robinson *et al.*'s study *Global Livestock Production Systems* builds from Seré and Steinfeld but adopts a classification based on landcover, human population density, length of growing period, and elevation data.

5.3 Dairy production data processing

The dairy herd intensification layer is processed from dairy cattle density and selected livestock production system (LPS) used as Boolean 1/0 layer.

LPS selected for the Tanzania pilot case:

- a. (TZA_LPS) = (7: MR Mixed Rainfed Humid) + (8: MR Mixed Rainfed Temperate) + (9: MI Mixed Irrigated Hyperarid) + (10 = MI Mixed Irrigated Arid) + (11: MI Mixed Irrigated Humid) + (12: MI Mixed Irrigated Temperate) + (13: Urban).

- b. Obtained by a raster calculation with the expression:

$$\left(\left("TZA_LPS" \geq 7 \right) \text{AND} \left("TZA_LPS" \neq 9 \right) \text{AND} \left("TZA_LPS" \leq 13 \right) \right)^{*} \quad (3)$$

$TZA_dairyHerd = TZA_dairyHerd_Intensification$

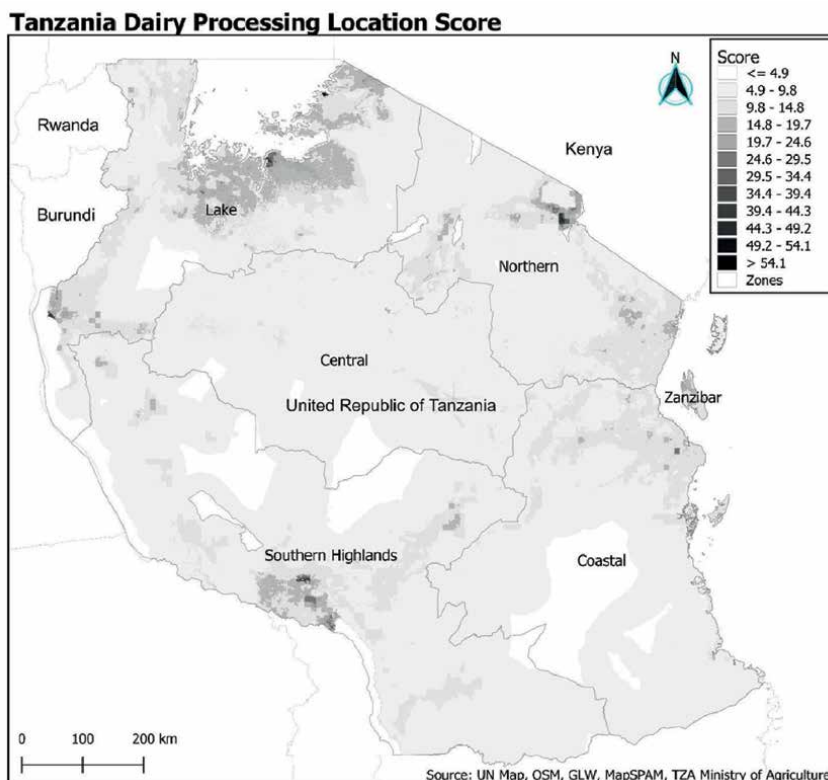


Figure 5.
 Dairy processing suitability index.

Again, a suitability index is achieved with a simple arithmetic weighted sum of the normalized/scaled input raster (map grids), varying from 0 to 100 (**Figure 5**):

$$\begin{aligned} & \left(\text{"dairy Intensification"} * 0.5 \right) + \left(\text{"crop Production"} * 0.3 \right) \\ & + \left(\text{"Human Population Density"} * 0.1 \right) \\ & + \left(\text{"Major Cities Accessibility"} * 0.1 \right) \end{aligned} \quad (4)$$

5.4 Recommended locations

Recommended locations for a large-scale milk processing investment are finally obtained using a top suitability index percentile and adding the exclusionary spatial criteria: proximity to urban areas, access to finance, distance from major roads, access to ICT (mobile broadband coverage). Expression (**Figure 6**):

$$\begin{aligned} & 10\text{Km buffer urban areas AND } 20\text{km distance from bank} \\ & \text{AND } 2\text{km distance from roads AND Mobile broadband coverage} \end{aligned} \quad (5)$$

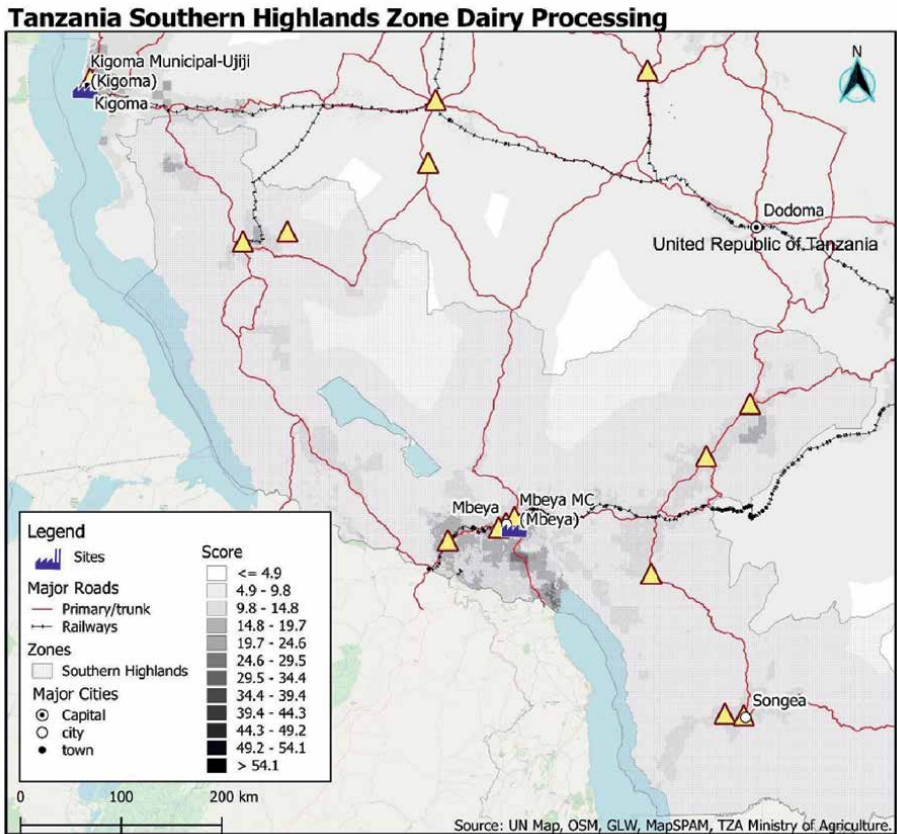


Figure 6.
Dairy processing recommended locations.

6. Livestock abattoir/slaughterhouse suitability assessment

The question of where the best suitable location for a slaughterhouse is, is answered by identifying where production occurs, where the highest livestock densities are, and/or where there are good conditions to expand, but also where consumption takes place. Considering that in most developing countries, and specifically in HiHI target countries (less developed, landlocked, and small island-developing states), transportation infrastructure, electrification, and cold chains are poor; in theory, this sort of infrastructure must be located closer to the market due to higher efficiency in the transportation of live animals.

Modeling therefore utilizes livestock production (animal density), accessibility to cities, and the existence of crop production for feed, while also factoring in poverty data when existing.

When there is no specific animal species defined, a combined density layer is created, based on the average weight of the animals. For specific animals (like poultry), the analysis does not use the combined data. Sometimes, it can sum different animal density layers (like goat + sheep).

A suitability index example (**Figure 7**):

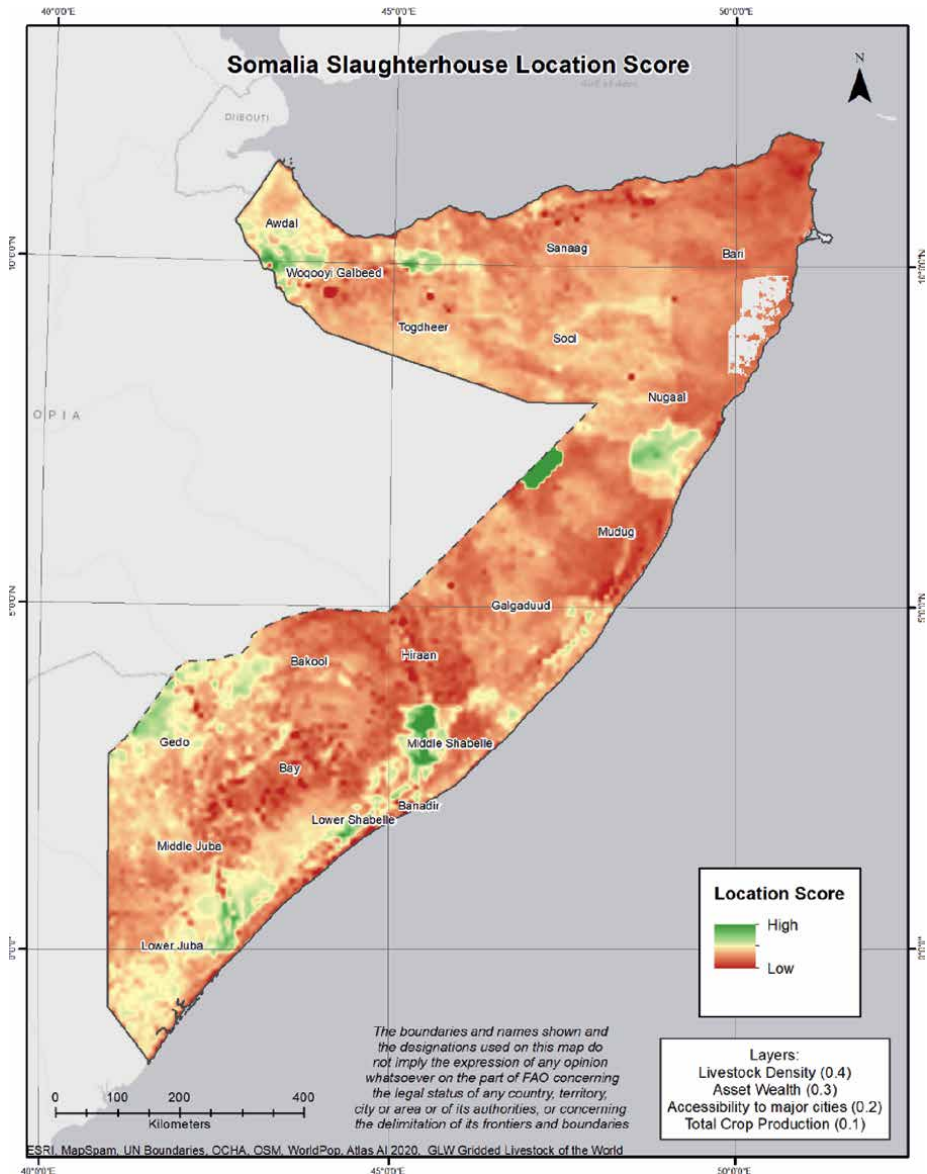


Figure 7.
 Slaughterhouse suitability index.

$$\begin{aligned} & \left(\text{"Cattle Density"} \times 0.4 \right) + \left(\text{"AWI"} \times 0.3 \right) + \left(\text{"Major Cities Accessibility"} \times 0.2 \right) \\ & + \left(\text{"Crop Production"} \times 0.1 \right) \end{aligned} \quad (6)$$

Modeling applies GLW, IFPRI's MapSPAM estimates of crop distribution, OpenStreetMap data, and Atlas AI AWI or other poverty data sources, for example, country data or FAO ESS Data Lab. When used as a poverty surrogate, the AWI normalization is inverted, the highest value representing the areas with the poorest population.

Final recommended location follows a common method, applying constraints as Boolean logic; access to finance, distance to roads, and urban areas, defined as linear

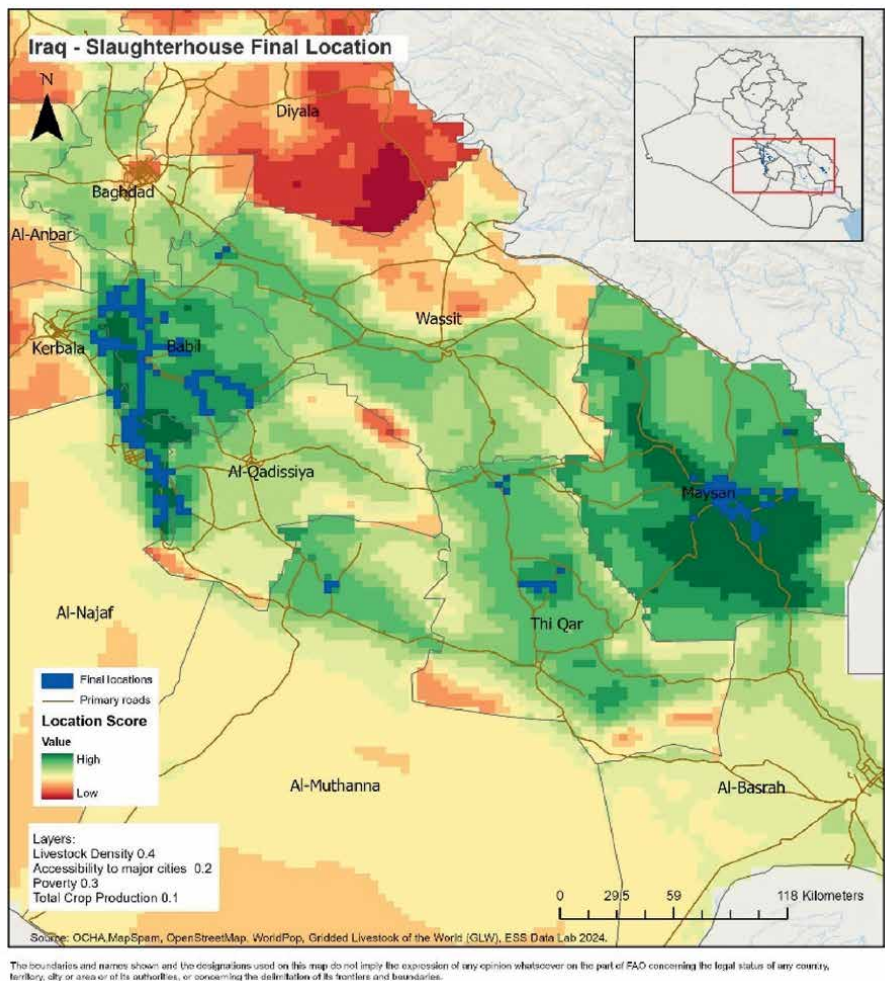


Figure 8.
Slaughterhouse recommended locations.

distance thresholds, and combining with access to ICT and electricity, the mobile broadband coverage map and the Atlas AI Electrification map (**Figure 8**).

7. Fish farming suitability assessment

The analysis builds on Aguilar-Manjarrez and Narh method to modeling fresh warm-water and temperate-water fish farming potential in continental Africa [17], a raster-based geographic information systems multi-criteria decision analysis (GIS-MCDA) approach, using fish-farming and land-quality factors.

The updated assessment framework refines location suitability modeling by integrating revised data sources, recalibrated sub-models, and adjusted criteria weightings and constraints. The analysis is structured around four interconnected categories: *biophysical factors*, *input availability*, *demand/market dynamics*, and *exclusionary constraints*. *Biophysical criteria* evaluate environmental viability, starting with

water requirements (precipitation and evapotranspiration rates), soil and terrain suitability (soil type, slope gradients), and potential yields based on climatic conditions—specifically, the number of days within optimal temperature ranges for fish growth. *Input availability* focuses on agro-resources, mapping proximity to crops and livestock systems that can provide fish-feed byproducts and manure. The *Demand/market criteria* prioritize economic viability, incorporating farm-gate sales potential (linked to population density classes) and proximity to large urban markets weighted by wealth metrics (e.g., Atlas AI AWI) to reflect purchasing power. *Constraints* act as exclusionary filters, excluding urban zones, protected areas, flood-prone regions, and large water bodies, while imposing proximity thresholds to roads, banking services, and ICT infrastructure to ensure operational feasibility. By harmonizing these layers—biophysical suitability, resource access, market pull, and logistical barriers—the model generates a spatially explicit suitability index, balancing ecological compatibility, input sustainability, market reach, and infrastructural readiness for optimized site selection.

Modeling is tailored to different fish farming systems following distinct objectives and business rules, varying modeling criteria, changing weighting, and by combination of different sets of constraints or exclusionary criteria.

For the *small-scale, extensive to semi-intensive, pond and integrated farming systems* modeling targets strategies and interventions for poverty alleviation, bettering nutrition, and diets, increasing food security and income diversification, diminishing risks an improving resilience. The main objective is to identify regions with the highest poverty incidence (priority) and at the same time strong suitability for the activity.

For *commercial intensive systems*, open or closed aquaculture techniques, the objective is the identification of top high return-on-investment sites. Location represents worthwhile investment opportunities that essentially depend on good accessibility to input and output markets:

Intensive closed-systems use closed water circulation technologies, like re-circulating tanks, raceways, flow-through systems, and inland ponds, and in many cases employing constructed or assembled manmade materials.

Open intensive tilapia pen/cage farming systems are implemented in water bodies, thus the primary location criterion is the presence of permanent waters.

We must now give a general description of sub-models that are differently combined and weighted for each farming system suitability assessment.

7.1 Farmgate sales

The farmgate sales concept refers to a direct marketing method where there is a direct relationship farmer-consumer. It is used for small-scale non-intensive or semi-intensive farming system assessment.

The criterion sub-modeling adapts Aguilar-Manjarrez and Narh classification to Atlas AI population density data, with the farmgate sales potential growing between 0 and 300 [h/km²], and with the population density considered unsuitable above that threshold.

7.2 Biophysical factors

7.2.1 Water

Although any reader will obviously agree that the existence of water is a, if not the, major factor for farming fish, its amount and availability can vary in importance based on the farming system. For example, non-commercial pond systems require

high water availability. In contrast, commercial intensive closed aquaculture systems in tanks are less dependent on water availability, as recirculatory methods can filter and reuse the water.

Water availability is estimated using an annual water balance from WaPOR precipitation and evapotranspiration data, and the seasonality layer from the Global Surface Water Explorer (GSW) - European Commission Joint Research Centre Copernicus Programme data [18].

An annual mean water balance is obtained by processing WaPOR *Precipitation* (PCP) and *Reference Evapotranspiration* (RET) time series, applying the formula $(PCP * 1.1) - (RET * 1.3)$. Results are normalized/scaled for suitability index calculations.

The GSW data is downloaded in tiles and merged into raster mosaics⁵. The *Seasonality* dataset is used to establish the persistence of surface water for cage farming systems, and the *Max_Extent* dataset (32-year time series) is used as a flood area constraint for non-intensive pond systems. The layers are polygonised⁶ both to be used as constraints and for the definition of permanent water areas (polygon features) for open tilapia cage system modeling.

7.2.2 Soil and terrain

This criterion sub-model identifies and measures soil and terrain suitability for fishpond construction. It uses FAO soil units and elevation data from HydroSHEDS DEM 30s [19].

Elevation is processed into slope, which defines suitability levels and is inversely normalized: values ranging from 0 (8° slope, unsuitable) to 100 (0° slope, optimal flat terrain) for pond construction. Slopes above 8° are considered unsuitable, as steep terrain is not adequate for fish farming.

Since different farming systems have distinct construction needs, this criterion is applied accordingly. For instance, soil and slope are combined into a single measure for modeling small-scale extensive to semi-intensive integrated pond farming systems. However, soil is not a relevant factor for farming systems in tanks using man-made materials such as plastic or fiberglass.

7.2.3 Potential yields

Once properly fed, fish growth is proportional to the number of days within the species optimal temperature range. Water temperatures were originally estimated using air temperature and wind velocity, modeled for the most farmed freshwater fish species, the African Catfish (*Clarias Gariepinus*) and Nile tilapia (*Oreochromis niloticus*), and the data is from the original Aguilar-Manjarrez and Narh study.

7.3 Sub-models: Inputs

Another group of factors, criteria, sub-models are those relevant as production inputs.

⁵ A *raster mosaic* is a collection of multiple raster datasets seamlessly merged into a single, continuous image, preserving spatial alignment and resolution.

⁶ *Polygonise* is the process of converting raster data into vector polygons by grouping contiguous cells with the same value into distinct polygon features.

7.3.1 Crops

Crop products and byproducts can be used directly as feed or as raw materials for feed mills. Local aquafeed production is in many cases determinant for fish farming sustainability and competitiveness, with documented evidence supporting its economic and technical interest in different sub-Saharan countries [20–25].

The crop input sub-model uses production aggregate from IFPRI MapSPAM 2017 [26].

A special case is the integration of rice-fish farming, where fish act as natural fertilizers and pest control, contributing to environmental sustainability. The presence of irrigate paddy rice fields is a pre-condition for this specific farming system.

7.3.2 Livestock

The livestock data is sourced from GLW. In fish farming, it can be utilized for organic fertilization (manuring) or as by-products (blood, bones, etc.) for feed ingredients. Different production system requirements also necessitate distinct sub-models. Integrated farming systems are common, with the association of chicken, duck, and pig with fish. Fish feeding on dejects and livestock food waste with ducks also contribute to as water aerators.

7.4 Suitability modeling

As previously detailed, the geospatial data analysis targets different farming systems, and suitability is influenced by criteria in distinct ways and degrees. The considered farming systems are as follows:

- a. Pond extensive to semi-intensive and integrated systems.
- b. Intensive/commercial closed (semi-closed) farming systems using ponds, tanks, RAS, flow-through, or recirculation.
- c. Intensive Tilapia open farming systems using cages in water bodies.

As described in the methodology, and in recap, once the objective/problem and business rules are defined, data are gathered and processed, input layers normalized, and criteria ranked. Suitability index mapping is processed by applying a weighted sum of the factors. Output maps display areas scored based on their adherence to the criteria, with constraints sequentially applied to highlight the potential sites that meet the desired conditions (**Figure 9**).

An example of the suitability index for the intensive commercial closed fish farming systems is as follows:

$$\begin{aligned} & \left(\text{"Weighted Accessibility Major Urban Areas"} \times 0.5 \right) \\ & + \left(\text{"Water Balance"} \times 0.15 \right) + \left(\text{"potential Yield"} \times 0.15 \right) \\ & + \left(\text{"CropsInput"} \times 0.075 \right) + \left(\text{"LivestockInput"} \times 0.075 \right) + \left(\text{"Slope"} \times 0.05 \right) \end{aligned} \quad (7)$$

Example mapping outputs generated:

The use of zonal statistics allows further classification of administrative boundaries according to their average suitability index, like in **Figure 10**.

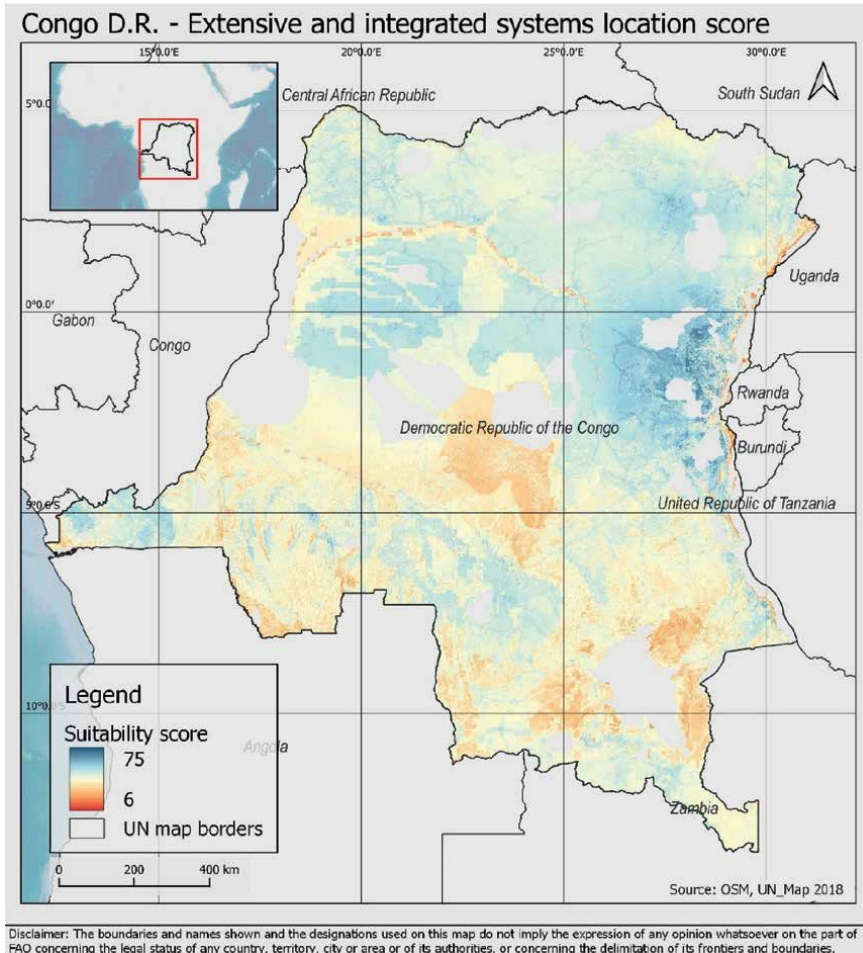


Figure 9.
Non-intensive fish farming suitability index.

Zonal statistics also permit the creation of indexes, for example crossing potential and poverty data, to identify priority provinces or districts where the impact on hunger, nutrition, and poverty alleviation is maximized, meaning, areas with the lowest incomes and highest suitability, like exemplified in **Figure 11**.

7.5 Recommended locations

Recommended locations are finally processed to intensive commercial farming systems. For closed farming systems, it follows a standard procedure using a top suitability index percentile and adding the exclusionary spatial criteria: proximity to urban areas, access to finance, distance from major roads, access to ICT (mobile broadband coverage). Expression (**Figure 12**):

10Km buffer urban areas AND 20 km distance from bank
AND 2 km distance from roads AND Mobile broadband coverage (8)

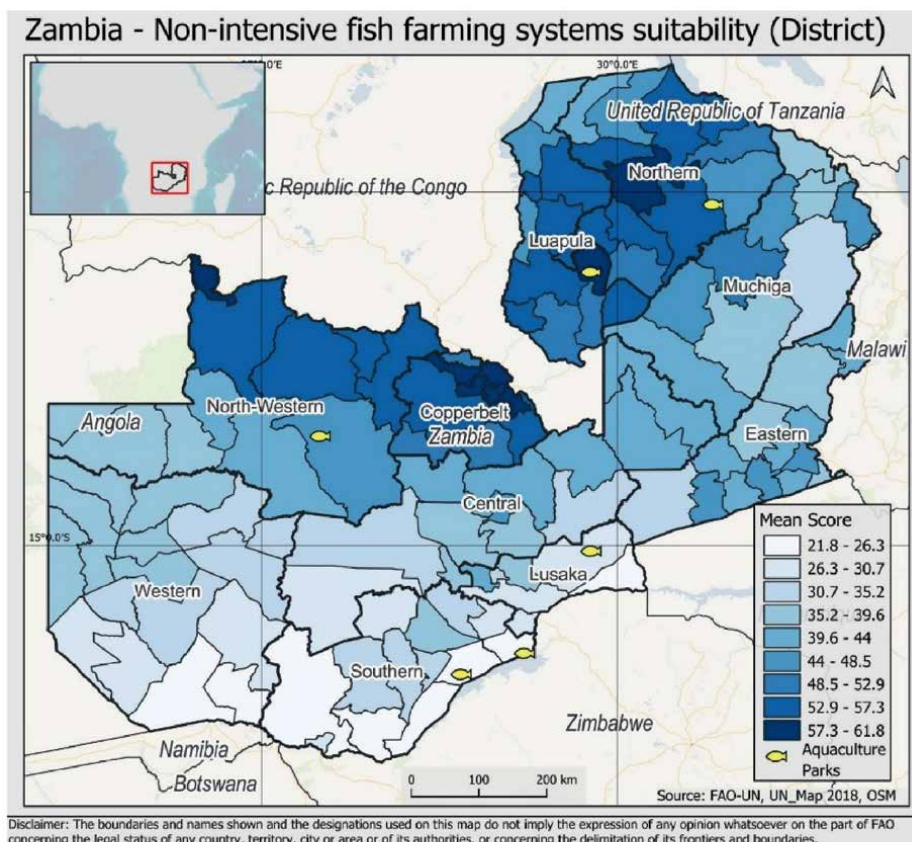


Figure 10.
 Average suitability.

The case for the open tilapia cage systems is significantly different since it depends on the existence of permanent waterbodies. Suitability index zonal statistics are extracted for the permanent waters using a buffer and the maximum index value for each polygon, and the water bodies are ranked and selected (recommended) using a high percentile (**Figure 13**).

8. Discussion

The analyses have clearly contributed to broadening the scope of agrifood systems and AgroInformatics geospatial analytics, integrating biophysical modeling data with socioeconomic factors into decision support tools focused on spatially enabled planning. This holistic approach can be considered a significant step forward.

However, the adoption of GIS-MCE in decision support frameworks has not met the anticipated levels. Stakeholder engagement in spatial collaborative decision-making and planning remains weak. The use of GIS-MCE mapping outputs, for investment planning and identifying investment opportunities, has fallen short of expectations, with only a few notable exceptions.

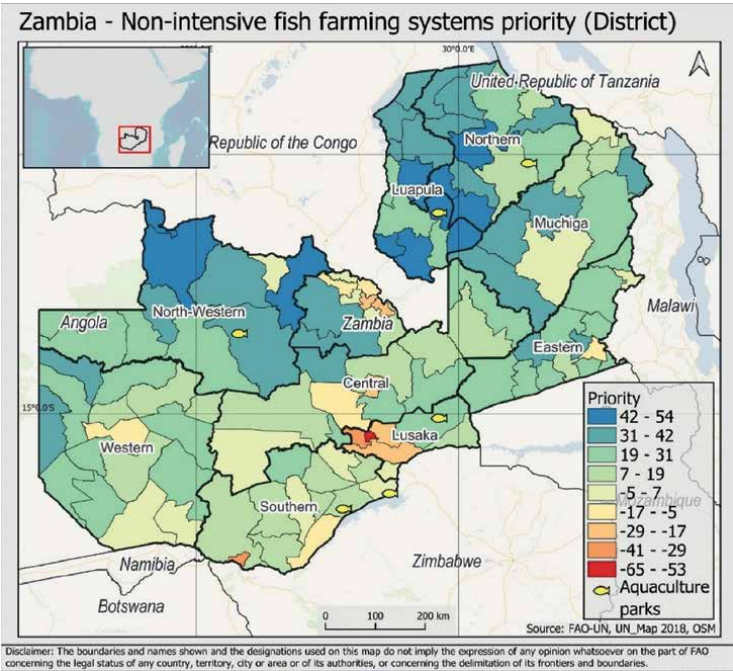


Figure 11.
Non-commercial system priority.

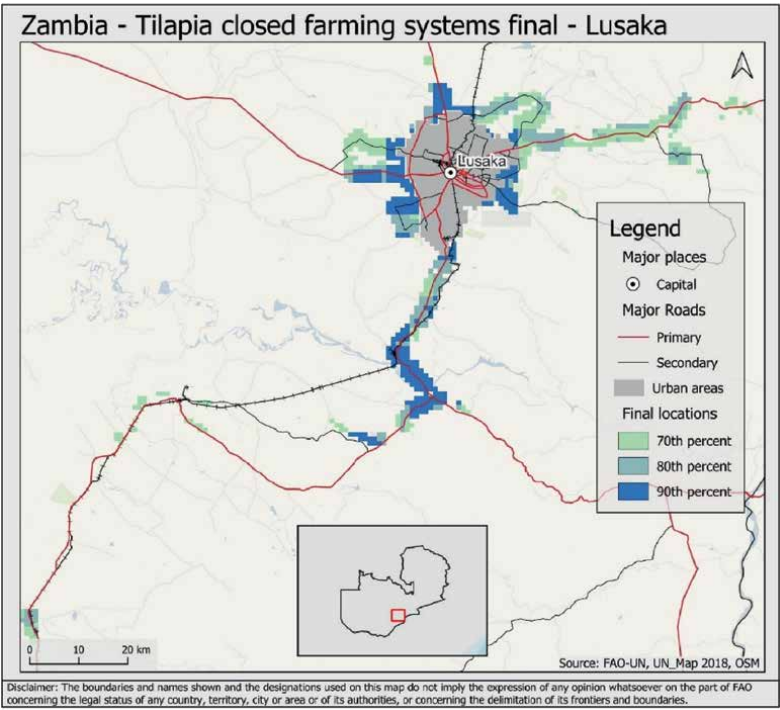


Figure 12.
Final locations closed farming systems.

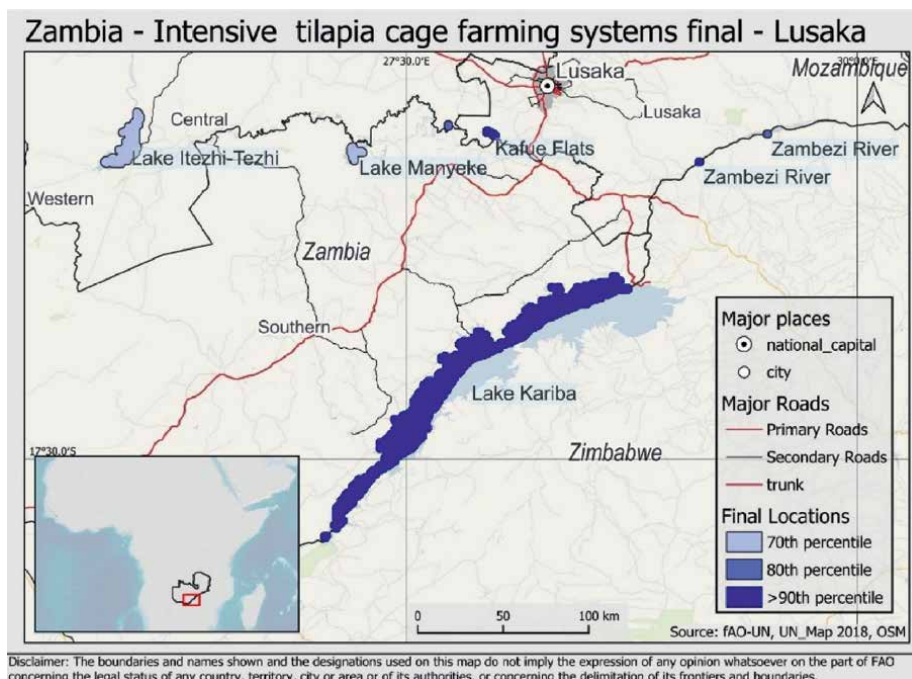


Figure 13.
 Recommended location open systems.

These advanced methodologies have demonstrated notable benefits, underscored by successful case studies and proactive requests from certain nations for sustained assistance. However, challenges persist. Key limitations include gaps in data quality—specifically spatial and temporal resolution, accuracy, and completeness—as well as insufficient organizational capacity to maintain consistent collaboration with country teams and government stakeholders across all phases of the processes. Strengthening knowledge transfer to ensure countries adopt and apply methodologies, data, and outcomes remains a priority. Furthermore, social, cultural, and political dynamics present barriers to engagement, though these elements are inherently complex to assess and quantify. Addressing these areas is critical for enhancing effectiveness and fostering long-term ownership.

Policy and practice are increasingly aware of the availability and benefits of geospatial data and approaches. Decision-makers are becoming more cognizant of what can be achieved, along with the benefits and limitations. However, further development in analysis and research should address the limitations caused by insufficient engagement with decision-making processes and local stakeholder expertise.

9. Conclusions

This chapter detailed the analysis undertaken under the scope of the FAO Hand-in-Hand initiative, applying social and economic geography and geo-AgroInformatics methodologies and perspectives, to support decision-making in agrifood systems-related challenges, with the aim to accelerate agricultural and rural development through targeted investments and partnerships.

The general geospatial analysis modeling research methodology was described, starting from the research question and literature review. It illustrates how geographic information systems are applied to sub-modeling criteria representing supply, demand, logistics, and poverty factors that influence infrastructure intervention locations. Multi-Criteria Evaluation is used to calculate suitability indexes that are then filtered with Boolean constraints to identify final recommended regions or sites.

The GIS-MCE methodology is applied to different agrifood systems interventions, including crop warehousing, storage, or aggregation centers; livestock dairy processing or slaughterhouses; and suitability assessments for different fish farming systems, ranging from small-scale non-commercial and integrated systems to intensive commercial systems. Location decisions involve a set of alternatives and multiple assessment criteria. GIS-MCE proposes a method to convert and combine spatial data, and decision-makers criteria to attain evidence for an informed decision. More importantly, it delivers a process, an auditable and replicable model, improving communication, offering diverse problem and solution standpoints, and helping refining specification and/or criteria.

The GIS-MCE modeling process theoretically pursues a three-stage hierarchy: intelligence, design, and choice.

- a. *Intelligence phase*: Data are acquired and processed, and exploratory data analysis is performed.
- b. *Design phase*: This involves formal modeling and the development of a solution set of spatial decision alternatives.
- c. *Choice phase*: Location alternatives are selected using specific decision rules to evaluate and rank the options.

It is important to note that these three stages do not necessarily follow a linear path.

From a critical standpoint, while data analysis and evidence gathering through GIS modeling can support decision-making processes, it is important to recognize that a more complex set of contextual and dynamic socioeconomic, political, cultural, ethno-anthropological aspects, and power relations shape and govern most spatial/location decision-making.

Modeling is also only as good as the input data. Quality and reliability determine the extent to which conclusions can be trusted, and these are as sound as the analysis conducted. From this perspective, specifications and objectives define assumptions and approximations, which can always produce distinct answers [27] (1).

Data are both social and material; they do not merely represent the world but can actively produce it. They are not just raw material for information and knowledge and do not exist independently of the ideas, techniques, technologies, people, and contexts that produce, process, manage, analyze, and store them. Positionality is always present, even when “data speaks for itself” [28] FAO’s mandate is clear: The Organization “leads international efforts to defeat hunger. Our goal is to achieve food security for all and make sure that people have regular access to enough high-quality food to lead active, healthy lives.” It is from this perspective that we should interpret technical endeavors, whether, or not, they can be considered scientific.

The research uses a well-documented approach to suitability mapping, employing a multi-criteria-based decision model that combines indicators into a single measure,

aligned with the objectives of the decision-making process (considering supply, demand, and infrastructure/accessibility). Each project essentially uses the same MCE approach—a geospatial site suitability analysis. This involves identifying an objective, setting criteria, and then scoring and weighting the factors in an additive model applied to various agrifood system challenges.

Preference modeling techniques include criterion weighting and Boolean logic in the application of constraints. Constraints can be biophysical (e.g., flood areas, excessive slope) or socioeconomic (e.g., access to ITC, finance, or distance to major roads).

A series of geographical data management, geoprocessing, and analysis components are applied in data exploration, with statistical and mathematical modeling techniques used to create the modeling data inputs.

Results consistency can sometimes be assessed by overlaying existing country data on value chain infrastructure or national policy/planning instruments that define high-priority and suitable areas. Sensitivity analysis could be introduced in the results and outputs by changing weights, buffer distances, and comparing and validating the different outputs.

There are several known methods for Multi-Criteria Decision Analysis (MCDA), such as the analytic hierarchy process, the analytic network process, the best-worst method, and others. However, the HiHI multi-criteria evaluation did not explore these methods. While providing mapping tools to differentiate territories and identify opportunities, the suitability assessments aim to demonstrate the use of data evidence and geographic information systems in support of intervention planning, and to prepare the stage for monitoring and evaluation. The process is proposed to participating countries and is intended to be a starting point for discussions. Although the mapping outputs can be particularly useful, they are meant as conversation starters. Stakeholder consensus measurement methods were not developed; criteria and constraints were defined and weighted following literature review and internal discussions.

It must be recognized that in the suitability assessments, the MCDA methodology is not properly applied. It does not consider decision-makers' preferences, and there are no stakeholder consultations in defining criteria or decision rules. The projects do not engage in spatial collaborative decision-making and planning, lacking both the deliberative dimension (consensus building) and the analytical dimension (generating a collective solution). This limitation should be understood in the context of organizational constraints, including resources and delivery timelines, which frame collaboration and coordination within the HiHI, FAO, country offices, and governments.

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Conflict of interest

The author declares no conflict of interest.

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Perspective Chapter: Advancements in Conventional Composting Techniques for Organic Farming

Chaichi Devi and Meena Khwairakpam

Abstract

Organic farming is a critical dimension for achieving the United Nations Sustainable Development Goals (SDGs), particularly those related to increasing agricultural productivity and ensuring food security. Over the past decades, various technologies, both mechanical and chemical, have been adopted to enhance efficiency in agricultural production. However, these advancements have had significant negative impacts on human health and the environment, such as soil quality degradation, pollution, and bioaccumulation of toxic elements in ecosystems. Theories and experimental findings have raised awareness among scientific communities, experts, citizens, and policymakers about the need for alternative solutions. This chapter examines conventional farming techniques practiced for centuries and highlights how recent research has led to the development of chemical-free, value-added products for soil enhancement, agriculture efficiency, and sustainable production. It also explores advancements in conventional techniques, such as large-scale composting, bioconversion of materials, and the combination of multiple technologies.

Keywords: organic farming, conventional techniques, composting, soil quality, sustainable development

1. Introduction

The advent of civilization gave rise to many traditional technologies, with farming emerging as one of the most essential occupations since the earliest human settlements. The domestication of wild plants for cultivation and consumption marked the beginning of agriculture. Various physiological and morphological characteristics distinguish domesticated species from their wild relatives.

Agriculture began nearly 10,000 years ago in regions located around 30°N and 30°S latitude, mostly in areas rich in biodiversity. Human evolution has been closely tied to various inventions, including those that transformed agricultural practices. The Neolithic Revolution marked a significant transition in biological, physical, chemical, and environmental aspects of human life.

According to the Food and Agriculture Organization (FAO) land use database, agriculture accounts for 38% of global land use. Many of the world's most famous natural landscapes, such as Tuscany in Italy and the Yunnan Province in China, have been used for agricultural purposes. Sophisticated agricultural practices have enabled food surpluses, economically stratified and complex societies, and technologically advanced farming methods. However, these advancements have come at an ecological cost, including habitat fragmentation, biodiversity loss, soil contamination from chemicals, and emission of greenhouse gases (GHGs) [1].

The United Nations Sustainable Development Goals (SDGs) for 2030 indirectly emphasize the importance of organic farming. SDG 2: Zero Hunger aims to eradicate global hunger by 2030. Food insecurity over the past few decades has been driven by a combination of natural and anthropogenic factors, with 9.2% of the global population experiencing chronic hunger as of 2022, an alarming statistic. This challenge not only hinders the achievement of SDG 2 but also impacts other SDGs. Livelihoods, health, malnutrition, and food insecurity are all linked to food availability and access.

Research continues to focus on achieving SDG2 by improving both production and consumption patterns of food [2]. These efforts require support from all stakeholders, along with incentive-based strategies and studies. A multidimensional approach is crucial to addressing hunger. This includes fostering inclusive practices with local communities, promoting sustainable farming in rural areas, implementing effective waste management in urban regions, and enacting government policies.

Organic farming is one potential approach to achieving global food security and nutrition. It focuses on restoring soil nutrition through chemical-free methods that promote plant growth. By its very nature, organic farming supports a food chain and food web free from harmful chemicals, reducing the risks of bioaccumulation and biomagnification [3, 4]. In addition, organic farming is aligned with global sustainability efforts, such as the European Green Deal. Under this initiative, the target is to increase organic farming land from 7–25% by 2030, supported by various promotional activities. These goals must be achieved without hindering crop yield or local biodiversity [5].

Composting is an age-old technique used to produce organic manure. Traditionally, organic debris was piled in open heaps or pits and left to degrade naturally, resulting in a soil quality enhancer for agricultural use. Scientific investigations into composting came much later, though traditional knowledge of this practice is documented in various literature [6]. The major investigation involves the nutrients in compost. Compost is derived from various substrates by various methods.

Composting involves stabilization of organic waste materials through biotechnological processes. Aerobic decomposition, occurring in the presence of oxygen across various temperature profiles, leads to humification, which is the transformation of organic matter into nutrient-rich hummus that plants can absorb. Both environmental and internal factors play critical roles during the composting process [7].

Recycling organic waste for agriculture purposes dates back more than 5000 years, as noted in Chinese literature. In the twentieth century, modern research on composting built on traditional knowledge, evolving through trial and error to become a promising technology both economically and environmentally. The demand for composting research surged due to the growing burden on landfill sites and the need for alternative organic waste management solutions. In addition, soil quality deterioration due to the use of chemical fertilizers highlighted the importance of eco-friendly approaches. Composting offers an environmentally friendly solution for manure production, mitigating GHG emissions associated with chemical fertilizer production and application [8].

2. Objectives

There is a lack of comprehensive documentation linking traditional composting to modern composting technologies. This chapter aims to address this gap. The major objective is to discuss advancements in different composting technologies as a method for organic farming. The chapter analyzes traditional composting techniques, which have formed the basis for the development of modern practices. The chapter also includes a detailed study of modern composting technologies adopted worldwide.

3. Methodology

The methodology adopted for this study is based on an extensive literature survey. The chapter provides insight into the available documentation to establish a link between traditional methods and current composting technologies. The strategy involves searching for and analyzing published works. We selected studies randomly and conducted a qualitative analysis of various findings and discussions from the collected articles.

4. Discussion and findings

4.1 Century-old technology

The history of composting history dates back centuries. The practice was associated with early farming and waste management at the beginning of civilization. Often referred to as “black gold,” compost is valued for its ability to enhance soil quality by replenishing essential nutrients. Composting is a natural process with a rich historical background, as shown in the literature. Some of the earliest discoveries were accidental, while others came from careful observations. Documentation, however, only began with more recent studies.

Early populations used natural fertilizers, as evidenced by archeological findings that indicate plants were grown on heaps of rotting organic debris. Many early civilizations used organic residues as fertilizers. For example, soil amendment pits made from decomposed organic debris were discovered in Sumerian cities dating back to around 6000 BC, ancient Scottish cities around 5000 BC, and the Minoan-Mycenaean civilization during 1800–1200 BC. Apart from this, additional archeological evidence and written records describe composting as a usual practice for agriculture.

In Mesopotamia, during the Akkadian empire (2350 BC) in present-day Iraq, clay tablets inscribed with details about compost preparation for farming were discovered [6]. Similarly, the emergence of Western civilizations in the pre-Renaissance era marked the use of composting as a solution to waste management. During this period, the daily transportation of food and goods into settlement areas led to an accumulation of waste. Ancient Roman cities pioneered early waste management systems, periodically collecting city waste and applying it to adjacent agricultural lands. The same practice was also evident in Florence, Italy.

Historical battles in Europe devastated arable land, and barren plots in Spain, France, and other countries were rented for cultivation. Techniques to restore the quality of depleted soil, documented in the archives of the National Library in Madrid from the thirteenth century, closely resemble conventional composting methods practiced in the twentieth century [7].

The methodologies outlined in these documents are very similar to modern wind-row composting. The basic preparation begins with careful attention to the characteristics of the substrate material and its ratio to amendments. Key parameters such as particle size, moisture content, and the diameter of materials had to be meticulously observed, according to these early documents.

Although the scientific explanations in historical documents were not detailed, the documentation reflects a foundational understanding of composting biology, soil fertility, and agronomy. This early knowledge contributed to the development of advanced composting technologies in the twentieth century [7, 8].

If we examine the history and regional evolution of composting, it is evident that its development was shaped by various factors. In the early period, as hunting communities transitioned to farming, one of the first observations was how plants grow. Early farmers used fertile soils rich in biodiversity, flourishing with wild plants. The domestication of these plants for food crops marked the beginning of prolonged land cultivation. At that time, natural fertilizers were the only means to replenish soil nutrients for prolonged cultivation.

Ancient Chinese and Hindu scriptures mention the use of organic soil enhancers, which later inspired modern proponents of organic farming. Similarly, ancient Americans used natural fertilizers for crop development. The methodologies of composting varied across regions depending on climate, geography, and soil properties [6, 9].

The Scottish were among the first to use compost to improve small-scale farms. In Mesopotamia, during the Akkadian Empire of the Stone Age, clay tablets recorded compost preparation methods. These references provide insight into the importance of organic manure for cultivation. The Scottish practice in situ composting in pocket heaps for small plots rather than large fields. Greek and the Mesopotamian farmers practiced recycling of agricultural waste in between crop cycles. Chinese farmers pioneered anaerobic composting (without oxygen) to fertilize their paddy fields, while Native Americans practiced sheet composting in their fields.

Soil fertility was not only a matter of agriculture but also a political concern. Many early American leaders, such as George Washington and Thomas Jefferson, emphasized the value of compost. Jefferson, who noticed the depletion of soil nutrients after intensive cultivation, emphasized the need for restoration [6, 10]. These leaders often built sheds for manure preparation adjacent to their fields, and farming practices as well as natural fertilizers were part of regular discussion.

A milestone in the history of composting occurred in 1933 with Sir Albert Howard's research on soil management in India. This marked the transition from conventional to modern composting. Sir Howard, in collaboration with colleagues, developed a method called the Indore process. This process involves stacking biodegradable materials in the open to return nutrients to the soil. The method incorporated both aerobic and anaerobic composting, akin to pile composting. Subsequent modifications to the Indore process focused on maintaining aerobic conditions by frequent turning and accelerating degradation to reduce composting time.

Based on those studies, many other advancements in composting methods were made in Malaysia, New Zealand, Africa, and India. One such method was the Bangalore process. Simultaneously, research in China contributed to the development of improved composting methods [6, 7].

The major advantage of historical evidence and early documentation is the emergence of new agricultural technologies in the twentieth century. Currently, the world is seeking solutions for food security and a sustainable future in the face of population

explosion, overexploitation of natural resources, soil degradation, and pollution. The middle centuries witnessed adverse impacts from the use of chemicals in agriculture.

Two theories evolved simultaneously around the nineteenth century. The Leibig Law of Minimum, proposed by German chemist Justus Von Leibig, states that plant growth can only be promoted by supplying limited, water-soluble nutrients to the soil, primarily nitrogen, phosphorus, and potassium (NPK). Nitrogen-based fertilizers are prominent plant-growth promoters compared to natural fertilizers [11].

The rapid emergence of chemical fertilizer manufacturing units sought to replenish soil nutrients and meet the food production demands of a growing global population. However, the widespread adoption of chemical fertilizers came with consequences, as their adverse effects were well documented by many researchers over time [12]. Research during this time mostly focused on chemical methods, whereas the values of organic fertilizer were overshadowed.

The early twentieth century presented additional challenges, as the demand for food increased due to overpopulation and increasing urban migration. A notable catastrophe was the Dust Bowl in the United States during the 1930s, caused by poor farming practices and recurring droughts. Land degradation is not only associated with chemical use but also various mechanical and physical agricultural practices. The Dust Bowl was caused by excessive plowing, which eroded the topsoil [13]. The loss of native grasslands weakened the land's ability to retain moisture. Millions of acres of natural grasslands were plowed to expand cultivation, making the soil more vulnerable to wind erosion during dry conditions.

The introduction of tractors further contributed to soil compaction and degradation. Criticism of the Dust Bowl was directed at poor soil management and blame was placed on farming practices. This catastrophe served as an alarming reminder for a holistic approach to farming practices, combining scientific research and sustainable methods to address natural and -based farming practices to address natural and anthropogenic disasters [6].

4.2 Emergence of advanced technology

Recent developments in composting technology in the twentieth century are a combination of traditional practices, modern techniques, technical expertise, and scientific knowledge. The major driving force behind recent research on composting is to reduce reliance on chemical inputs in farming. Numerous studies have highlighted the adverse effects of chemical fertilizers and pesticides on the environment and human health [14].

One of the most successful initiatives was the NYC Compost Project in the United States, launched in 1993. This project aimed to educate citizens about composting, its benefits, and the management of food and yard waste at the household level. This initiative was meant to address the heavy burden of organic waste on landfills while encouraging the reuse of waste as a resource for personal gardens and farms [15]. Present-day concepts like recycling, green economies, and circular economies were reflected in similar projects across the world. Composting is often seen as a practical embodiment of the zero-waste concept.

In addition, composting has emerged as a critical tool in addressing global challenges such as climate change and GHG emissions. Recent research indicates that compost produced using modern methods offers greater nutritional value compared to traditional composting. Technological advancements have also addressed common challenges in composting, such as foul odors, leachate management, and maintaining compost

quality. Major achievements include the development of low-cost technologies, shorter processing time, and the capability to handle large quantities of waste. These advancements make modern composting technologies more practical than traditional methods.

The methods adopted for composting depend on the societal structures of their time. Initially, when cities had not yet expanded, agricultural waste was composted on-site and recycled back into the same fields. However, with urban sprawl, the volume of municipal waste has increased significantly. Today, this waste is processed at facilities within municipal areas and monitored by local authorities. The compost is then sold locally through commercial outlets.

There is huge potential for the growth of small-scale industries based on composting, particularly through public-private partnerships (PPP). Industrial waste, which often includes large amounts of bio-waste, also presents a significant opportunity. Ongoing research is exploring methods for composting various types of industrial waste. Currently, major emphasis is placed on both the economic and technological aspects of composting. Economic turnover has proven beneficial for industrial bio-waste management, with profitability depending on compost quality, government subsidies, and market value [16].

Raw materials can either be sold to composting units or processed in composting facilities, generating substantial profits. Composting could capture a large share of economic growth if managed properly. Scientific and technological advancements in recent decades are paving the way toward a sustainable environment. However, successful implementation depends on the policies and regulations set by concerned stakeholders, including researchers, farmers, government bodies, industrialists, entrepreneurs, and citizens.

4.2.1 Types of substrates

Organic materials of all kinds are suitable for composting. The characteristics of the substrate often determine the type of composting method used. In the past, waste was typically homogenous, with one specific type of material being processed. Today, however, most waste generated in municipal areas is heterogenous due to industrial development and urbanization. Over time, the diversity of waste has grown, prompting experiments with various types of biomass for bioconversion processes.

The types of bio-waste from industry depends on the raw materials used. For example, waste from the paper industry is different from waste from the sugar industry. It is important to evaluate the quality of compost produced, as it is directly influenced by the characteristics of the substrate material. Research has shown promising results in the quality of compost derived from recycling various sources [17–20].

The agricultural sector also generates significant amounts of bio-waste as an byproduct of various farming processes. This waste has been used at various levels to produce soil enhancers. The major advantage of agri-based bio-waste is that it can be recycled directly at the source and applied on site [21].

4.2.2 Role of bulking agent

The composting process is complex. Recent research has highlighted various factors that influence the biodegradation of organic matter, including particle size, pH, temperature, and moisture. Detailed studies show that parameters such as free air space and other physical characteristics play a role in determining the quality of compost. All these parameters must be monitored to ensure an efficient composting

process. The carbon-to-nitrogen (C/N) ratio of the substrate is particularly important, as it directly affects the final nutritional quality of the soil enhancer.

A bulking agent is a material that improves the composting process by enhancing biodegradation kinetics, maintaining free air space and equilibrium of C/N ratio for the smooth functioning of degradation process. Early research in the twentieth century focused on identifying and analyzing various bulking agents. The selection of bulking agents depends on factors such as regional availability, cost, and the desired C/N ratio based on substrate characteristics. Ideally, bulking agents should possess sufficient carbon content, capacity to balance moisture by absorption, and appropriate physical properties. Their addition improves aeration and facilitates gaseous exchange, enhancing the composting process.

Initially, most bulking agents were agricultural byproducts [12, 22, 23]. Bulking agents not only help to maintain aerobic condition by allowing free-flowing oxygen but also prevent the release of GHGs such as methane and nitrous oxides. One important bulking agent is biochar, which is hot topic of current research. Biochar has been shown to sustain a micro-ecosystem during composting which accelerates the activity of methane-reducing microbes like *Methylococcaceae*. This microbial shift reduces methane emissions [24]. Thus, these advancements position composting as a viable zero-emission technology.

The addition of bulking agents influences the physicochemical characteristics of the compost matrix. By altering nitrogen pathways, bulking agents help reduce the nitrogen loss during the process. This helps in maintaining the final nitrogen content, which is essential for replenishing soils that have been depleted of nitrogen due to intensive agricultural practices [25].

4.2.3 Large-scale technology

Rapid urbanization has increased the need to manage large volumes of waste effectively. The composting process, being time-intensive, often struggles to handle the overload of organic matter in small-scale compost pits, particularly in home yards, near farming sites, and in industrial contexts. Technological advancements have introduced various large-scale composting techniques to process large quantities of waste. These advancements also offer significant economic benefits. Common large-scale composting methods include static pile, windrow, and in-vessel composting.

One challenge in large-scale composting is determining the optimal mixing ratio and environmental conditions for effective biodegradation. Batch studies using different combinations in various composting processes have proven essential for identifying optimized conditions for large-scale operations [26]. These pilot-scale studies are important for promoting bio-economy initiatives and supporting organic farming at a larger scale.

Rotary drum in-vessel composters are an advanced mechanical composting technology. These systems can process large amounts of waste directly at the source. They can be installed in a decentralized manner at the local level. Compared to traditional open composting methods, the compost maturation period in rotary drums is significantly reduced. Pilot-scale studies have demonstrated rotary drum composting to be a suitable technology for biodegrading various types of bio-waste [26, 27].

Recent engineering advancements in in-vessel composting have addressed problems like degradation inefficiencies, limited space, and the need for continuous agitation and aeration. One novel innovation is mechanically enhanced dynamic composting (MEDC) technology. This process resolves issues related to intensive

agitation through a stratified fermentation method. The system prevents premature discharge by promoting partial microbial activity. With a retention period of just 15 days, this approach allows for efficient processing and produces a nutrient-rich compost product with distinct zonation, ideal for soil enhancement [28].

4.2.4 Combined technology

The efficiency of composting technology is enhanced through the integration of multiple technologies. The combination of various methods has proven to be effective in managing diverse types and quantities of waste in recent years. By compensating for the limitations of one technology with the strengths of another, this integrated approach offers a more versatile and efficient solution. Depending on the methodology, these combined technologies are referred to as either co-composting or pre-composting.

Co-composting involves combining different substrates to balance their physicochemical properties before the composting process begins. The inclusion of specific materials creates optimal conditions for bioconversion within the composting unit. Over the past several decades, significant research has been conducted on the co-composting of diverse biomass, with ongoing exploration continuing to refine these methods [29–32].

In contrast, pre-composting focuses on the partial degradation of substrates using various pretreatment methods to speed up the subsequent composting phase. This is particularly beneficial for lignocellulosic biomass, which is difficult to degrade. Pretreatment methods break down the complex lignin molecules in such materials, producing partially degraded substrates that are more readily processed by microbes. This approach enables efficient nutrient release within a shorter timeframe once the material enters the composting unit [33, 34].

4.2.5 Vermitechnology

Vermicomposting is an advanced biotechnological composting process in which earthworms are used for the bioconversion of organic matter. Earthworms have a special mechanism for breaking down organic molecules and play a vital role in improving soil quality in nature. These surface-dwelling organisms mostly feed on leaf litter, although they are capable of processing a diverse range of organic substrates.

This concept was first mentioned by Charles Darwin in his book, *The Formation of Vegetable Mold Through the Action of Worms with Observations on Their Habits*, in which he famously states that all fertile soil on Earth must have passed through the guts of earthworms [3]. Historical records from ancient civilizations also emphasize the importance of earthworms in maintaining soil fertility. For example, Queen Cleopatra of Egypt, around 50 BC, declared it a punishable offense to remove worms from the soil. Egyptian, Roman, and other ancient histories all recognize the value of earthworms and their conservation.

In modern times, author Mary Appelhof highlighted the potential of earthworms in her book, *Worms Eat My Garbage*, demonstrating how organic waste can be transformed into valuable products with the proper methodology [6]. Today, earthworms not only play an essential role in natural ecosystems but also contribute significantly to modern waste management practices. Research in bio-waste management using earthworms has established vermicomposting as a promising and effective method.

The modern application of this process, referred to as vermitechnology, produces vermicompost, which is an end product of higher quality than traditional compost [35].

Lab-based research has advanced our understanding of creating ideal environments for various earthworm activities, studying their lifecycle, and exploring their role in converting various bio-wastes. These contributions have been instrumental in advancing composting technology in recent times [36–43].

Vermicompost replenishes soil, plant growth and serving as a sustainable alternative to chemical fertilizers. Encouraging the adoption of decentralized vermicompost facilities in rural areas with low-cost capital investment is essential for promoting organic farming. Proper guidelines and policies for these facilities can further enhance the use of vermitechnology in sustainable agriculture.

4.2.6 Major findings

The discussions in this chapter have led to several key findings. The advancement of composting technologies, based on traditional knowledge, represents a significant milestone in the evolution of composting process. Various contemporary challenges can be resolved with the adoption of various composting methods.

The benefits of composting extend far beyond its use as a fertilizer. It offers solutions to numerous pressing issues, including social, environmental, and economic challenges. For instance, the composting process can play a critical role in mitigating climate change at a local level. By replacing chemical fertilizers with organic manure such as compost, greenhouse gas emissions can be significantly reduced.

Advancements in composting technologies and their effective implementation are important for promoting sustainable agriculture. These emerging technologies, inspired by traditional practices, provide a pathway to achieving food security without compromising health or the environment. Compost application serves as a natural soil enhancer, enabling the restoration of depleted soil quality caused by intensive farming. It replenishes vital nutrients in the soil, thereby revitalizing land for crop production.

Composting also offers economic benefits, particularly for marginal farmers, by reducing costs and providing opportunities for economic gains. At the local level, decentralized composting facilities, alongside large-scale operations, have the potential to become profitable enterprises. Such initiatives create opportunities for small-scale entrepreneurs and contribute to sustainable economic growth.

5. Conclusion

The overall conclusion of this chapter is based on a comparative qualitative analysis of literature spanning several decades. The collection of articles, chapters, and published texts highlights the significant advancements in composting processes, which were once considered an ancient practice. The true value of composting has only been fully recognized through the advancements in research and technology over recent decades.

Composting has proven to be a versatile solution for addressing various social, economic, and environmental challenges of our time, either directly or indirectly. Its low-cost nature and the ability to recycle biowaste into a valuable resource make composting an integral component of the circular and green economy.

Conflict of interest

The authors declare no conflict of interest.

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Section 2

Advanced Technologies and Innovations in Agriculture

Development of Machine Learning Models for Predicting Soil Texture Variables through Hyperspectral Imaging

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Abstract

Soil texture is a crucial property that can provide insight into its productive capacity. However, determining soil texture can be a complex and time-consuming process. To address this challenge, we aimed to develop machine learning (ML) models that could predict the composition of sand, clay, and silt in soil based on hyperspectral imaging (HSI) data. We collected and analyzed 500 soil samples and processed the HSI data by masking samples with reflectance and transforming the texture variables with Box-Cox. We also employed various techniques, such as moving average, Savitzky–Golay filtering (SG), first and second derivatives (FD and SD), gap-segment (GS) with FD and SD, standard normal variate (SNV), SNV with detrending (DT), SNV-SG, multiplicative scatter correction (MSC), and GS-DT for the covariates. We applied cubist models (CUB), principal component regression (PCR), partial least squares regression (PLSR), and artificial neural networks (ANN). A total of 1240 models were obtained. For clay, the models with the best performance in the TRAIN and TEST sets were a CUB-tuned model, where $R^2\text{-TEST} = 0.93$ and the test root-mean-square error (RMSE-TEST) = 3.63%. For silt and sand, CUB models without refinement were selected, with $R^2\text{-TEST}$ values of 0.63 and 0.61 and RMSE-TEST of 5.55 and 8.65%, respectively. In conclusion, clay prediction with HSI is feasible if purified spectra are used, with outlier detection techniques, evaluation in the overlap zone, and transformations such as GS-FD. The models for silt and sand prediction are not recommended due to their low performance.

Keywords: algorithms, clay, cubist models, hyperspectral cameras, partial least squares regression, principal component regression, sand, silt, soil physical properties, spectral technology, transformation techniques

1. Introduction

Texture is a critical physical property of soil that influences various aspects of soil health, such as air permeability, moisture retention, nutrient availability, water movement, and overall productivity [1]. It is determined by the proportion of soil particles smaller than 2 mm in size, including sand (0.05–2 mm), silt (0.002–0.05 mm), and clay (<0.002 mm) [2]. The traditional methods for determining soil texture, such as the Bouyoucos method, can be time-consuming and expensive [3–6], taking up to 2 hours per sample [1].

In response to these limitations, new methodologies based on spectral technology [7], remote sensing [8], and laboratory sensors [9] have emerged as an alternative. Among these, hyperspectral imaging (HSI) stands out as a highly promising technology that enables the simultaneous analysis of both spectral and spatial data, in comparison to near-infrared spectroscopy systems that only provide spectral information [10]. These features may enhance the capability to efficiently execute predictions for soil texture in a shorter period, improving the overall workflow time to carry out multiple soil analyses at the laboratory level [11].

Achieving soil texture through HSI requires preliminary processing of the obtained information. It is important to homogenize the soil sample before capturing the image, as the soil can exhibit considerable variability even within the same geographical location. This pretreatment aims to increase the signal-to-noise ratio of the images and improve the quality of the data before its use in soil property prediction [12]. Various transformations can be applied to the spectral data to remove noise, correct for scatter, and standardize the spectra, including moving average (MA), Savitzky–Golay filtering (SG), standard normal variate (SNV), multiplicative scatter correction (MSC), detrending (DT), and derivatives.

For instance, the MA transformation involves averaging neighboring wavelengths within each window size [12]. The SG transformation employs both a window size and a designated degree polynomial to smooth the spectrum effectively [12, 13]. Additionally, as outlined by [14], the SNV transformation is also known as the *z*-transformation or the centering and scaling of spectra, where every spectrum is adjusted to have a mean of zero and a standard deviation of one by subtracting the mean of the spectrum from each data point and dividing the result by the standard deviation of the spectrum. This method is employed to rectify scattering effects that are dependent on wavelength. Another normalization method known as MSC, addresses the variable scattering effect in the spectra influenced by sample sizes as well as irregular distribution in powder samples [15].

Additionally, the DT transformation aims to remove the mean value or linear trend from the spectra [12]. It also enables the normalization of an individual sample in a matrix by applying the SNV transformation and fitting a *p*-order polynomial [13].

Regarding the first derivative (FD), Ref. [14] stated that this method also removes the baseline from the spectra and highlights the absorption characteristics. On the other hand, the second derivative (SD) is used for eliminating background noise and distinguishing overlapping signals. Algorithms such as the gap-segment (GS) can extract vibrational information from the spectra and improve the robustness of the models [16]. This is accomplished by smoothing a segment, applying a derivative of a specified order, and using a gap size [17].

Although pretreating the data through several transformations can improve the quality of the raw spectra (RAW), the data can still exhibit high dimensionality and

complexity, which can result in multicollinearity and make it difficult to determine the individual effect of the covariates on the dependent variable [18]. For this reason, various algorithms within the field of artificial intelligence (AI) and machine learning (ML) have been developed to address these challenges.

Some algorithms, such as principal component regression (PCR) and partial least squares regression (PLSR), reduce the dimensionality of the information through principal component analysis (PCA). The latter is unique in a way that maximizes the covariance between the scores of the X and Y variables [19].

Other algorithms, such as artificial neural networks (ANN), are helpful in HSI analysis [20, 21]. Artificial neural networks (ANN) consist of an input layer, one or more hidden layers, and an output layer. The number of hidden layers and the number of neurons in each layer should be designed based on the number of input and output variables to mitigate issues such as underfitting, high statistical bias, or overfitting [22]. In contrast, tree-structure algorithms, such as Cubist (CUB) are rule-based models, where each branch depends on a condition based on linear regression, and the results are adjusted by committees (like boosting) and the nearest neighbor algorithm [23]. To evaluate and compare the models built with these algorithms, it is important to use evaluation metrics commonly employed in AI.

According to Ref. [24], the coefficient of determination (R^2), root-mean-square error (RMSE), and the ratio of performance to deviation (RPD) are the most reported evaluation metrics in the scientific literature for predicting soil physicochemical properties. Additionally, the mean absolute deviation (MAD) and the mean absolute percentage error (MAPE) are useful for evaluating the accuracy of the predictions made by the models [25]. Regarding the application of wet chemistry in soil analysis, the physicochemical analyses of soil provide insight to determine some fertility parameters, but they require considerable time, specialized personnel, and the use of chemical reagents, which in turn generate waste. For this reason, spectrophotometric methodologies offer an alternative that will not replace wet chemistry but can help reduce the number of analyses conducted using those techniques, as well as contribute to mitigating the environmental impact they produce. Given these considerations, our objective was to develop machine learning models to predict the percentage of sand, clay, and silt based on HSI. To do so, we first prepared and processed the physical soil samples and then built the database for training and evaluating the models.

2. Materials and methods

2.1 Study site, sampling, and texture determination

In this study, we analyzed the textural information of soil samples obtained from November 2020 to November 2021, totaling 500 samples collected from various subregions in Antioquia, Colombia. These subregions included: North (118 samples), Northeast (93 samples), East (42 samples), West (35 samples), Southwest (36 samples), Urabá (173 samples), and Aburrá Valley (3 samples) (see **Figure 1**). Each collected sample was mixed and homogenized to ensure uniformity. Drying was conducted for 48 hours at 40°C, followed by sieving to a size of 2 mm. Half of each sample was then sent to a wet chemistry laboratory, where the content of clay, silt, and sand was determined using the Bouyoucos sedimentation method as stipulated by Ref. [1]. This methodology was based on previous studies conducted by authors such as [26].

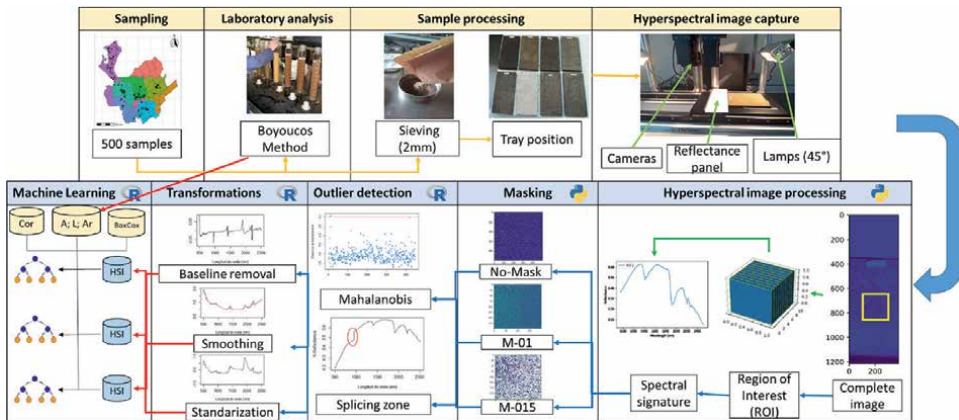


Figure 1.

Flowchart for the processing of physical samples, hyperspectral image capture (HSI), treatment of sand, silt, and clay data, and construction of Machine Learning models.

2.2 Capture and extraction of hyperspectral information

In this study, each dry soil sample was placed in a $10 \times 20 \times 1$ cm acrylonitrile-butadiene-styrene (ABS) plastic tray for analysis using a plain plastic surface to homogenize the sample and avoid shadows within the image. The necessary lighting conditions were achieved using HySpex lamp units with integrated sensors, operating between 400 and 2500 nm. Moreover, reflectance values were corrected using a Zenith LiteTM Diffuse Reflectance Target 50%R SG31XX calibration panel, which maintains a reflectance of 50% from 250 to 2500 nm on average.

The HSI was then captured using two hyperspectral cameras: the HySpex Baldur V-1024 N and the HySpex Baldur S-384 N. The first camera covers the visible and near-infrared (VNIR) regions, with a range of 485–955 nm, a spectral resolution of 5.40 nm (88 bands), a spatial resolution of 3289×1024 pixels, and a field of view measuring 9.33 cm. The second camera covers part of the NIR and short-wave infrared (SWIR) regions, with a range of 951–2517 nm, a spectral resolution of 5.45 nm (288 bands), a spatial resolution of 1216×384 pixels and a field of view of 9.47 cm.

After completing the image capture process, we extracted the reflectance in the VNIR and SWIR ranges in a region of interest (ROI) by selecting coordinates within the images, avoiding the inclusion of the reflectance panel, container, and areas with limited samples. All images were cut, and the average of all pixels in each band or layer was calculated to construct the representative spectral signatures of the entire image (**Figure 2**). This process facilitated the iterative spectra extraction process for the same ROI in all images using the *Spectral* [27], *NumPy* [28], and *Python 3.8.2* libraries [29]. Moreover, pixels with reflectance values below 10 and 15% were masked, as the spectral signatures from the same sample showed differences of 0.16 and 0.41 when subjected to the Euclidean Distance test [12]. As a result, three databases (No-Mask, M-01, and M-015) were obtained, which served as inputs for creating the prediction models.

2.3 Outlier detection

We applied the Mahalanobis distance measure to the principal components (PCs) that retained up to 97% of the variance, as recommended by Ref. [12], and eliminated

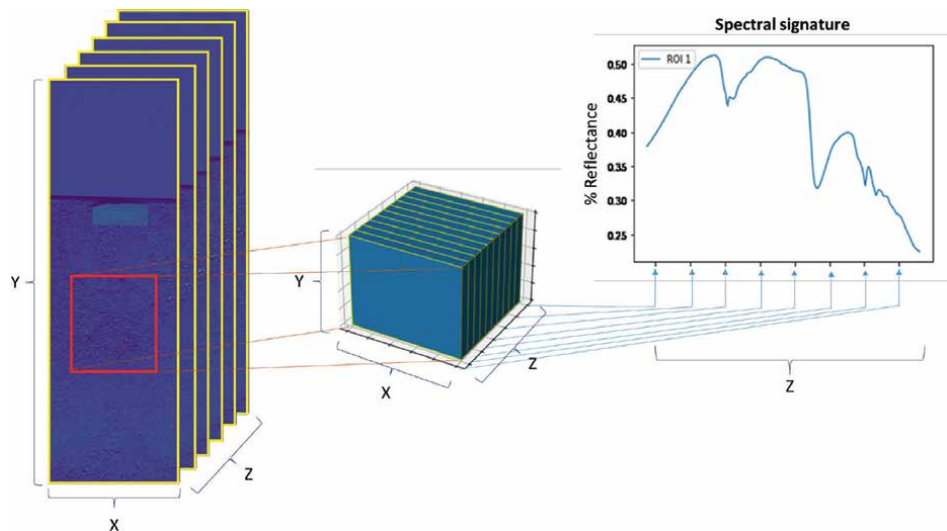


Figure 2.
Extraction of a region of interest (red box) and obtaining the corresponding spectral signature of the pixels that compose the image.

spectra with distances greater than three. Overlapping bands were identified using the *Spectrolab* library developed by Ref. [30] and the R programming language, a free and open-source tool for statistical computing [31, 32]. Our goal was to eliminate the 951 nm band in the junction region between 945 and 960 nm since it was the band that appeared duplicated at the junction of both images, VNIR and SWIR. As a result, the VNIR camera recorded spectra ending in band 955 and the SWIR camera starting in band 957. However, an anomaly was observed in the reflectance levels at the junction point (**Figure 3**), prompting an analysis of the difference between the 957 and 955 nm bands. Spectra exhibiting differences of less than -0.055 and greater than 0.097 were identified as missing values and subsequently discarded.

2.4 Training and evaluating ML models for soil texture prediction

The variables sand, silt, and clay were transformed using the Box-Cox technique [33] and incorporated into nonparametric models based on neural networks [34].

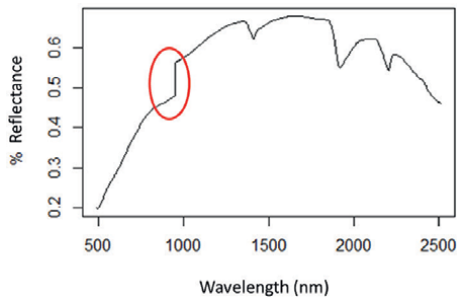


Figure 3.
Anomaly in the junction region between the VNIR and SWIR cameras in soil samples from productive systems in Antioquia.

These models were used to predict edaphic components through regression trees [35], and with the use of PLSR [36] and PCR [37], optimization of massive data processing in Big Data was facilitated [38]. The lambda values obtained for sand, silt, and clay were 1.4, 0.35, and 0.55, respectively. These lambda values make the data have a normal distribution, in addition to minimizing their standard deviation.

The raw spectra (RAW) were transformed into absorbance values (ABS) and further processed with MA, SG, FD, SD, and GS with FD and SD, SNV, SNV-DT, SNV-SG, MSC, and GS-DT transformations, using the *prospectr* library developed by Ref. [17]. The PCR, PLSR, CUB, and ANN algorithms were applied to bands with moderate to high correlations (-1 to -0.5 or 0.5 to 1) among the clay, silt, sand content, and spectral bands. These algorithms have been widely used in the scientific literature to predict various soil characteristics using spectral or multidimensional data [39–44].

Considering that hyperparameters are the parameters used to configure a model before training [45] and the optimal selection requires time and computational resources [46], to simplify the result extraction process, the hyperparameters for the PCR and PLSR models were standardized using 10-fold cross-validation (CV) with a maximum of 30 PCs based on their evaluation metrics.

The ANN model's structure was determined according to Ref. [22], with several hidden neurons between the size of the input and output layers, comprising 2/3 of the total size of the input layer, but less than twice its total length. A structure of two rules and 50 committees' structure was used to build the CUB models, considering that hyperparameter tuning by CV for each model would consume too many computational resources and its iterative application would be infeasible for many models. The best-performing models were identified and refined to improve their predictive capacity.

2.5 Total number of models and their evaluation

Three variables were evaluated using two approaches: untransformed using Box-Cox (STB) and transformed using Box-Cox (TB). The covariates included 13 approximations, including RAW, ABS, DT, FD, SD, GS-FD, GS-SD, GS-DT, MSC, MA, SG, SNV, and SNV-SG. This process was replicated in three databases with different masking techniques (No-Mask, M-01, and M-015), resulting in 936 models built using four algorithms (ANN, CUB, PCR, and PLSR). Only the bands with moderate to high correlations (-1 to -0.5 or 0.5 to 1) were used in the analysis, resulting in 468 models and a total of 1404 models.

Based on the literature review of previous research, the data set was divided into two groups [47]. The models were tested using the same hyperparameters and a split dataset (75% for training and 25% for testing) to streamline the process and extract results. The PCR and PLSR algorithms were implemented using the *pls* library [48], the cubist algorithms using the *Cubist* library [49], and ANN using the *h2o* library [50] in R. Models were evaluated using RMSE, R^2 , RPD, MAPE, MAD, and overfitting (the difference between training and testing results), which are metrics reported in recent literature [24, 51].

3. Results and discussion

3.1 Characterization of the samples used in this study

The textural fractions of the soils included in this study (**Table 1**) vary in terms of range but have similar meaning values for clay and silt. The soils were classified as

Fraction	Mean	SD	Min	Max	Range
Clay	27.80	13.43	3.14	64.00	60.86
Sand	44.70	14.40	5.74	80.91	75.17
Silt	27.50	9.08	8.05	61.99	53.94

Table 1.
Composition of the textural fractions of the soils belonging to productive systems in Antioquia.

sandy loam (0.22%), clay (19.46%), sandy clay (2.23%), loam (15.43%), sandy loam (21.25%), silt loam (1.11%), clay loam (15.65%), sandy clay loam (23.93%), and silty clay loam (0.67%).

The classification and distribution of the samples within the textural triangle, particularly those with extreme values, may impact on the training of the predictive models. This is demonstrated by the differing results obtained in this study compared to those reported by [52, 53], where most of the samples were classified as clay (Figure 4).

3.2 Bands correlated with each variable, masking, and transformation

For identifying bands with moderate correlations between the clay, silt, sand content, and spectral bands, we considered only bands or ranges with values greater than 0.5 or less than -0.5 . A limited number of regions in the electromagnetic spectrum showed moderate correlations for sand, regardless of the transformation used. However, the M-01 and M-015 images were more effective in finding more correlated ranges using the FD, SD, GS-FD, GS-SD, GS-DT, and SG transformations compared to No-Mask images (Table 2).

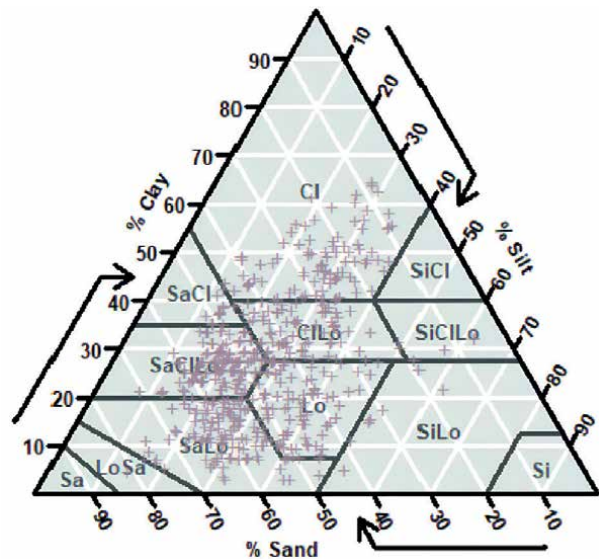


Figure 4.
Distribution of soil samples from productive systems in Antioquia within the textural triangle (Retrieved from Soil Science Division Staff, SSDS, 2017 [54]).

Transformation	Bands with moderate correlation
FD	M-01: 1442, 1917–1933, 2321, 2326; M-015: 1917–1933, 2321, 2326
SD	M-01: 1933, 1944; M-015: 1933, 1939
GS-FD	M-01: 1923–1933, 2321–2332; M-015: 1923–1933, 2321, 2326
GS-SD	M-01 and M-015: 1890, 1895
GS-DT	M-01 and M-015: 1923–1933, 2261
SG	M-01: 1437, 1917–1933, 2315, 2321; M-015: 1917–1928, 2315, 2321
SNV-SG	No-Mask: 1923, 2321; M-01: 1431, 1437, 1917–1933, 2315–2332; M-015: 1431, 1437, 1912–1933, 2315–2326

Note: Individual bands or portions of the spectrum are separated by commas, and ranges are separated by dashes. FD = first derivative; SD = second derivative; GS-FD = gap-segment-FD; GS-SD = gap-segment-SD; GS-DT = gap-segment-detrending; SG = Savitzky–Golay filter; SNV-SG = standard normal variate-SG; No-Mask = reflectance values without masking; M-01 = reflectance values <10% with masking; M-015 = reflectance values <15% with masking.

Table 2.

Bands with moderate to high correlations with the sand variable, according to the transformations and masking used for the soil samples from productive systems in Antioquia.

On the other hand, sand and silt showed a higher number of ranges with moderate to high correlations (**Table 3**), using transformations such as FD, SD, GS-FD, and GS-SD for baseline removal and transformations such as SG, SNV, and SNV-SG for smoothing. Masking was also significant in discovering correlations in various regions of the spectrum.

In contrast to the previous two variables, when all transformations were used, more bands were found to be correlated with clay content, except for the RAW data (**Table 4**). Although using ABS and MA resulted in less correlated ranges in the VNIR

Moderate to high correlation bands based on transformation and masking techniques for silt			
Transformation	No-mask	M-01	M-015
DT	2043, 2190–2212	2179–2212	2168–2217
FD	1420, 1813, 2081, 2103–2114, 2124–2163, 2201–2217, 2392–2403	1420, 1813, 2103–2114, 2124–2163, 2201–2217, 2348, 2392–2403	1420, 2108, 2124–2163, 2201, 2212, 2392–2403
SD	1399, 1410, 1420–1431, 1475, 2141, 2146, 2201, 2212, 2223, 2234, 2305, 2326, 2343, 2359, 2386	1399, 1410, 1420–1431, 1475, 2141, 2146, 2201, 2212, 2223–2234, 2261, 2305, 2343, 2359	1410, 1420, 1431, 2146, 2201, 2212, 2223, 2234, 2359
GS-FD	793–815, 1797, 1802, 2086–2168, 2184, 2190, 2397	2092–2168, 2184, 2190, 2397	2097–2163
GS-SD	1475, 1480, 2119–2135, 2184–2201, 2228–2239, 2288, 2294, 2359–2386	733, 1202, 1208, 1475, 1480, 2119–2141, 2184–2201, 2228–2239, 2359–2386	1197–1208, 2119–2135, 2184, 2190, 2228–2239, 2359–2386
GS-DT	766, 793–809, 1410, 2097–2168, 2184, 2190	1835, 1841, 2103–2168, 2184, 2190, 2212, 2217	1835, 2103–2163, 2184, 2190, 2212, 2217
MSC	2146–2463	2152–2217	

Moderate to high correlation bands based on transformation and masking techniques for silt			
Transformation	No-mask	M-01	M-015
SG	815, 1300, 1410, 1420, 1808, 1813, 2081, 2097–2114, 2124–2157, 2195, 2201, 2212, 2386–2397	1300, 1410, 1420, 1808, 1813, 2103–2114, 2124–2157, 2195, 2201, 2212, 2217, 2348, 2386–2397	1410, 1420, 2103, 2108, 2124–2157, 2195, 2201, 2212, 2386–2397
SNV	2146–2468, 2485	2146–2397	2146–2392
SNV-SG	1388, 1410, 1420, 1781, 1813, 2108, 2124–2157, 2195, 2201, 2212, 2217, 2261, 2305, 2343, 2348, 2392	1410, 1420, 1808, 1813, 2103, 2108, 2124–2157, 2195, 2201, 2212, 2217, 2261, 2343, 2348, 2386–2397	1300, 1344, 1349, 1410, 1420, 2097–2108, 2124–2157, 2195, 2201, 2212, 2217, 2343, 2348, 2386–2397

Note: Individual bands or portions of the spectrum are separated by commas, and ranges are separated by dashes. DT = detrending; FD = first derivative; SD = second derivative; GS-FD = gap-segment-first derivative; GS-SD = gap-segment-second derivative; GS-DT = gap-segment-detrending; SG = Savitzky–Golay filter; SNV = standard normal variate; MSC = multiplicative scatter correction; No-Mask = reflectance values without masking; M-01 = reflectance values <10% with masking; M-015 = reflectance values <15% with masking.

Table 3.
 Bands with moderate to high correlations with the silt variable, according to the transformations and masking used for the soil samples from productive systems in Antioquia.

Moderate to high correlation bands based on transformation and masking techniques for clay			
Transformation	No-mask	M-01	M-015
ABS	539–815		
MSC	566–696, 2375–2512		
MA	539–815		
DT	593–712, 1404–1420, 2059–2141	652–760, 1399–1426, 2075–2135	739–750, 771–798, 1399–1426
FD	517–631, 766, 787, 793–825, 836, 842–967, 1737, 1742, 1835, 1923, 1928, 2163, 2179–2195, 2315, 2321	523–577, 593, 598, 809–820, 847–869, 879, 890–901, 912, 923–934, 939, 944, 962, 1431, 1737, 1742, 1770, 1835, 1917–1933, 2163, 2179–2195, 2315, 2321	847–863, 890–901, 928, 934, 1431, 1737, 1742, 1917–1928, 2179–2195, 2315, 2321
SD	1933, 2152	1442, 1928–1944	1442, 1933, 1939
GS-FD	517–571, 750–934, 1819, 1824, 2163–2195, 2310–2343	517–587, 798–934, 1388, 1393, 1431–1442, 1819–1830, 1923–1933, 2163, 2168, 2174, 2179–2195, 2310–2343	852, 858, 928, 934, 1819–1830, 1923, 1928, 2168–2184, 2195, 2310–2343
GS-SD	566–614, 782, 896, 901, 1022–1115, 1410, 1415, 1726–1737, 2053, 2059, 2141, 2283, 2288, 2436, 2441	571–587, 782, 787, 798, 1028–1109, 1371, 1404–1420, 1721–1742, 1890, 1944–1955, 2048–2070, 2141, 2217, 2283, 2288, 2436, 2441	782, 1055–1104, 1410–1420, 1726–1742, 1944–1955, 2048–2064, 2141, 2217, 2283, 2288, 2436
GS-DT	523–577, 658, 663, 690, 696, 760, 793–934, 1426–1453, 1912–1928, 2168–2195, 2310, 2315, 2332–2370	533–571, 798–934, 1420–1453, 1644–1671, 1699–1715, 1906–1933, 2168–2195, 2305–2370	847–934, 1426–1453, 1650–1666, 1704–1715, 1906–1933, 2168–2195, 2305, 2310–2370

Moderate to high correlation bands based on transformation and masking techniques for clay			
Transformation	No-mask	M-01	M-015
SG	512–566, 625, 760, 787–820, 836–944, 1732–1742, 1830, 1835, 1917, 1923, 2163, 2179, 2184, 2190, 2310, 2315, 2354	517–571, 593, 598, 804–815, 842–939, 1404, 1426, 1732–1742, 1830, 1835, 1917–1928, 2163, 2179–2190, 2310–2321	847–863, 890, 896, 923, 928, 1404, 1732–1742, 1835, 1917–1928, 2163, 2179–2190, 2310–2321
SNV	571–712, 2343–2512	658–674, 690–804, 2397–2512	777–831
SNV-SG	512–571, 798–820, 842–896, 906–934, 1393, 1404, 1426, 1732–1742, 1759–1770, 1830, 1835, 1868, 2163, 2179–2195, 2310, 2315, 2337–2381, 2414–2430, 2474–2485	523–571, 593, 598, 804–815, 842–863, 885–901, 912, 923–934, 1404, 1426, 1431, 1732–1742, 1764, 1770, 1835, 1917–1928, 2163, 2179–2195, 2310–2321, 2337, 2354, 2370, 2425	847–863, 890, 896, 923–934, 1404, 1426, 1431, 1732, 1737, 1742, 1764, 1835, 1917, 1923, 1928, 2163, 2179, 2184, 2190, 2195, 2310, 2315, 2321, 2337, 2354

Note: Individual bands or portions of the spectrum are separated by commas, and ranges are separated by dashes. DT = detrending; FD = first derivative; SD = second derivative; GS-FD = gap-segment-first derivative; GS-SD = gap-segment-second derivative; GS-DT = gap-segment-detrending; SG = Savitzky–Golay filter; SNV = standard normal variate; MSC = multiplicative scatter correction; MA = moving average; No-Mask = reflectance values without masking; M-01 = reflectance values <10% with masking; M-015 = reflectance values <15% with masking.

Table 4.
Bands with moderate to high correlations with the clay variable, based on transformations and masking techniques employed for soil samples from productive systems in Antioquia.

region using No-Mask images, the FD, GS-FD, GS-SD, GS-DT, and SNV-SG transformations stood out from the rest due to a higher number of detected regions. This may be due to the electrical charge of clay, which behaves as a colloid, as opposed to sand and silt which are inert components [1], indicating that light interacts with the clay component differently.

3.3 Models for predicting texture variables

A total of 1240 models were obtained, which is fewer than the initially calculated 1404 models. This reduction occurred because not all bands exhibited moderate correlation in the transformations of the raw spectra, as discussed earlier. Consequently, a varying number of models was obtained for each textural variable, as illustrated in **Figure 5**, through the utilization of masking techniques.

The performance of the models can be evaluated through the distribution of the R^2 -TEST metric (**Figure 6**). In this case, the CUB and PLSR models showed relevant results with values greater than 0.70 for clay, 0.50 for sand, and 0.55 for silt. The PCR models performed best for the clay variable, while no model achieved a value greater than 0.60 for the other textural variables. The ANN models displayed low generalizability, as no result exceeded 0.60 for any variable, indicating that they are not effective in predicting textural variables. Additionally, the CUB and PLSR models for the clay variable had RMSE-TEST values less than 10% in most cases. For sand, 100% of the models had RMSE-TEST values greater than 7.5%, while for silt, most models had RMSE-TEST values less than 7.5%.

Referencing the review by Ref. [24], the R^2 values obtained in the present study for clay were lower than the average reported in at least 115 articles on the prediction of

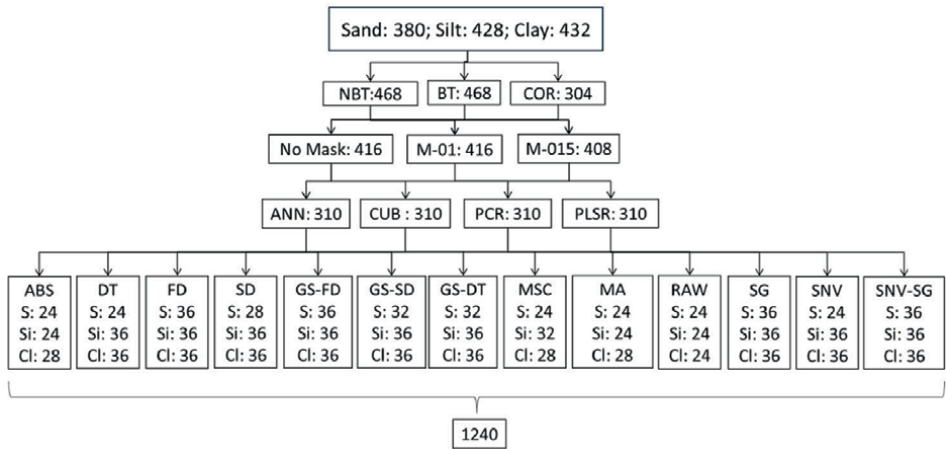


Figure 5. Number of models generated for sand, silt, and clay variables, with Box-Cox transformation (BT) and without Box-Cox transformation (NBT), correlated bands (COR), masking (No-Mask, M-01, M-015), utilizing artificial neural networks (ANN), cubist (CUB), principal component regression (PCR), and partial least squares regression (PLSR), trained using ABS, DT, FD, SD, GS-FD, GS-SD, GS-DT, MSC, MA, RAW, SG, SNV, and SNV-SG transformations for soil samples from productive systems in Antioquia.

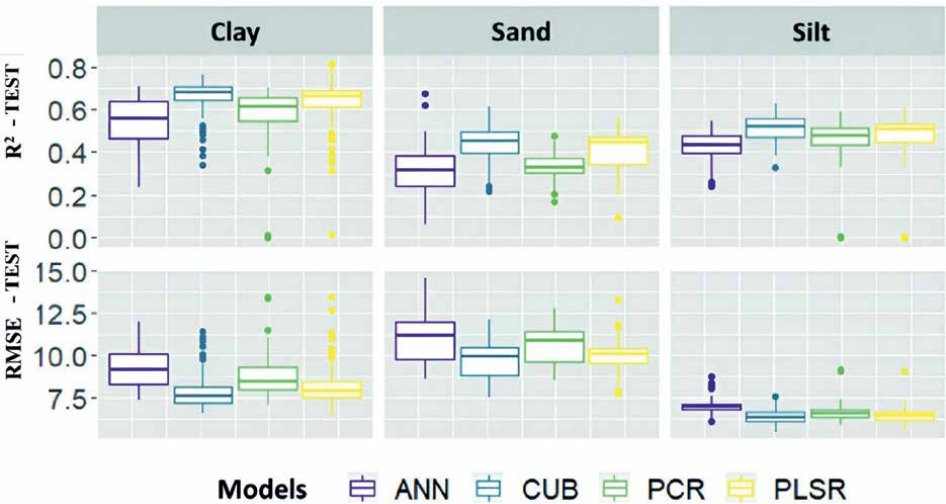


Figure 6. General distribution of R^2 -TEST and RMSE-TEST for clay, sand, and silt in soil samples from productive systems in Antioquia, employing cubist models (CUB) and models based on artificial neural networks (ANN), principal component regression (PCR), and partial least squares regression (PLSR).

edaphic variables ($R^2 = 0.8$). However, some approximations using PLSR were found to be above this average. The values obtained for sand and silt were below the mean reported by Ref. [24], which was $R^2 > 0.6$ for both variables.

Concerning overfitting, as indicated by the R^2 and RMSE values on the TEST set, the models had low generalization capacity when tested with unseen data, particularly for the ANN and PLSR models used to predict sand (Figure 7). The above may be due to the number of samples used for training, the structure chosen for the ANNs,

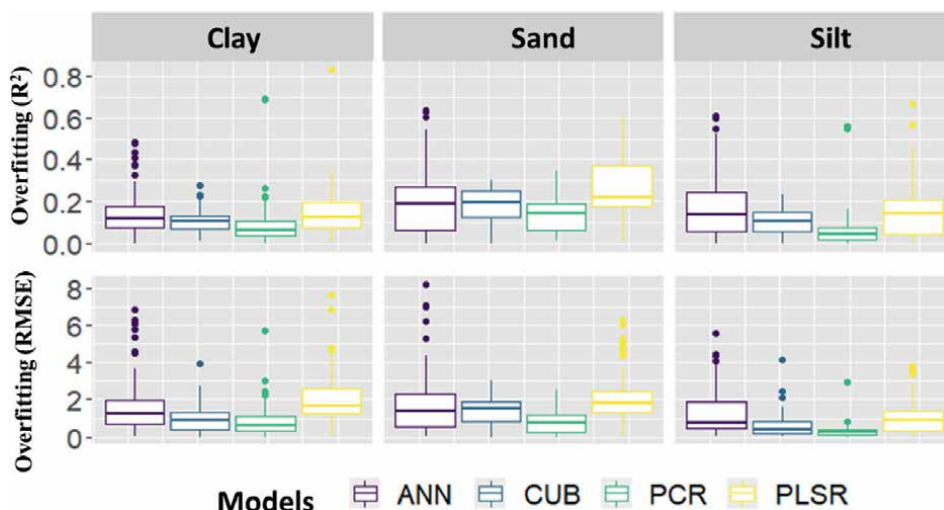


Figure 7.

Distribution of overfitting of R^2 and RMSE on TEST sets for clay, sand, and silt models using soil samples from productive systems in Antioquia, employing cubist models (CUB) and models based on artificial neural networks (ANN), principal component regression (PCR), and partial least squares regression (PLSR).

and the hyperparameters selected before the individual training of each model. For clay and silt, the CUB and PCR models had R^2 values less than 0.2 and RMSE values less than 2% on the TEST sets, with lower overfitting for silt compared to the other variables, suggesting that the selected structure for building these models is adequate in reducing overfitting.

The values obtained for the RPD metric for the evaluated models were classified as “very poor” (0–1.9) for sand and silt, and “poor” (2–2.4) for clay, according to Ref. [51]. Furthermore, according to Ref. [24], the values obtained correspond to “unsuccessful” models (< 1.5) for sand and silt and can only “detect high and low values” (1.5–2) for clay. Some clay models, however, had “approximate quantitative predictions” (2–2.5), which was common among most models for this variable, with almost all having an RPD less than three. It can therefore be concluded that the selection of hyperparameters and model training techniques is not optimal for this metric.

Regarding the MAD metric, the models with the best performance corresponded to silt, as almost all of them (392) had values lower than six, indicating low dispersion in the results, and most of the models (409) had MAPE values below 0.25%, showing minimal variation. For sand, 276 models had MAPE values below 0.25%, but only four had MAD values below six. For the clay variable, only 118 models had MAD values below six, with the majority being CUB (69) and PLSR (34) models. Only 27 models had MAPE values below 0.3%. This implies that the models for silt had lower dispersion but also low predictive capacity.

We also evaluated the effect of the transformations on the performance of the models for the texture variables (**Figure 8**). For clay, the ABS, SD, MA, and SNV transformations and the raw spectra were found to increase variability in the R^2 -TEST results, with values ranging from 0.3 to 0.8. The FD, GS-FD, GS-SD, GS-DT, SG, and SNV-SG transformations showed a smaller range of R^2 -TEST values (0.5–0.7). The results for sand were similar, with the ABS, MA, and raw data exhibiting wide ranges in R^2 -TEST between 0.1 and 0.6. The GS-FD, GS-SD, and SG transformations showed

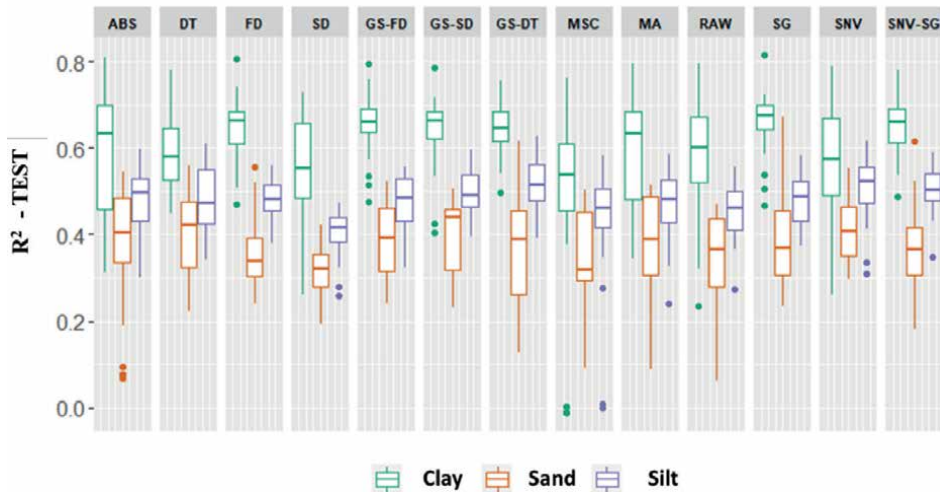


Figure 8.
Distribution of the determination coefficients (R^2) of the models with the absorbance (ABS), detrending (DT), first derivative (FD), second derivative (SD), gap-segment (GS), multiplicative scatter correction (MSC), moving average (MA), raw, standard normal variate (SNV) transformations for the variables: clay, silt and sand in soils test samples from productive systems in Antioquia.

a decreased overall range for R^2 -TEST, though there was not a significant improvement. For silt, all transformations showed less variability in R^2 -TEST compared to the previous variables, but values greater than 0.6 were only achieved with the GS-DT and SNV transformations.

On the other hand, the Box-Cox transformation on the textural variables did not have representative effects in general. However, when applied to clay together with M-01, the R^2 -TEST value increased, since 20% of the results were higher than 0.70 and corresponded to the ANN (1), CUB (13), and PLSR models (16). As for masking, the most marked effect was for clay with M-01, where most R^2 values were between 0.5 and 0.81. The other variables did not show a significant effect compared to the No-Mask group, as the R^2 -TEST performance did not improve according to the evaluation metrics, and the variability of the results remained similar.

3.4 Selection of the final models

Based on the evaluation metrics, including overfitting, RPD, MAD, MAPE, and predictive capacity in the test sets, 1240 models were filtered, and subsequently, five models were selected for each textural component (**Table 5**). For the silt and sand variables, the CUB models outperformed the PLSR models. For the clay variable, the PLSR models were more suitable for prediction due to superior R^2 , RMSE, RPD, MAD, and MAPE values, likely due to their ability to handle multicollinearity and extract latent values from variables. However, improving the fit of the PLSR models by modifying hyperparameters was limited, as it depends on the selection of principal components.

For the silt and sand variables, the CUB models performed better than the PLSR models, probably due to their ability to handle nonlinear relationships and multiple interactions between dependent variables. As a result, the best-performing CUB models were chosen for hyperparameter refinement using different committee numbers

Code	Mask	Var.	Alg.	Box-Cox	Trans	R ² -TRAIN.	R ² -TEST.	RMSE-TRAIN (%)	RMSE-TEST (%)	RPD-TEST	MAPE	MAD	COMP
1	M-01	Clay	PLSR	BT	ABS	0.84	0.81	5.18	6.66	2.28	0.24	4.85	29
2	M-01	Clay	PLSR	BT	GS-FD	0.83	0.80	5.32	6.84	2.20	0.24	5.00	28
3	M-01	Clay	PLSR	BT	MA	0.82	0.80	5.38	6.82	2.21	0.25	5.09	26
4	M-01	Clay	PLSR	BT	RAW	0.81	0.79	5.48	6.72	2.20	0.25	5.15	29
5	M-01	Clay	CUB	NBT	GS-FD	0.83	0.76	5.59	6.66	2.02	0.31	5.06	
1	No-Mask	Silt	CUB	NBT	GS-DT	0.64	0.63	5.53	5.55	1.64	0.19	4.42	
2	No-Mask	Silt	CUB	BT	GS-DT	0.67	0.61	5.79	5.51	1.61	0.18	4.37	
3	M-01	Silt	CUB	BT	GS-DT	0.71	0.61	6.40	5.61	1.59	0.18	4.41	
4	M-01	Silt	PLSR	NBT	DT	0.70	0.60	4.90	5.72	1.59	0.20	4.75	30
5	No-Mask	Silt	CUB	BT	GS-FD	0.57	0.59	6.32	5.59	1.57	0.19	4.37	
1	M-015	Sand	CUB	NBT	GS-DT	0.74	0.61	7.61	8.65	1.61	0.19	6.63	
2	M-01	Sand	PLSR	NBT	DT	0.72	0.56	7.66	9.22	1.52	0.18	7.57	19
3	M-01	Sand	CUB	NBT	FD	0.73	0.56	7.84	9.33	1.49	0.19	6.82	
4	M-01	Sand	PLSR	NBT	SNV	0.73	0.55	7.51	9.30	1.50	0.17	7.61	25
5	M-015	S	CUB	BT	GS-DT	0.72	0.55	6.63	7.45	1.50	0.19	5.70	

Mask = masking; M-01 = reflectance values <10% with masking; M-015 = reflectance values <15% with masking; Trans = transformations; MA = moving average; ABS = absorbance; SNV = standard normal variate; GS-FD = gap-segment-first derivative; RAW = raw data; GS-SD = GS-second derivative; GS-DT = GS-detrending; DT = detrending; FD = first derivative; BT = Box-Cox transformed; NBT = not Box-Cox transformed; RMSE-TRAIN = root-mean-square error in training set; RMSE-TEST = root-mean-square error in test set; R²-TRAIN = coefficient of determination in training; R²-TEST = coefficient of determination in test set; RPD-TEST = ratio of performance to deviation in test set; MAPE = mean absolute percentage error; MAD = mean absolute deviation; COMP = principal components.

Table 5.
Predictive models with superior performance based on the evaluation metrics for clay and silt.

and nearest neighbors across all textural variables, as this approach could offer greater flexibility for hyperparameter tuning.

The models selected for silt belong to M-015, M-01, and No-Mask groups, with differences less than 0.01 between R^2 -TRAIN and R^2 -TEST and between 0.01 and 0.06% between RMSE-TRAIN and RMSE-TEST. As a result, sand prediction was based on the difference between clay and silt using M-01 masking. This approach ensures that the workflow is not dependent on multiple masking applied to the original images, making the model more parsimonious and scalable for use in other regions.

3.5 Hyperparameter tuning in CUB models

The hyperparameter tuning process was conducted on models 5 for clay, 1 for silt, and 1 for sand using cross-validation (CV), with a range of 5, 10, 15, 20, 25, 30, 35, 40, 45, and 50 committees to prevent overfitting and a range of 0, 1, 5, and 9 nearest neighbors to enhance the model's predictive power. The results showed that the CUB models for silt and sand tended to overfit, regardless of the number of committees and nearest neighbors selected, as R^2 -TRAIN was greater than 0.95 and R^2 -TEST was less than 0.63, while RMSE-TRAIN was less than 1% and RMSE-TEST was greater than 5%. Therefore, model 1 was selected as the best model for both silt and sand.

For clay, the results indicated that using 45 committees and nine nearest neighbors as hyperparameters of the predictive model had a significant impact, yielding an R^2 -TRAIN of 0.94, R^2 -TEST of 0.93, RMSE-TRAIN of 3.30%, RMSE-TEST of 3.64%, RPD of 3.70, MAPE of 0.11, and MAD of 1.94 (**Figure 9**), which classifies it as “very good” according to Ref. [51] and “excellent” according to Ref. [24]. Models 1 (silt) and 2 (sand) would be classified as “very poor” [51] and only capable of “detecting high and low values” [24] respectively.

Considering that the most critical variables in a CUB model, defined as a linear combination of the use of the variable in the rules and models, are ranked according to the percentage of times that each variable was used inside a condition or linear model [49], the first 20 variables with more than 30% importance are shown in **Figure 10**. Furthermore, our findings reveal that the most significant bands for predicting clay are in the SWIR region (1431, 1437, 1912, 1917, 1928, 1939, 2174, 2179, 2310, 2315, 2321, 2326, 2337, and 2343). This could be attributed to the presence of vibrational groups OH and H₂O (1410 and 1920 nm), minerals such as Kaolinite (~2205 nm), Chlorite (1400 and 2300 nm), and Illite (~2350 nm), as reported by Ref. [55]. On the other hand, a lower proportion of bands from the VNIR region (550, 847, 852, 858, and 863) was found, which could be attributed to the low presence of minerals such as Hematite and Goethite, commonly found in the VIS region (400–700 nm), as reported by Ref. [55].

It is important to highlight that numerous studies have been conducted to determine soil texture using near-infrared spectroscopy (NIRS). For instance, Ref. [56] employed PLSR models and achieved R^2 values of 0.56 for clay, 0.87 for silt, and 0.94 for sand. Similarly, Ref. [57] utilized ANN and reported R^2 values of 0.35 for sand, 0.69 for silt, and 0.80 for clay. Additionally, Ref. [58] employed NIRS spectroscopy with PLRS models and obtained fits of 0.87 for clay, 0.60 for silt, and 0.80 for sand. Last, Ref. [5] applied CUB models to soil texture data obtained across the visible, near, and middle regions, yielding R^2 values of 0.94 for clay, 0.14 for silt, and 0.88 for sand.

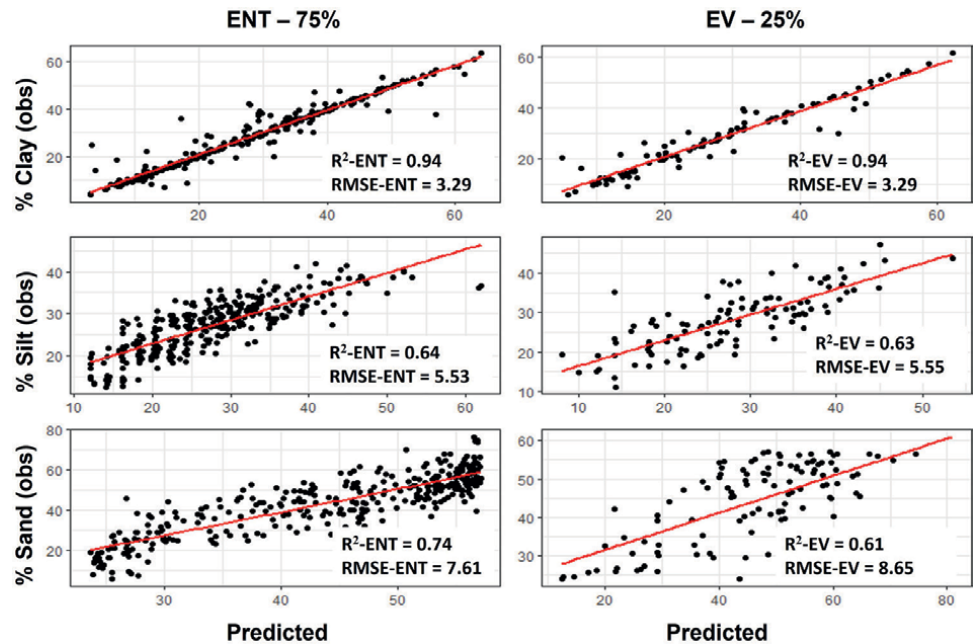


Figure 9. Performance of the models for predicting clay, silt, and sand on training (TRAIN) and validation (TEST) sets according to R^2 and RMSE.

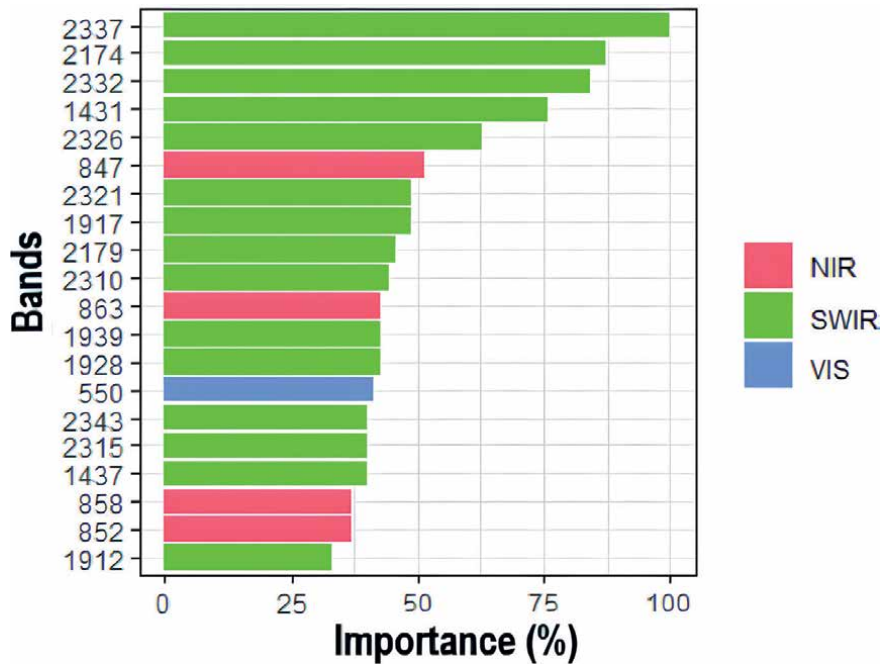


Figure 10. Bands with the highest percentage of importance within Model 5 for clay based on the use of variables in the conditions and models, sorted by the visible (VIS), near-infrared (NIR), and short-wave infrared (SWIR) regions.

4. Conclusions

The prediction of clay in soil using hyperspectral imaging (HSI) is feasible, as 93% of the variation can be explained by the CUB model with 45 committees and nine nearest neighbors. The above is achieved through the use of refined spectral signatures obtained from techniques such as Mahalanobis distance and evaluation of the VNIR-SWIR transition zone, as well as transformations such as GS-FD to remove the baseline on VNIR bands (550, 847, 852, 858, and 863) and SWIR bands (1431, 1437, 1912, 1917, 1928, 1939, 2174, 2179, 2310, 2315, 2321, 2326, 2337, and 2343). However, the models obtained for silt and sand variables are not recommended for the prediction of unknown data, as these models are classified as “very poor” and suitable only for “detecting high and low values”.

The models and equations derived from this research can serve as valuable references for calibrating equipment and optimizing soil texture analysis in agriculture.

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Conflicts of interest

The authors declare that there are no conflicts of interest.

Data availability

The University of Antioquia reserves the right to share the databases resulting from the Development and Establishment of the Center for Agrobiotechnological Development for Innovation and Territorial Integration, El Carmen de Viboral, Antioquia, Western subregion project (CEDAIT), since the method of organization of the different parts involved in its construction constitutes an original creation, and according to the Berne Convention, approved by Law 23 of 1982 and Law 33 of 1987 the databases are protected as ‘collective works’.

However, the programming used for hyperspectral image processing in Python is made available at the following link: <https://github.com/Mateoudea93/Hyperspectral-images-processing-in-Python>.

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Optimizing the Performance of a Wheeled Mobile Robot for Use in Agriculture

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Abstract

Utilizing wheeled mobile robot systems may be essential to solving some of agriculture's upcoming problems. The present state of wheeled mobile robot systems necessitates the development of an adequate controller algorithm due to their instability, which calls for a control mechanism to enhance stability. As such, much study is needed to address this issue. Currently, proportional, integral, derivative (PID) controllers are widely employed for this purpose; however, because of parameter variations or disturbances, the PID approach is often not acceptable. Some of the problems with PID controllers can be solved with alternative control strategies, such as linear-quadratic regulator (LQR) control. For this work, a four-wheel skid-steering mobile robot's kinematic model was created in order to evaluate the performance of LQR control. Three scenarios—only non-zero state expensive; control expensive, non-zero state cheap; and control cheap, non-zero state expensive—were analyzed using the capabilities of the wheeled mobile robot. Based on these circumstances, the peak time, settling time, and rising time for cheap control were determined to be 0.1, 7.82, and 4.39 s, respectively.

Keywords: wheeled mobile robot, agricultural robot, optimization, quadratic regulator, four-wheel skid-steering mobile robot

1. Introduction

One of the key challenges in the deployment of agricultural mobile robots is the optimization of path tracking, particularly given the diverse steering mechanisms employed by different robots. Research by Shamshiri and Redmond [1] addresses this issue by exploring various algorithms and control strategies to optimize the path-tracking performance of agricultural robots with different steering configurations, ensuring that these robots can navigate complex terrains with high precision, which is crucial for tasks such as planting, spraying, and harvesting. To support path optimization, the integration of advanced sensors, algorithms, and software is essential for the autonomous navigation of agricultural robots. According to Shamshiri and Redmond [2], the fusion of these technologies enables robots to perceive their

environment accurately, make informed decisions, and execute tasks with minimal human intervention. This comprehensive approach is fundamental to advancing the field of agricultural robotics, as it allows for the seamless operation of robots in dynamic and unpredictable farming environments. The broader implications of these advancements are highlighted in the study by Shamshiri et al. [3], which discusses how agricultural robotics is set to revolutionize farming. The chapter underscores the potential of robotics to transform agricultural practices by increasing productivity, reducing the need for manual labor, and enabling precision agriculture. This transformation is particularly significant in the context of global challenges such as food security and sustainability. The development of autonomous electrical tractors, as discussed in the study by Shamshiri and Redmond [4], represents another critical aspect of this revolution. These tractors are designed to operate autonomously, leveraging electric power to reduce environmental impact while maintaining high levels of efficiency. The shift toward electric and autonomous tractors is aligned with the broader goals of sustainable agriculture, offering a cleaner and more efficient alternative to traditional farming machinery. Moreover, the integration of modular sensing systems with communication protocols such as CANBUS, as described in the study by Shamshiri et al. [5], plays a crucial role in enhancing the navigational capabilities of agricultural robots. These systems provide real-time data to assist in navigation, ensuring that the robots can adapt to changing field conditions and perform their tasks with greater accuracy. The concept of the Internet of Robotic Things (IoRT), coupled with a local LoRa network, as explored in the study by Shamshiri et al. [6], introduces a novel approach to the teleoperation of agricultural robots. By utilizing digital shadows, this approach allows for remote monitoring and control of robots, further extending their operational capabilities and reducing the need for direct human intervention.

In the last 10 years, there has been a surge in research on wheeled mobile robot systems to address the intricate dynamics, uncertainties, and constantly changing disturbances that these robotic systems face [7]. Wheeled mobile robots are already used in many different fields, such as data collection and acquisition, logistics, monitoring forest fires, military and civilian surveillance, and wireless-powered communication networks (WPCN) [8]. As better qualities such as smaller size, capacity to navigate in small spaces, and less complex technology than other robotic systems develop, the number and variety of applications will only grow in the future [9].

Wheeled mobile robots, however, are more susceptible to many uncertainties and disturbances during operation; therefore, their control systems need to be robust, dependable, and functional [10]. The dynamics of wheeled mobile robots have been proposed to be regulated by various control systems. Linear control theories provide the basis for some of them, including the linear-quadratic regulator (LQR), proportional integral derivative (PID), and H-infinity. There have also been other systems established based on nonlinear control theories, such as sliding mode, backstepping, feedback linearization, and model predictive control (MPC) [7, 11, 12]. Furthermore, fuzzy logic and neural networks, as well as learning-based flight control theories, have been used in hybrid control to govern the dynamics of wheeled mobile robots. Based on minimizing a specific quadratic cost function, LQR is one of the best control strategies that has been extensively researched for controlling the dynamics of wheeled mobile robots. Two weighting matrices, Q and R , make up the quadratic cost function of the LQR controller; the Q is linked to variations in the state variable trajectories, while the actuator saturation and control effort are coupled with the R weighting matrix [13–15]. Since the Q and R weighting matrices are trade-offs by

nature and are usually adjusted through trial and error, selecting the right values for them is the main issue when utilizing the LQR optimal controller for real-time applications. For example, selecting very small values for the R matrix means trying to stabilize the system using a cheap control method. However, in order to optimize the cost function, choosing large coefficient values for the R matrix penalizes the control effort more harshly, resulting in a costly control solution [16, 17]. Large coefficient values for the Q matrix imply an effort to stabilize the system with the fewest possible state changes, whereas smaller values suggest less care for state changes [18, 19].

Trial-and-error and designer experience are important selection factors; however, when adjusting the weighted performance matrices Q and R through trial-and-error, the effects of disturbance and uncertainty are ignored. LQR controllers' exceptional performance and robustness enable them to decrease control effort and reduce deviations in the state trajectories of wheeled mobile robots, which is a problem in this area [20–22]. This chapter investigates the suitability of LQR control for a wheeled mobile robot designed for agricultural uses.

The rest of this chapter is structured as follows: The relevant material is reviewed in Section 2, and the design of a fixed version of a mobile robot with four wheels intended for use in agriculture is shown in Section 3. Section 4 describes control system design and Section 5 reports outcomes for the proposed wheeled robot with LQR system implemented in wheeled mobile robot. Conclusions are drawn in Section 6.

2. Related paper/literature review

Currently, agriculture accounts for 6.4% of global economic productivity, and it is the main economic sector in many nations. Besides giving food to billions of people, agriculture employs a significant percentage of the world's workforce. Amidst apprehensions over food security, accelerating global population growth, and unanticipated climate change, the agriculture sector is seeking novel and inventive approaches to enhance crop yields. Wheeled mobile robots are becoming more common in the industry as a result of these efforts, contributing to the ongoing technological revolution [23–29].

The objective of this work is to optimize the control system algorithm for a group of robotic assets using a multi-generic decision-making technique. While several research teams use operator decision support approaches and control algorithms to create diverse robotic means to meet agricultural monitoring duties, they are not able to offer a comprehensive solution. The technique relies on model optimization, specifically the concept of internal auctions within the system that is built, to determine which robotic system has the best chance of finishing the given task [30].

In order to address the discrete-time (DT) nonlinear state tracking problem and input time delay system of the wheeled mobile robot (WMR), this work suggests an adaptive control approach based on reinforcement learning. Once the typical model of the WMR is converted into an affine nonlinear DT system, an appropriate Lyapunov-Krasovskii functional and a delay matrix function are offered to tackle the issues caused by the state and input time delays, respectively. Furthermore, adaptive laws are defined for the adaptive controller, the critic NN, and the action NN using the approximation of the radial basis function neural networks (NNs) to ensure the tracking errors' convergence to a small compact set to zero and the uniform ultimate boundedness of all signals in the WMR system [31].

A discrete-time linear-quadratic regulator (LQR) predictive controller is developed for this purpose. To test such a method, multi input multi output (MIMO) time-delay processes presenting large, non-minimum phase modes, integrating, stable, and unstable modes were successfully treated with the LQR predictive controller. The output anomalies were randomly selected [32].

In this work, a model-free optimal control method called reinforcement learning is employed, which directly interacts with the environment to optimize a control policy. Common discrete-action techniques are not well suited for achieving goals that finish in regulation because of chattering in the goal state. The authors compared three methods for combining classic LQR control with reinforcement learning to address this problem. They specifically offer a method that uses learned dynamics to incorporate LQR control into the action set, allowing for generalization and eliminating the requirement to fix calculated control that is generated from learned dynamics in the replay memory. Include LQR control in a continuous action strategy. They demonstrated that adding LQR control can improve performance in both scenarios, while the impact is stronger if it can be used to supplement a distinct action set [33].

This chapter presents a reinforcement learning (RL) application using a tracking controller that is augmented by a tracking error component and is based on the linear-quadratic regulator (LQR). By including an integration term of the tracking error in the state variable, the linear-quadratic tracker with integrator (LQTI) is built to address steady-state errors. An online learning technique based on integral reinforcement learning (IRL) is applied to find the optimal control on the partially unknown continuous-time systems for the tracking problem by adjusting the augmented state variable. The LQTI is the foundation of this approach. Numerical simulation is used to verify the approach's efficacy and the optimal control solution in two instances [34].

The wheeled mobile robot systems used in this chapter may be crucial to resolving some of the issues that agriculture may face in the future (**Figure 1**). To assess the performance of LQR control, a kinematic model for a four-wheel skid-steering mobile robot was built. Using the capabilities of the wheeled mobile robot, three situations



Figure 1.
A field-based wheeled mobile robot in operation [23].

Specification	Individual-wheel [34–37]	Double-wheel [38–40]	Three-wheel [41–44]	Four-wheel [45–47]
Traveling across an uneven terrain	The one point of contact with the earth makes it incredibly difficult to maintain equilibrium.	Challenging to stabilize	Reached a stable condition	Most reached a stable condition
Gravitational center	Not at the right place	Robotics body is maintained beneath the axle	Within the established triangle	Remains within the defined rectangle
Quantity of inputs	Individual (single)	Twice (Double)	Three	Four or multiple
Energy consumption	Minimum	Less than with three wheels, but more than with one wheel	Less than with four wheels and more than with two wheels	Large
Control	The hardest	More advantageous than having just one wheel than having three.	Not as good as two wheels, not as good as three wheels	Excellent
Mathematical representation	The most basic	Easy	Superior to having four wheels	Intricate
Route efficiency	The hardest	Hard	Improved	The most improved

A four-wheeled robot design was chosen for this study's modeling based on its excellent qualities.

Table 1.
Types of wheels currently available for wheeled robots.

were analyzed: only non-zero state expensive; control expensive, non-zero state cheap; and control cheap, non-zero state expensive.

2.1 Wheeled mobile robot types and their characteristics

2.1.1 Forms and attributes of wheeled mobile robots

Robots with wheels propel themselves across the ground with the help of motorized wheels. **Table 1** shows a list of the wheel kinds that are currently available along with their salient features.

3. Design of a fixed version of a mobile robot with four wheels intended for use in agriculture

3.1 Prerequisite to design kinematic models

The four-wheel undercarriage of the chosen mobile robot was believed to have differential steering, with each wheel being controlled independently by a servo-mechanism (a suggested wheeled undercarriage design). When developing the kinematic model, the following assumptions were made: Wheel distortions are minimal or

consistent, wheels roll smoothly, allowing the center of the wheel's velocity to match the periphery speed; chassis velocity is minimal; and there is point-to-point contact between the wheels and pad. These kinds of factors are inherently present in nearly any task that involves the mobility of a vehicle. The so-called matrix kinematics methodology is a comprehensive and effective way to study vehicle motion.

3.2 A mobile robot that steers itself (SSMR)

A skid-steering mobile robot (SSMR) was tested using the kinematic model. This robot was thought to be functioning on a planar surface with an inertial orthonormal foundation (X_g, Y_g, Z_g) , as shown in **Figure 2**.

A local coordinate, located by (X_l, Y_l, Z_l) , was put in place near the robot's center of mass (COM). The coordinates of COM in the inertial frame can be expressed as COM (X, Y, Z) based on **Figure 2**. The Z-coordinate of COM was constant because this study solely took plane motion into account ($Z = \text{const}$). It was assumed that the robot moved at a linear speed expressed in the local frame on a planar surface as $V = |V_x V_y V_z|^T$ as well as to spin using an angular velocity vector $\omega = [00\omega]^T$, where $q = |XY\theta|^T$. The state vector represents the robot's generalized coordinates, which includes the COM location, X and Y, and the orientation, θ , of the local coordinate frame in relation to the inertial frame. Thus, $\dot{q} = |\dot{X}\dot{Y}\dot{\theta}|^T$ symbolized the generalized velocity vector. **Figure 3** illustrates the relationship between coordinates and the variables X, and, and Y. The free-body kinematics mathematical equations were:

$$\begin{cases} X = X_{ICRx}\sin\theta + X_{ICRy}\cos\theta \\ Y = X_{ICRx}\cos\theta + X_{ICRy}\sin\theta \end{cases}$$

$$\begin{cases} \frac{dX}{dt} = \dot{X} = \frac{d}{d\theta} (X_{ICRx}\sin\theta + X_{ICRy}\cos\theta) \\ \frac{dY}{dt} = \dot{Y} = \frac{d}{d\theta} (X_{ICRx}\cos\theta + X_{ICRy}\sin\theta) \end{cases}$$

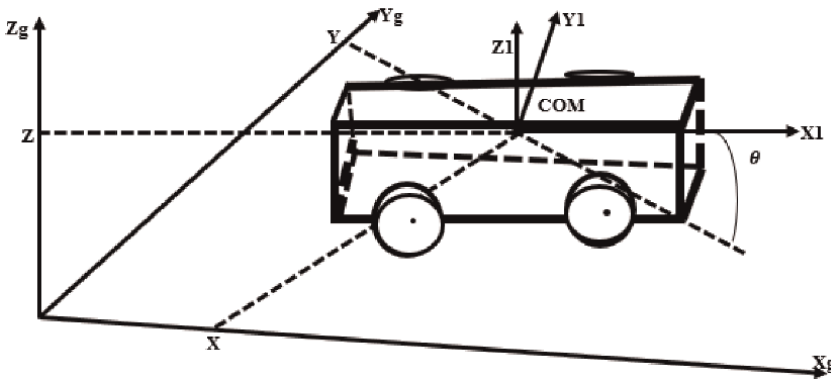


Figure 2. Mobile robot with skid-steering in the inertial frame (COM, center of mass) [27].

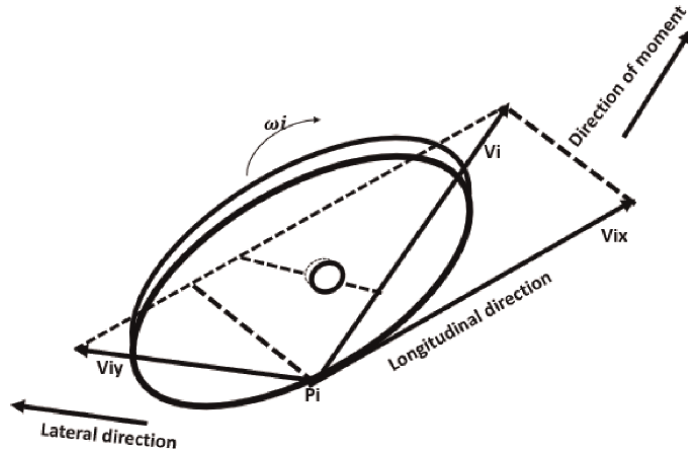


Figure 3.
 Velocity at one wheel of the mobile robot with four wheels, angular velocity vector at point (P_i) [25].

Using chain rules:

$$\begin{cases} \frac{dX}{dt} = \dot{X} = (X_{ICRx} \dot{\theta} \cos \theta - X_{ICRy} \dot{\theta} \sin \theta) \\ \frac{dY}{dt} = \dot{Y} = (X_{ICRx} \dot{\theta} \sin \theta + X_{ICRy} \dot{\theta} \cos \theta) \end{cases}$$

With:

$$\begin{cases} V_x = X_{ICRx} \dot{\theta} \\ V_y = X_{ICRy} \dot{\theta} \end{cases}$$

Where X_{ICRx} is the local coordinate y-axis; X_{ICRy} is the local coordinate along the x-axis.

The system equation may then be expressed as follows using Ref. [4] as a guide:

$$\begin{bmatrix} \dot{X} \\ \dot{Y} \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} V_x \\ V_y \end{bmatrix} \quad (1)$$

For planar motion, $\dot{\theta} = \omega$.

3.3 Connection between local and wheel velocities

In **Figure 3**, the wheel was taken to be in touch with the plane surface at point P_i , disregarding the wheel's thickness for simplicity's sake. The lateral velocity of the SSMR, where $i = 1, 2, 3, 4 \dots$, is typically non-zero, in contrast to the majority of wheeled vehicles. The SSMR's mechanical design gives rise to this characteristic, which requires lateral sliding in the event that the vehicle's orientation shifts. Consequently, the wheels are only tangent to the route at $\omega = 0$, at which point the robot travels in a straight line. We exclusively examined a streamlined instance of SSMR motion, wherein the longitudinal slip between the wheels and the surface can be disregarded. The relationship between linear velocity and angular velocity was then established as follows: $V_{ix} = r_i \omega_i$, where r_i is the wheel's effective rolling radius and

V_{ix} is the longitudinal component of the i^{th} wheel's total velocity vector V_i represented in the local frame. All four wheels had to be taken into account in order to create a kinematic model.

The radius vectors then changed, as seen in **Figure 4**, to become $d_i = [d_{ix} d_{iy}]^T$, and $d_C = [d_{Cx} d_{Cy}]^T$, instantaneous center of rotation (ICR) re-defined with regard to the local frame.

The following formula was calculated using the geometry in **Figure 5**: $\left\| \frac{V_i}{d_i} \right\| = \left\| \frac{V}{d_C} \right\| = |\omega|$. Accordingly [8–10], the Euclidean norm equation indicates that:

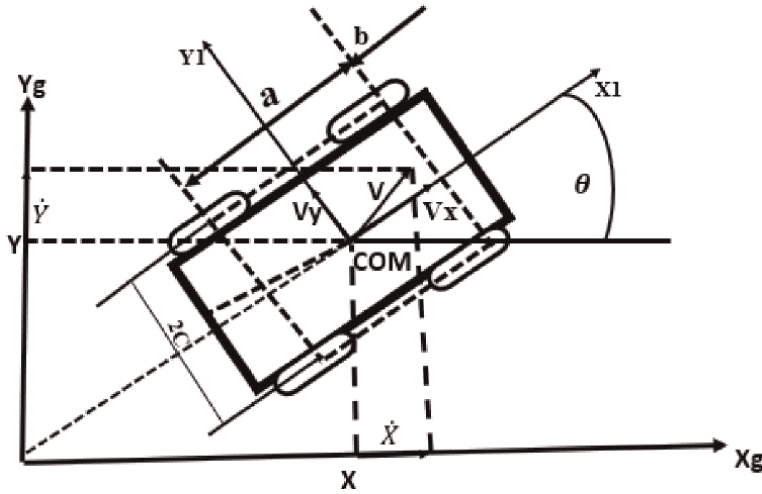


Figure 4. Diagram of the mobile robot's free body with four wheels (COM, center of mass) [35].

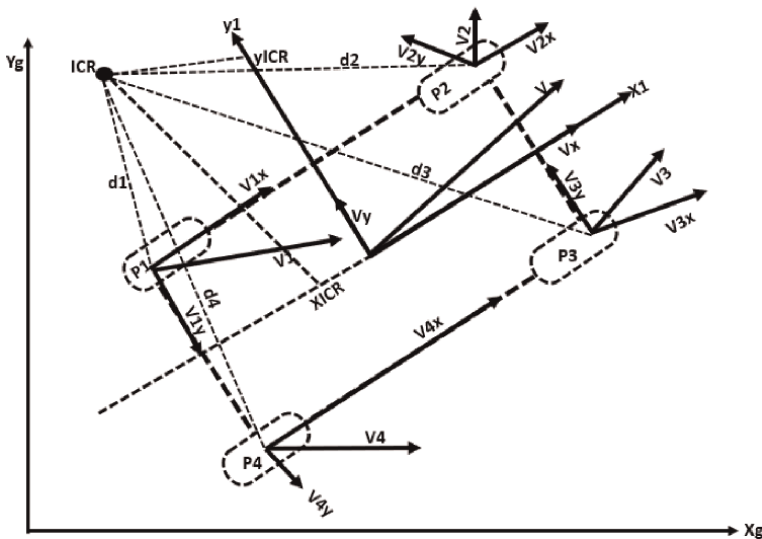


Figure 5. Wheel velocities for the four-wheeled mobile robot [35].

$$\frac{V_{ix}}{-d_{iy}} = \frac{V_x}{-d_{Cy}} = \frac{V_{iy}}{-d_{ix}} = \frac{V_y}{-d_{Cx}} = \omega. \quad (2)$$

From instantaneous center of rotation (ICR) in the local frame:

$$ICR = (X_{ICR}, Y_{ICR}) = (-d_{Cx}, d_{Cy}) \quad (3)$$

Then, Eq. (2) becomes

$$\frac{V_x}{Y_{ICR}} = \frac{-V_y}{X_{ICR}} = \omega \quad (4)$$

From **Figure 5**, it is clear that the coordinates of vectors d_i satisfy the following relationships:

$$\begin{cases} d_{1y} = d_{2y} = d_{Cy} + C \\ d_{3y} = d_{4y} = d_{Cy} - C \\ d_{1x} = d_{4x} = d_{Cx} - a \\ d_{2x} = d_{3x} = d_{Cx} + b \end{cases} \quad (5)$$

where a , b , and c are positive kinematic parameters for the robot depicted in **Figure 4**.

On combining Eqs. (2) and (5), the following relationships between wheel velocities were obtained:

$$\begin{cases} V_L = V_{1x} = V_{2x} \\ V_R = V_{3x} = V_{4x} \\ V_F = V_{2y} = V_{3y} \\ V_B = V_{1y} = V_{4y} \end{cases} \quad (6)$$

where V_L and V_R symbolize the left and right wheel velocities' longitudinal coordinates, respectively; the front and rear wheel velocities' lateral coordinates are represented by the variables V_F and V_B , respectively. The link between the robot's velocity and its wheel velocities thus follows from Eqs. (2)-(6):

$$\begin{bmatrix} V_L \\ V_R \\ V_F \\ V_B \end{bmatrix} = \begin{bmatrix} 1 - c \\ 1c \\ 0 - x_{ICR} + b \\ 0 - x_{ICR} - a \end{bmatrix} \begin{bmatrix} V_x \\ \omega \end{bmatrix} \quad (7)$$

Presuming that the radius of effectiveness is $r_i = r$ back substitution into the equation for every wheel (7) gives:

$$\begin{bmatrix} \omega_L \\ \omega_R \end{bmatrix} = \frac{1}{r} \begin{bmatrix} V_L \\ V_R \end{bmatrix} \quad (8)$$

where ω_L and ω_R are the left and right wheels' angular velocities, respectively. This approximate relationship which served as the rod profile for the robotics was created by combining Eqs. (7) and (8) and relating the angular wheel velocities to the robot velocities.

$$\beta = \begin{bmatrix} V_x \\ \omega \end{bmatrix} = r \begin{bmatrix} \frac{\omega_L + \omega_R}{2} \\ \frac{-\omega_L + \omega_R}{2c} \end{bmatrix} \quad (9)$$

where β is a fresh control input that the kinematic level introduces. It is evident from Eq. (9) that velocities V_x and ω , as well as the pair of velocities ω_L and ω_R , can be considered as control kinematic input signals in theory. However, the accuracy of the relationship in Eq. (9), which can only be true if longitudinal slip is negligible, is greatly influenced by longitudinal slip. The parameters R and C in Eq. (9) can also be found experimentally in order to ensure high validity in determining the angular velocity of the robot with respect to the angular velocities of the wheels. In the event that the system is given a velocity constraint, then:

$$V_y + x_{ICR}\dot{\theta} = 0 \quad (10)$$

Since Eq. (10) cannot be solved, it is a nonholonomic constraint. As a result, it may be rewritten as $[-\sin\theta \cos\theta x_{ICR}] [\dot{x} \dot{y} \dot{\theta}] = A(q)\dot{q} = 0$, where the use of Eq. (1) occurs. As a result of the generalized velocity $\dot{q}$ always being in A 's null space,

$$\begin{cases} \dot{q} = S(q) * \beta \\ S^T(q)A^T(q) = 0 \\ S(q) = \begin{bmatrix} \cos\theta x_{ICR} \sin\theta \\ \sin\theta - x_{ICR} \cos\theta \\ 01 \end{bmatrix} \end{cases} \quad (11)$$

It should be mentioned that $\text{dull}(\beta = 2) < \text{dim}(q = 3)$. The robot's underactuated kinematics are described by Eq. (7). Since Eq. (10) describes the constraint, this system is also nonholonomic. It is interesting to notice that the kinematic model of the examined SSMR resembled the kinematics of a mobile robot with two wheels quite a bit. It is evident from Eqs. (4) and (7) that control over the V_y and V_{yi} velocity coordinates is impossible without understanding the ICR's x_I -axis projection. Thus, compared to the previously suggested parameters, taking into account the linear velocity V_x and the angular velocity ω as control signals appear to offer an advantage. In this investigation, velocity V_y was utilized in place of ω .

3.4 Validation of control of the linear wheeled mobile robot model

Control models have to be holonomic systems that are controllable or influenced; that is, if the model is not holonomic, control or influence cannot occur. Here, the notion of "controllable" was developed in order to verify this. The ability to modify a system across its configuration space with precise allowed manipulations is a general definition of controllability. A deterministic system's state, or the collection of values for all of its state variables (those defined by dynamic equations), provides a complete description of the system at any given moment. To be more precise, no knowledge of the system's past is needed to help with future prediction if the states of the system are known, as well as the values of the control variables, both present and future (those whose values may be chosen). If there exists an input sequence that can transfer the

system state from x_0 to x_f in a finite duration for any beginning state, x_0 , and any final state, x_f , then the system that the state-space representation replicates is controllable:

$$\begin{cases} \dot{x} = Ax(t) + Bu(t) \\ y = Cx(t) + Du(t) \end{cases} \quad (12)$$

There exists a control u from state x_0 at time t_0 to state x_1 at time $t_1 > t_0$ if and only if $x_1 - \varnothing(t_0, t_1)x_0$. The state-transition matrix $\varnothing$ is also smooth. We introduced the $n \times m$ matrix-valued function $M_0(t) = \varnothing(t_0, t)B(t)$ to give:

$$M_k(t) = \frac{d^k M_0}{dt^k}(t), k \geq 0 \quad (13)$$

Next, we looked at the matrix of matrix-valued functions that was produced by counting every column of the $M_i, i = 0, 1, \dots k$:

$$M^{(k)}(t) = [M_0(t), \dots M_k(t)] \quad (14)$$

If any such thing exists a $\hat{t} \in [t_0, t]$ as well as a positive integer k such that $\text{rank} M^{(k)}(\hat{t}) = n$, after which, considering the state $x(0)$ initially, indiscriminately indicated $k = 0$, the state equation provides $x(1) = Ax(0) + Bu(0)$, and $x(2) = Ax(1) + Bu(1) = A^2x(0) + ABu(0) + Bu(1)$, and so forth, repeatedly substituting the state variable backward, until finally obtaining:

$$x(n) = Bu(n-1)ABu(n-2) + A^{n-1}Bu(0) + A^n x(0).$$

Comparatively:

$$x(n) - A^n x(0) = [BAB \dots A^{n-1}B] [u^T(n-1)u^T(n-2) \dots u^T(0)]^T \quad (15)$$

At angle 30° and $x_{ICR} = 0.6\text{cm}$, the matrix of states is transformed into:

$$A = \begin{bmatrix} 0.500 \\ 0.5 - 0.30 \\ 001 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.5 \\ 0 \\ 0 \end{bmatrix}$$

$$C = [100]$$

$$D = 0$$

$$C_{\text{controllable}} = \begin{bmatrix} 0.50.250.125 \\ 00.250.05 \\ 000 \end{bmatrix}$$

$$\text{Uncontrollable} = \text{Length}(A) - \text{Rank}(\text{controllable})$$

$$\text{Length}(A) = 3$$

$$\text{Rank}(\text{controllable}) = 2$$

$$\text{Uncontrollable} = 3 - 2 = 1$$

The degree to which the internal states of a wheeled mobile robot system may be inferred from data about its external outputs is known as the system's observable.

The matrix that can be observed is:

$$\text{Observable} = \begin{bmatrix} 100 \\ 0.500 \\ 0.2500 \end{bmatrix}$$

$$\text{Unobservable} = \text{length}(A) - \text{rank}(\text{observable})$$

$$\text{Unobservable} = 3 - 2 = 1$$

Consequently, wheeled mobile robots are undetectable and unmanageable. This suggests that the system is nonholonomic, supporting the developed mathematical models. As a result, the matrix of projected state space becomes:

$$S(q) = \begin{bmatrix} \cos \theta & x_{ICR} \sin \theta \\ \sin \theta & -x_{ICR} \cos \theta \end{bmatrix}$$

Furthermore, the equation is the input matrix (9).

4. Control system design

4.1 Control system for the wheeled mobile robot model

Reducing expenses while managing a dynamic system is the aim of optimal control theory. When the cost is described by a quadratic function and the system dynamics are described by a set of linear differential equations, this is known as the Q issue. The parameters of a (regulatory) controller that controls wheeled mobile robots are determined mathematically. A cost function with the necessary weighting elements is minimized using the algorithm. *Via* a cost function, an event or the values of one or more variables are translated onto a real number that intuitively corresponds to some "cost" associated with the occurrence. The total of the significant measures' departures from the intended values, such as the condition of the wheeled mobile robot, is a common way to characterize the cost function. Thus, the program finds the controller settings that minimize undesirable deviations. The size of the control action itself may also be considered by the cost function [30]. Examine the following wheeled mobile robot model at an angle that is linearly time-invariant 30° and $x_{ICR} = 0.6\text{cm}$, the state matrix becomes: $\dot{x} = Ax + Bu$,

$$A = \begin{bmatrix} 0.5 & 0 & 0 \\ 0.5 & -0.3 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix}$$

Using the index of performance

$$\begin{cases} J = \int_0^{+\infty} (x_1^2 + ru^2) dt \\ Q = \begin{bmatrix} 10 \\ 00 \end{bmatrix}, R = r. \end{cases} \quad (16)$$

The open loop system's eigenvalues are 0.5, -0.3 , and 1. The system's initial state was penalized by the state penalty matrix Q in the performance index. It was possible to observe how small and large values of r alter the closed-loop dynamics since the controller penalty r was left as a parameter. It is imperative to consistently verify if the design problem is well-posed. Conditions on the plant and the performance index for the well-posed problem need to determine if the system's unstable modes are observable *via* the state penalty matrix and whether they can be controlled. To verify if (A, B) is stabilizable and $(A, Q^{\frac{1}{2}})$ is detectable. Now computing the controllable matrix:

$$\begin{cases} P_C = [BAB] \\ \begin{bmatrix} 0.50 & .43 \\ 00 & .25 \end{bmatrix} \\ Rank = 2 \end{cases}$$

The system can be controlled because the matrix has full rank. Therefore, any unstable modes can be managed. The state penalty matrix can then be factored into square roots.

$$Q = (Q^{\frac{1}{2}})^T Q^{\frac{1}{2}} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$

After that, use the square root of Q to determine the observability:

$$\begin{bmatrix} Q^{\frac{1}{2}} \\ Q^{\frac{1}{2}}A \end{bmatrix} = \begin{bmatrix} 10 \\ 00 \\ 0.860.3 \\ 00 \end{bmatrix}, Rank = 2$$

The penalty matrix allows for the observation of all system modes because it has full rank. It is now able to solve the algebraic Riccati equation (ARE) [30]

$$PA + A^TP - PBR^{-1}B^T + Q = 0 \quad (17)$$

For P , using A, B, Q , and $R = r$. Let $P = \begin{bmatrix} P_1 & P_2 \\ P_2 & P_3 \end{bmatrix}$. Then the ARE is

$$\begin{bmatrix} P_1 & P_2 \\ P_2 & P_3 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & -1 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} P_1 & P_2 \\ P_2 & P_3 \end{bmatrix} - \begin{bmatrix} P_1 & P_2 \\ P_2 & P_3 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \frac{1}{r} [01] * \begin{bmatrix} P_1 & P_2 \\ P_2 & P_3 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = 0 \quad (18)$$

The Riccati matrix P can derive three equations from Eq. (1) since it needs to be real symmetric and positively defined for P_1, P_2 , and P_3 . These are

$$\frac{-P_2^2}{r} + 1 = 0 \quad (19)$$

$$1 - P_2 - \frac{P_2^2}{r} = 0 \quad (20)$$

$$2(P_2 - P_3) - \frac{P_3^2}{r} = 0 \quad (21)$$

The initial formula provides $P_2 = \sqrt{r}$. It is necessary to check both positive and negative values of m to determine which is the solution.

Using $P_2 = \sqrt{r}$, P_1 , $\wedge P_3$ are

$$P_3 = r \left(\sqrt{1 + \frac{2}{\sqrt{r}}} - 1 \right) \quad (22)$$

$$P_1 = \sqrt{r \sqrt{1 + \frac{2}{\sqrt{r}}}} \quad (23)$$

The feedback gain matrix in constant state is

$$K = R^{-1}B^TP = \left[\frac{2}{\sqrt{r}} \sqrt{1 + \frac{2}{\sqrt{r}}} \right] \quad (24)$$

The characteristics equations for closed-loop state dynamics then become

$$\phi_{cl}(s) = s^2 + s \sqrt{1 + \frac{2}{\sqrt{r}}} + \frac{1}{\sqrt{r}} \quad (25)$$

The optimal feedback gains' values correspond to the respective magnitudes of Q and R . Big values of Q significantly penalize the state in comparison with the control for a fixed R value. As a result, the closed-loop system reaction quickens and the optimal feedback gains increase. Conversely, low values of Q lead to smaller control efforts because they penalize the control more than the state. This results in a slower response by maintaining the gains minimal. Common problems in control include the ability of the stabilization system and the output system to follow a reference. In case the output has to align with reference r , it is necessary to include an integrator and specify the error state (γ) as the integrator output. The difference between the input and output of the wheeled mobile robot system is represented by γ .

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \\ u = -Kx + k_I \gamma \\ \dot{\gamma} = r - y = r - Cx \end{cases} \quad (26)$$

In this example, y represents the output, u is the control signal, r is the reference (step function, scalar), and γ is the integrator output. Eq. (17) represents the kinematic system as follows:

$$\begin{cases} \begin{bmatrix} \dot{x} \\ \dot{\gamma} \end{bmatrix} = \begin{bmatrix} A0 \\ -C0 \end{bmatrix} \begin{bmatrix} x \\ \gamma \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u + \begin{bmatrix} 0 \\ I \end{bmatrix} r \\ \begin{bmatrix} \dot{x}(\infty) \\ \dot{\gamma}(\infty) \end{bmatrix} = \begin{bmatrix} A0 \\ -C0 \end{bmatrix} \begin{bmatrix} x(\infty) \\ \gamma(\infty) \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u(\infty) + \begin{bmatrix} 0 \\ I \end{bmatrix} r(\infty) \end{cases} \quad (27)$$

Tracking must be designed to make system stabilize. If $x(\infty), \gamma(\infty) \wedge u(\infty)$ approach constant values, then $\dot{\gamma} = 0, \text{so } \gamma(\infty) = r$. In steady state, Eq. (18), because $r(t)$ is signal step, then $r(\infty) = r(t) = r$ is constant value. For $t > 0$ subtracting Eq. (18) gives:

$$\begin{bmatrix} \dot{x}(t) - \dot{x}(\infty) \\ \dot{\gamma}(t) - \dot{\gamma}(\infty) \end{bmatrix} = \begin{bmatrix} A0 \\ -C0 \end{bmatrix} \begin{bmatrix} x(t) - x(\infty) \\ \gamma(t) - \gamma(\infty) \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} [u(t) - u(\infty)] \quad (28)$$

This implies that:

$$\begin{cases} x(t) - x(\infty) = x_e(t) \\ \gamma(t) - \gamma(\infty) = \gamma_e(t) \\ u(t) - u(\infty) = u_e(t) \\ \begin{bmatrix} \dot{x}_e(t) \\ \dot{\gamma}_e(t) \end{bmatrix} = \begin{bmatrix} A0 \\ -C0 \end{bmatrix} \begin{bmatrix} x_e(t) \\ \gamma_e(t) \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} [u_e(t)] \\ u_e(t) = -Kx_e(t) + K_I\gamma_e(t) \end{cases} \quad (29)$$

Vector error size $(n + 1)$ can be defined as: $e(t) = \begin{bmatrix} x_e(t) \\ \gamma_e(t) \end{bmatrix}$

Then, Eq. (20) becomes: $\dot{e} = \hat{A}e + \hat{B}u_e$, with: $\hat{A} = \begin{bmatrix} A0 \\ -C0 \end{bmatrix}, \hat{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}$, into: $u_e = \hat{K}e$, $\hat{K} = [KK_I]$, into: $\dot{e} = (\hat{A} - \hat{B} * \hat{K})e$. The LQR approach is used to determine the value of K . The optimization problem is solved to (J)min in order to define the cost function in LQR. $J = \int_0^{+\infty} (x^T Q x + u^T R u) dt$

Subject to:

$$\begin{cases} \dot{x} = Ax + Bu \\ u(t) = -Kx(t) \end{cases} \quad (30)$$

where $K = R^{-1}B^T S$, which are full-state feedback controllers, and where S is the solution to Riccati's algebraic equation $(n \times n)$ and $A^T S + SA - SBR^{-1}B^T S + Q = 0$.

4.2 Analyzed linear features for each of the scenarios

Settling time (T_s), that is the mathematical expression for the amount of time needed for the output to stabilize within a certain tolerance band is:

$$T_s = \begin{cases} \frac{4}{\sigma \omega_n}, & 0 < \sigma < 1 \\ \infty, & \sigma = 0 \\ \frac{6}{\omega_n}, & \sigma > 1 \end{cases} \quad (31)$$

where σ is damped ratio.

Rise time (T_r) indicates the amount of time needed for the solution to increase in underdamped systems from 0 to 100% of its final value, or in overdamped systems from 10 to 90% of its final value. In mathematic:

$$Tr = \frac{\pi - \theta}{\omega_d} \quad (32)$$

Peak time (T_p) is the amount of time needed for the response to initially reach its peak value. In mathematics:

$$Tp = \frac{\pi}{\omega_d} \quad (33)$$

The Peak overshoot, or maximum overshoot (M_p), is characterized as the response's peak-time departure from its final value. It says this:

$$Mp = \left(e^{-\left(\frac{\sigma\pi}{\sqrt{1-\sigma^2}}\right)} \right) * 100 \quad (34)$$

At steady-state time (T_{ss}), the rate of intake and the rate of elimination are equal.

4.3 An analytical theory

The distinction between y and steady state will be assumed. The state space will be stable if that approaches 0. That is unstable if that blows up and y deviates more from the steady state. So $\frac{dy}{dt}$ is f of y . The capital of $\frac{dY}{dt} = 0$. That continuous stable state is represented by capital Y , and f of y is also equal to zero. Hence, we have simply written 0 on the left and 0 on the right, keeping in mind that capital Y solves the equation completely.

$$\frac{dy}{dt}(y - Y) = f(y) - f(Y) \quad (35)$$

Let us verify Eq. (36) by examining the derivative of state space from Eq. (36) both prior to and following the use of the LQR method. Before applying LQR, let us assume that $y = x$, and $\frac{dy}{dt} = \frac{dx}{dt} = \dot{x}$

$$\begin{cases} \frac{dy}{dt} = \dot{x}_1 = x_1 * \cos\theta + x_2 * x_{ICR} \sin\theta \\ \frac{dy}{dt} = \dot{x}_2 = x_1 * \sin\theta - x_2 * \cos\theta \end{cases} \quad (36)$$

At $\theta = 0$, between $\theta = 90$

There is positive state space. Thesis asserted that the state space is unstable in the absence of control. Nevertheless, the state returns to 0 following the application of the control algorithms, suggesting that $y = Y$, if $\frac{dy}{dt} < 0$ upon which the state space is steady.

5. Outcomes of the simulation and discussion

5.1 Outcomes for the uncontrollably wheeled robot

Without a control system, the velocity time profile was unstable (**Figure 6**). The system's inputs were various road profiles, while its outputs were positions and velocities. The system was represented mathematically using a state-space model, which is a set of road profiles (input), variables, and outputs coupled by first-order differential equations or difference equations without the need for second derivatives. Depending on their current value as well as the values of other externally imposed variables, these variables fluctuated over time. For instance, the state variables' values had an impact on the values of the output variables. The wheeled robot stayed stable for the first 20 seconds without any disturbances, but after 21 seconds, the system began to become unstable (slow disturbance) (**Figure 6**). There was no way to determine the settling time, rise time, peak time, or steady-state time for the wheeled mobile robot system. This resulted from the wheeled robot's low impact and uneven mobility on a rough surface, which made the system unstable overall. The system stabilized after the model was updated with the proper controller system. Because the set of first-order differential equations was linear in the state and road profiles (input) variables, this model was a linear state-space representation. LQR, or linear-quadratic regulation, was the chosen control strategy.

By choosing certain weighting parameters and minimizing the cost function, a mathematical LQR controller for the wheeled mobile robot was constructed. Sometimes, the cost function is characterized by the total deviation of important metrics, like ground surface, road profiles, or height, from ideal values. The controller settings that minimize undesired deviations are then determined by the LQR software. It is also possible for the cost function to consider the size of the control action itself.

5.2 Outcomes for the proposed wheeled robot with LQR system

To overcome the drawbacks of the trial-and-error method, the Q and R weighting matrices were modified using Bryson's method. By computing the reciprocal of

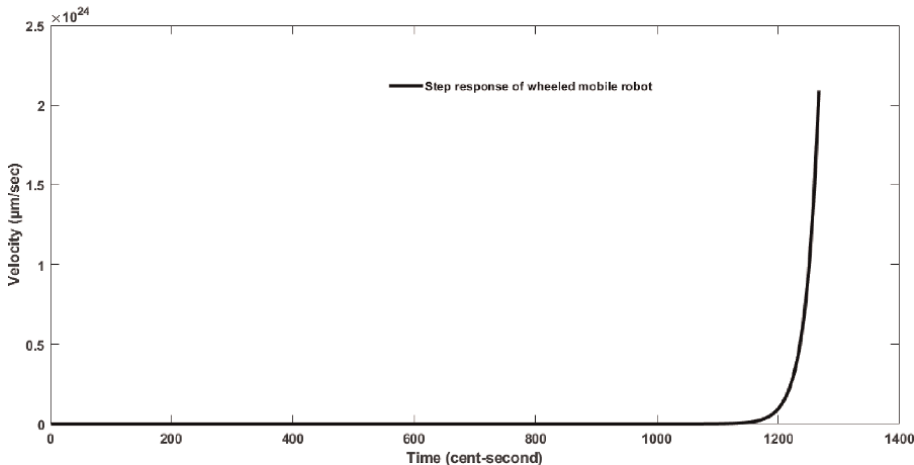


Figure 6.
Step response of the wheeled robot without a control mechanism.

squares of the maximum allowable values of the state and input control variables, Q and R were determined using this procedure. **Figure 7** illustrates how control was cheap and a non-zero state was costly. As a result, the wheeled mobile robots' position decreased for 5 seconds before settling at a less costly location (**Figure 7**). Because the velocity's state was significantly more expensive than the mobile robot's position on its wheels, the wheeled mobile robot system's velocity grew concurrently for 10 s before stabilizing throughout. For all non-zero states, the force required to stabilize the system as a whole was not very costly. This low cost and negative rise suggested that non-zero conditions were being controlled with greater control. Attempts were made to use a relatively inexpensive control mechanism to stabilize the system by selecting modest coefficients.

Figure 8 Non-zero states were inexpensive when control was expensive. As a result, the location of the wheeled mobile robot system dropped and stabilized after

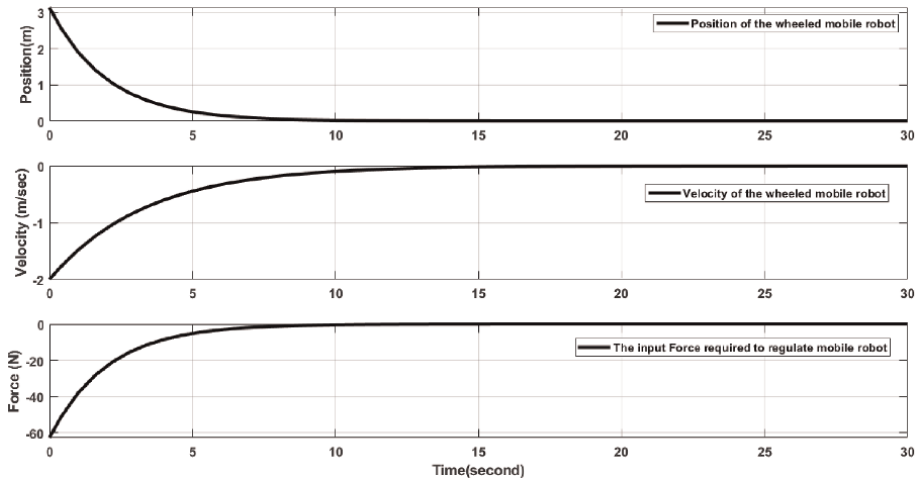


Figure 7.
Position, velocity, and force states in cheap control of the wheeled mobile robot.

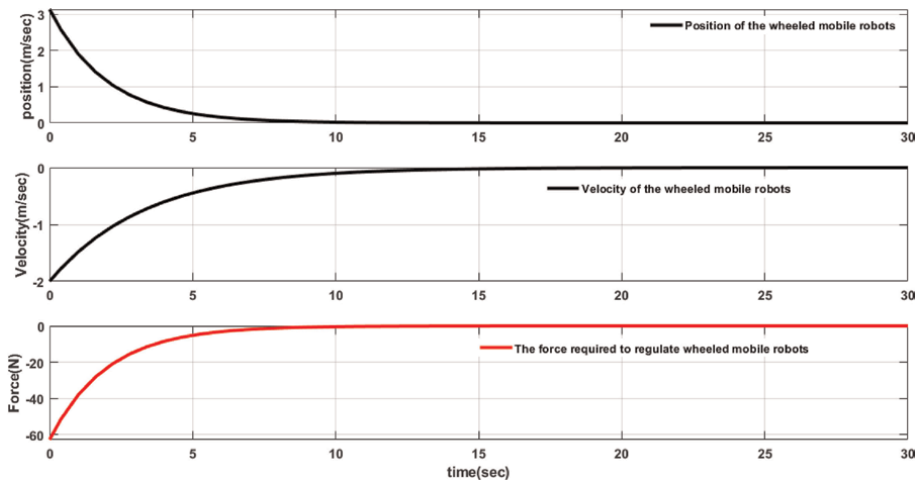


Figure 8.
Position, velocity, and force states in expensive control of the wheeled mobile robot.

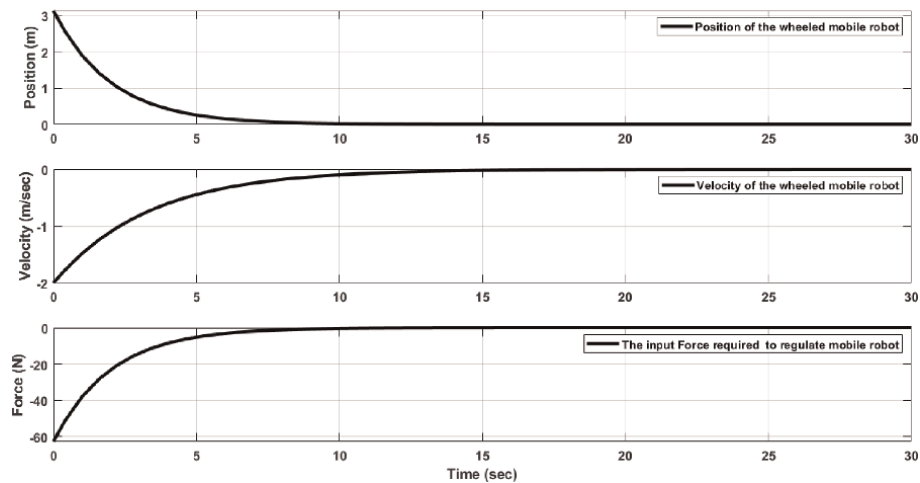


Figure 9.
Position, velocity, and force states of the wheeled mobile robot when ignoring the position.

Scenario	R (input penalization matrix)	Q (state penalization matrix)	K (Gain values)	Peak time (T_p , s)	Settling time (T_s , s)	Rise time (T_r , s)	Steady-state time (T_{ss} , s)
Control cheap, non-zero state expensive	[0.1]	$\begin{bmatrix} 10 \\ 01 \end{bmatrix}$	[2.4140]	0.707	5.33	3.01	0.707
Control expensive, non-zero state cheap	[100]	$\begin{bmatrix} 10 \\ 01 \end{bmatrix}$	[20]	0.1	7.32	4.09	0.1
Only non-zero velocity expensive	[1]	$\begin{bmatrix} 0.010 \\ 0100 \end{bmatrix}$	[2000]	0.01	7.02	4.09	0.1

Table 2.
The linear properties of the wheeled mobile robot in the various control scenarios that were examined.

8 seconds. As a result, the state of position was less expensive. Owing to the velocity state's far higher cost than the mobile robot's wheeled position, the wheeled mobile robot system's velocity increased simultaneously for 10 s before stabilizing throughout. The force needed to stabilize the entire system was very costly for all non-zero states, with the negative rise indicating that extra control was needed to manage the non-zero states (**Figure 8**). For wheeled mobile robot systems in real-time applications, the key determinant of the LQR optimal controller is the selection of values for the Q and R weighting matrices, which involves trade-offs and is usually modified by trial-and-error. Expensive control means sacrificing control while selecting big coefficients for the R matrix in order to maximize the cost function.

While choosing lower values for Q ignored state changes, using larger coefficients for the Q matrix stabilized the system with the fewest possible state changes (**Figure 9**). The effects of uncertainty and disruption are ignored in favor of experience and trial-and-error in each of these situations. The fact that Bryson's rule mostly

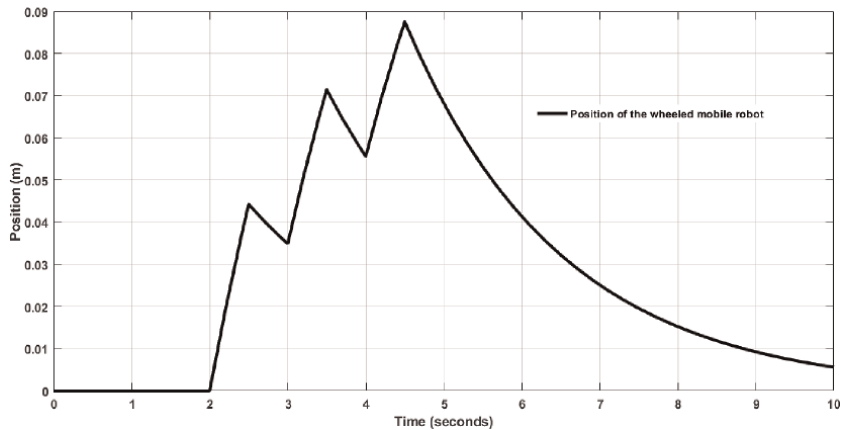


Figure 10.
Positions of wheeled mobile robot with the linear-quadratic regulator (LQR) control system.

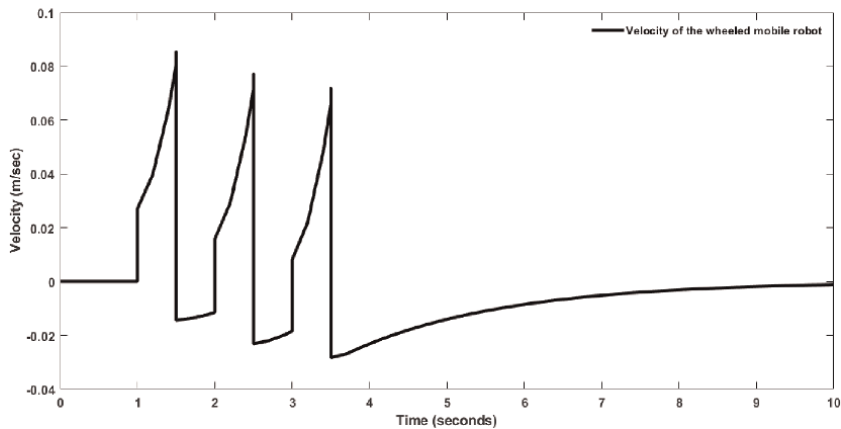


Figure 11.
Velocity response of the wheeled mobile robot with the linear-quadratic regulator (LQR) control system.

depends on the designer's experience and ignores interruptions and uncertainty is one of its main weaknesses. The response in expensive control became comparable to that of the cheap solution by using Bryson's method as a starting point for selecting Q and R values and then using the trial-and-error method to obtain the required features of the closed-loop system (Figure 9).

Table 2 displays the peak, settling, rising, and steady-state times for each of the three situations that were examined.

Figure 10's vertical axis displays the wheeled mobile robot's position (measured in meters), while the horizontal axis displays the time horizon. In order to enable closed-loop stable and high-performance system design, three pumped road profiles were used as inputs after the appropriate feedback gains were optimally managed. For the robotic arm to remain upright, the system needed to be stable when the appropriate control gains were implemented.

The wheeled mobile robot's response speed is displayed in Figure 11. Three uneven road profiles were used as input. The velocity response was similar to the inputs, which are road profiles, suggesting that it is possible to trace the wheeled robot's

response. As a result, the LQR control system that was evaluated proved suitable for operating a mobile robot with wheels in the agricultural industry.

6. Conclusion

As this study combining the ideas of controllable and observables confirms, mathematicians have unhappily created four-wheeled mobile robots using nonholonomic mathematical models for which control or influence is impossible. Here, LQR was chosen as an appropriate control design for a wheeled mobile robot intended for agricultural application, based on the expected mathematical models. Finding the optimal mathematical formula for computing the Q and R weighting matrices is the main objective of control in order to get around the limitations of the current subjective, trial-and-error methods. As a result, the procedure aims to establish a robust control system. The approach used in this work includes directly calculating the matrix Q from the dynamics of the state matrix, also known as the designer target states. Since some states in the scenario under consideration (such as altitude and yaw angle) were thought to be more important than the others, the relevant Q values were maintained as high as possible to punish the other states. The value of matrix R was then determined using this Q value. By varying the weighting matrix's values, the method's strength is its capacity to track changes in the dynamics of the model brought about by errors, uncertainties, and parameter modifications. Three scenarios were studied (control expensive, non-zero state cheap; solely non-zero state expensive); non-zero velocity was the only costly option. These scenarios were used to evaluate the performance of the LQR control system. Based on these circumstances, the peak time, settling time, rising time, and steady-state time for cheap control were found to be 0.707, 5.33, 3.01, and 0.707 s, respectively. This suggests that wheeled mobile robot systems in agricultural applications may be suitable for the LQR control system to operate.

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Technological Advances and Innovative Tools for Revolutionizing Yam Research and Productivity

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Abstract

Yam (*Dioscorea* spp.) is a critical staple crop, particularly in West Africa, where it serves as a primary source of carbohydrates for millions and contributes significantly to rural livelihoods. However, yam production faces numerous challenges, including pest and disease pressures, declining soil fertility, and the impacts of climate change. Advancements in technology and innovative practices are transforming yam agriculture to address these issues. Traditional breeding techniques are being enhanced by molecular tools such as marker-assisted selection, genomic selection, and CRISPR/Cas9, enabling the development of high-yielding, disease-resistant, and climate-resilient varieties. Tissue culture and propagation methods ensure the availability of disease-free planting materials, while digital agriculture tools such as remote sensing and precision farming optimize resource use and productivity. Sustainable practices, including integrated pest management and climate-smart agriculture, further mitigate environmental impacts and enhance resilience. Post-harvest innovations, such as improved storage systems, reduce losses and maintain tuber quality. In this book chapter, we explored most appropriate technologies that offer a holistic approach to boosting yam production, ensuring food security, and improving the livelihoods of smallholder farmers.

Keywords: yam, breeding, innovation, tuber quality, resistance/tolerance

1. Introduction

Yam, a vital food source for millions in Africa, has significantly benefited from technological advancements and innovations. Breeding programs have yielded varieties boasting higher yields, improved disease resistance [1], and better eating qualities. Techniques such as mini-sett technology and vine multiplication [2] have increased the availability of high-quality seed yams, a crucial factor for farmers. Herbicides, integrated weed management strategies [3], and improved soil fertility practices have

all contributed to higher yields. Storage innovations such as ventilated cribs and processing methods such as parboiling have reduced post-harvest losses and added value to the crop [4]. Disease and pest control methods are evolving by introducing biocontrol agents and integrated pest management strategies [5]. Marker-assisted selection, a powerful tool in plant breeding, promises even faster development of improved yam varieties [6]. Yam breeding has made significant progress in recent years, addressing key production challenges and enhancing crop performance. High-yielding varieties with improved disease resistance and varieties resistant to yam mosaic virus and anthracnose have been developed. Advances in genomics, such as high-quality reference genomes and SNP arrays, have accelerated marker discovery for traits such as plant sex and tuber quality. Strategies to address yam's genetic complexity, including polyploidy, have improved breeding efficiency, while genomic selection initiatives are reducing breeding cycles. A critical scientific gap in yam breeding research is the limited integration of genomic tools and/or advanced technologies to accelerate breeding cycles. While advances in genomic selection (GS), molecular markers, and emerging technologies hold promise, their adoption remains hindered by incomplete genomic resources. Additionally, the slow generation turnover and genetic complexity of yam (polyploidy, vegetative propagation) pose challenges for efficient trait discovery and introgression. Other challenges limit adoption by small-scale farmers due to a lack of resources and infrastructure, hindering progress [4]. The yield gap between research stations and real-world production persists [7]. New and emerging diseases and pests, such as yam anthracnose, threaten yam production [8]. Consistent and affordable seed yam supply is a hurdle in many regions [2]. Significant post-harvest losses due to inadequate storage and transportation remain an issue [4]. Developing cost-effective processing methods for value-added yam products, such as flour and chips, requires further attention [9].

The future of yam technologies and innovations lies in addressing these challenges. Climate-smart yam varieties and production systems are crucial to adapt to changing weather patterns. Developing and adapting machinery for yam cultivation, mainly for planting, harvesting, and processing, can improve efficiency and reduce labor requirements. Information and communication technologies can bridge the gap between farmers and best practices, markets, and resources. More efficient and cost-effective seed yam production and distribution systems are needed. Finally, exploring the potential of gene editing and other biotechnology tools could further improve yam traits, such as disease resistance and drought tolerance. Researchers and agricultural development organizations can ensure a more sustainable and productive future for yam production by overcoming these challenges and focusing on innovations.

This chapter delves into these advancements, highlighting their contributions to yam agriculture and their potential to revolutionize the yam breeding.

2. Traditional breeding techniques

2.1 Selective breeding

Yam farmers have a long-standing history of engaging in selective breeding practices to improve the quality and resilience of their crops. For generations, farmers have meticulously identified and propagated plants exhibiting desirable traits such as large, uniform tubers, high yield potential, and resistance to pests and diseases. This traditional practice, widely referred to as phenotypic selection, relies on observable

characteristics of the plants to guide decision-making in seed selection. Over time, this approach has resulted in the gradual enhancement of yam varieties, ensuring they meet both agronomic and consumer preferences.

An important aspect of yam farming is the exchange of yam varieties among farmers. This practice not only promotes the diversification of planting materials but also expands the genetic base of yam populations. By sharing varieties, farmers introduce new traits into their gene pools, such as tolerance to local environmental stresses or resistance to emerging diseases. This dynamic system of variety exchange fosters collaboration within farming communities and strengthens their resilience to agricultural challenges.

Although these traditional methods have been rooted in yam cultivation, similar practices are common across the globe in the cultivation of other crops [10]. Farmers worldwide have employed selective breeding and seed exchange as effective tools for improving the genetic diversity and performance of their crops, particularly in regions where modern breeding technologies may not be readily accessible.

The integration of these age-old methods with contemporary scientific approaches, such as genomic selection and molecular breeding, presents a unique opportunity to accelerate crop improvement efforts. By combining the insights gained from traditional practices with advanced breeding techniques, yam breeders have developed superior yam varieties that are better equipped to meet the demands of growing populations and changing climates.

2.2 Crossbreeding in yam improvement: Techniques, successes, and collaborations

Crossbreeding is a powerful method for improving yam varieties by intentionally crossing different parent plants to combine their desirable traits. This approach has been deployed in the yam breeding and allows yam breeders to create yam varieties with enhanced characteristics, such as higher yields, improved disease and pest resistance, and superior nutritional qualities. The process involves selecting parent plants with complementary traits, performing controlled pollination, and rigorously evaluating the progeny to identify the best-performing hybrids.

The International Institute of Tropical Agriculture (IITA) has been at the forefront of using crossbreeding to address key challenges in yam production. By developing improved varieties, IITA has significantly contributed to improving food security and farmer livelihoods in tropical regions where yam is a staple crop. Additionally, crossbreeding efforts have resulted in varieties with high productivity, better storage potential, and good tuber quality, addressing both agronomic and market needs.

For example, IITA has developed several notable yam varieties, including high-yielding white yam (*Dioscorea rotundata*) and water yam (*Dioscorea alata*) lines. These varieties have demonstrated resilience to environmental stress, making them suitable for cultivation in diverse agro-ecological zones. Beyond productivity, efforts have also focused on enhancing nutritional profiles, such as increased levels of carotenoids in tubers to combat vitamin A deficiency.

The success of crossbreeding in yam improvement has been made possible through collaborative partnerships between IITA and national research institutes. Institutions such as the National Root Crops Research Institute (NRCRI) in Nigeria, the Centre National de Recherche Agronomique (CNRA) in Côte d'Ivoire, and the Council for Scientific and Industrial Research-Crops Research Institute (CSIR-CRI) in Ghana have played critical roles in testing and disseminating improved yam varieties. These

partnerships ensure that breeding programs address region-specific challenges and meet the needs of local farmers.

Looking ahead, integrating crossbreeding with modern technologies like genomic selection, marker-assisted breeding, and pan-genome analysis has the potential to accelerate the development of even more robust yam varieties. This combination of traditional and modern breeding approaches ensures the sustainability and adaptability of yam cultivation, benefiting both smallholder farmers and consumers across the yam-growing regions. Through crossbreeding, yam improvement programs continue to unlock the potential of this staple crop, providing solutions to global challenges such as food security, nutrition, and climate resilience. The list of the released yam varieties with their characteristics can be found through the following link. https://docs.google.com/document/d/1Nu_nwoVj8MCle-hWvnRMK6FWwFgUDuktXfozGkYfBOK/edit?tab=t.0.

3. Emerging and advanced breeding technologies

3.1 Marker-assisted selection in yam breeding: Advancements and future potential

Marker-assisted selection (MAS) is a powerful tool in modern plant breeding that utilizes molecular markers to select individuals with desirable traits, speeding up the breeding process. Unlike traditional breeding methods, which rely on phenotypic selection (observable traits), MAS uses specific genetic markers linked to important traits, allowing breeders to make selections at the DNA level. This enables more precise and efficient selection of plants, even before they exhibit the traits in question [11]. In the context of yam breeding, MAS has been used to identify and select plants with improved resistance to pests, diseases, and environmental stresses, which are crucial for increasing yields and ensuring food security in yam-producing regions.

In yam breeding, MAS is primarily employed in trait mapping and linkage mapping studies. These approaches involve associating specific molecular markers with key agronomic traits such as resistance to diseases, yield [11], and high tuber quality. By identifying chromosomal regions that control these traits, IITA yam breeding program focuses on breeding lines that carry the beneficial genes. For instance, marker-trait association studies have helped identify markers linked to YMV, plant vigor, dry matter content, tuber browning, and other relevant traits.

Trait mapping is a critical aspect of this process, where the genetic control of traits such as tuber size, shape, and quality, as well as disease resistance, is studied in-depth. These studies have led to the discovery of markers associated with key characteristics of yams, including tuber shape, carotenoid content, and disease resistance. The identification of these markers in yam genomes allows for more targeted breeding, with breeders being able to select individuals that possess the desired genetic makeup early in the breeding cycle, even before the plants are grown and evaluated for their phenotypic traits.

Although several promising markers linked to key agronomic and tuber quality traits have been developed and validated, their deployment in yam breeding programs has been relatively slow. Challenges such as the complex genetic structure of yam, limited genomic resources, and the labor-intensive nature of marker validation in a crop like yam have hindered the full-scale implementation of MAS. However, research

is ongoing, and the recent development of high-throughput sequencing technologies and the construction of better yam reference genomes are expected to accelerate the use of MAS in yam breeding programs.

Recent work by researchers (unpublished), has focused on improving the identification and validation of these markers, further advancing the potential of MAS in yam breeding. These advances offer the promise of accelerating the development of improved yam varieties that are not only high yielding but also resistant to diseases and pests, making them more resilient to changing environmental conditions.

As these markers continue to be validated and integrated into breeding programs, they will become a valuable tool for the efficient improvement of yam varieties, leading to better crop performance, enhanced disease resistance, and increased nutritional quality. The continued development and application of MAS, combined with other modern breeding tools such as genomic selection and CRISPR-based gene editing, will likely transform yam breeding into a more precise, rapid, and sustainable endeavor, ensuring better varieties for farmers and consumers alike.

3.2 Genomic selection

Genomic selection involves using genome-wide markers to predict the performance of breeding lines. This method allows for selecting superior genotypes at an early stage, significantly reducing the breeding cycle. Recent studies have demonstrated the potential of genomic selection to improve complex traits such as yield and drought tolerance in yam [10]. Numerous genomic selection and prediction models have been tested using the additive, dominance, additive-dominance, and epistasis. Recently, the yam breeding has developed and implemented the Genomic Prediction of Cross Performance (GPCP), using both genomic and phenotypic information to predict the performance of prospective crosses among diverse genotypes. This methodology enhances the efficiency and precision of breeding programs by empowering breeders to select crosses anticipated to superior offspring strategically. Consequently, GPCP expedites the development of advanced yam varieties to meet evolving agricultural demands and challenges.

3.3 Advancing yam breeding through genome editing technologies

Genome editing technologies, particularly CRISPR/Cas9, have revolutionized plant science by enabling precise genetic modifications, offering unprecedented opportunities for crop improvement. In yam breeding, these technologies are being actively explored to enhance traits critical to agricultural productivity, food security, and economic viability [12]. Genome editing allows for targeted modifications, making it a valuable complement to traditional breeding techniques that often rely on phenotypic selection and take years to achieve desired results.

One of the pioneering applications of genome editing in yam has focused on conferring resistance to the yam mosaic virus (YMV). By using CRISPR/Cas9 to knock out specific susceptibility genes, researchers have demonstrated the potential for developing virus-resistant yam varieties, significantly reducing yield losses caused by this pervasive disease. Additionally, yam breeding programs are investigating genome editing strategies to improve plant architecture. Efforts are underway to create non-climbing yam varieties that reduce the reliance on high-cost staking—a major constraint for smallholder farmers [13]. Such innovations could substantially lower production costs while maintaining or enhancing tuber yield.

Beyond disease resistance and architectural improvements, genome editing holds promise for enhancing the nutritional content of yam. Efforts to increase levels of essential nutrients such as iron, zinc, and vitamin A aim to address malnutrition in regions where yam is a dietary staple. Similarly, modifications to improve drought tolerance and adaptation to changing climatic conditions are underway, ensuring yam's sustainability in diverse agro-ecological zones.

While CRISPR/Cas9 and related technologies are advancing yam breeding, earlier methods, such as *Agrobacterium*-mediated transformation, remain essential tools. These approaches have successfully introduced beneficial genes into yam, paving the way for genetic engineering as a complementary approach to traditional breeding. The integration of genome editing into breeding pipelines not only accelerates the development of improved yam varieties but also enables breeders to tackle complex traits that are difficult to address through conventional methods.

Research under the CGIAR's Roots, Tubers, and Bananas (RTB) program exemplifies how genome editing technologies are applied to address key challenges in yam production. These efforts align with broader objectives to enhance disease resistance, increase yields, and improve nutritional value across RTB crops, contributing to global food security.

However, the adoption of genome editing in yam must navigate ethical considerations and regulatory frameworks surrounding genetically modified organisms (GMOs). Ensuring public trust, addressing biosafety concerns, and adhering to international guidelines are critical for the widespread acceptance and success of genome-edited yam varieties. Despite these challenges, genome editing represents a transformative tool for modernizing yam breeding and meeting the demands of a growing global population.

3.4 Advancing yam production and conservation through tissue culture techniques

Tissue culture techniques have emerged as a cornerstone in modern yam breeding and production, offering innovative solutions for the rapid multiplication and conservation of high-quality planting materials. These methods include micropropagation and somatic embryogenesis, both of which allow for the efficient generation of disease-free yam plants. By addressing the key challenges in traditional propagation, tissue culture plays a vital role in enhancing the productivity and sustainability of yam cultivation [14].

Micropropagation, a widely used tissue culture technique, enables the rapid multiplication of yam plants under controlled laboratory conditions. This process begins with the selection of disease-free mother plants, from which small tissue samples, or explants, are taken. These explants are then grown in nutrient-rich media to produce large quantities of genetically identical, pathogen-free plants. This method ensures the consistent quality of planting materials and significantly accelerates the multiplication rate compared to traditional methods, which rely on slow and often disease-prone tuber propagation.

Somatic embryogenesis, another advanced tissue culture approach, involves the development of plants from somatic (non-reproductive) cells. This method is particularly valuable for regenerating plants from genetically engineered tissues or for conserving yam germplasm. By inducing somatic cells to form embryos that can develop into full plants, somatic embryogenesis allows for the large-scale production of uniform, high-quality yam plants [14].

One of the most significant contributions of tissue culture is the production of virus-free planting materials. Yam crops are highly susceptible to viral infections, such as yam mosaic virus (YMV), which can drastically reduce yields and compromise the quality of tubers. Tissue culture techniques, particularly thermotherapy combined with meristem culture, are used to eliminate viruses from infected plants. The resulting virus-free plants serve as a foundation for establishing healthier and more productive yam fields, ultimately benefiting farmers and improving food security.

Tissue culture is also an indispensable tool for germplasm conservation. By preserving genetic material *in vitro*, breeders and researchers can maintain a diverse collection of yam varieties, including rare or endangered genotypes. This genetic reservoir serves as a resource for future breeding efforts, enabling the development of improved yam varieties with desirable traits such as higher yields, better disease resistance, and enhanced nutritional content.

In addition to its applications in breeding and conservation, tissue culture supports the dissemination of improved yam varieties to farmers. By providing high-quality planting materials, this technology helps overcome the limitations of traditional propagation, such as low multiplication rates and susceptibility to pests and diseases. The widespread adoption of tissue culture has transformed yam production systems, contributing to the resilience and sustainability of yam farming in regions where it is a staple crop.

The impact of tissue culture techniques extends beyond yam to other crops in the CGIAR's Roots, Tubers, and Bananas (RTB) program. These methods align with global efforts to enhance food security, improve agricultural sustainability, and support the livelihoods of smallholder farmers. As tissue culture technologies continue to evolve, their integration into yam production systems promises even greater advancements in the future.

3.5 Genetic transformation

Genetic transformation involves introducing new genes into the yam genome to confer desired traits. Although still in its early stages, genetic transformation holds promise for developing varieties with improved resistance to pests and diseases, enhanced nutritional content, and better stress tolerance. Efforts are underway to optimize transformation protocols and identify suitable genes for introduction into yam [14].

3.6 Rapid seed multiplication: Innovative solutions for addressing seed yam scarcity

Yam, a staple crop feeding over 300 million people globally, is primarily produced in West Africa, accounting for 95% of the world's yam production. Grown in about 50 tropical countries, global annual yam production stands at approximately 50 million tons, with an average yield of 11 tons per hectare in key-producing regions. Despite its critical role in food security and livelihoods, yam production faces significant challenges, particularly the high cost of seed yam tubers, which hampers the sustainability of its cultivation [15].

The high cost of seed yam results from the scarcity of quality planting materials and the limited adoption of efficient propagation technologies. This disparity has created a significant gap between the annual demand for seed yam and its actual production, directly impacting yields. The inadequacy of quality planting material arises from the lack of access to high-ratio propagation technologies (HrPT) and a

limited understanding of existing seed yam production methods. Addressing this challenge requires alternative, cost-effective, and scalable approaches for rapid seed yam multiplication [15].

To mitigate these challenges, several innovative techniques have been developed and refined by research organizations such as the International Institute of Tropical Agriculture (IITA). Among these is the minisett technique, which involves cutting seed yam tubers into small pieces with sufficient periderm cover. This method enhances the multiplication rate and reduces the overall cost of planting materials without compromising the quality of the yam plants produced [16].

Other advanced methods complementing the minisett technique include the following:

1. **Aeroponics system (AS):** This soil-less method grows yam plants in a nutrient-rich mist environment, promoting efficient root development and higher propagation rates.
2. ***In vitro* propagation:** Tissue culture techniques ensure the production of virus-free yam plantlets, facilitating the dissemination of disease-free planting materials.
3. **Temporary immersion bioreactor system (TIBS):** This advanced tissue culture technology accelerates the multiplication of yam plantlets by optimizing growth conditions in a liquid medium.
4. **Vine-cutting techniques:** Yam vine cuttings are rooted to produce planting materials, offering an alternative to traditional tuber propagation.
5. **Semi-autotrophic hydroponics (SAH):** This innovative hydroponic system enhances yam growth and reduces the time required to produce planting materials.

These technologies not only address the seed yam scarcity but also improve productivity by providing high-quality, cost-effective planting materials.

3.7 The potential of precision agriculture to revolutionize yam breeding

Precision agriculture, an emerging approach that leverages digital tools and data analytics, holds significant promise for transforming yam cultivation and breeding programs. While not yet fully adopted in yam production systems, the integration of precision agriculture techniques is being explored to enhance decision-making processes, improve resource use efficiency, and accelerate the development of superior yam varieties [17].

Remote sensing technologies, including satellite imagery and drone-based monitoring, are also being considered for their potential in yam cultivation. These tools can help monitor crop growth, assess canopy structure, and detect early signs of pest or disease outbreaks. For yam breeders, remote sensing could streamline the evaluation of field trials by providing rapid, non-invasive assessments of traits such as plant vigor, drought tolerance, and pest resistance [18].

GPS-guided machinery represents another prospective innovation, particularly for yam planting and land preparation. Although adoption is still limited, the precision offered by such technology could ensure uniform planting depths and spacing,

critical for standardizing experimental conditions in breeding trials. This would enhance the reliability of trial data, allowing for more accurate selection of promising yam genotypes [19].

A particularly exciting avenue in yam breeding is the potential use of image analysis for tuber evaluation. This technology, still under the development for large-scale application, could enable breeders to assess tuber shape, size, and other critical traits more efficiently and objectively. By automating these evaluations, breeding programs could significantly reduce the time and labor required to phenotype large populations, thereby accelerating the development of improved yam varieties.

If fully implemented, precision agriculture tools have the potential to revolutionize yam breeding by enabling data-driven decisions, optimizing resource use, and enhancing the precision of trait evaluation. These innovations could reduce breeding cycles and improve the selection of high-performing varieties, ultimately boosting productivity and sustainability in yam cultivation. While much work remains to be done to integrate these technologies into routine practice, their potential impact on the yam breeding landscape is substantial.

3.8 Disease phenotyping in yam: Methods and applications

Disease phenotyping is critical for yam breeding programs, enabling the identification of resistant varieties and the development of strategies to mitigate disease impacts. Several methods are employed to assess the presence, severity, and impact of diseases on yam plants, ranging from visual assessments to advanced molecular and imaging techniques.

The most common approach involves visual assessment of disease symptoms on yam leaves, stems, and tubers. Symptoms are evaluated using predefined scales, such as the percentage of affected tissue or the severity of lesions. For instance, symptoms of yam mosaic virus (YMV) are frequently scored on a scale from 0 (no symptoms) to 5 (severe mosaic and stunting), providing a standardized method for disease assessment [20]. This approach, while simple and cost-effective, relies heavily on the expertise of the evaluator and can be subjective.

To enhance accuracy, molecular techniques such as enzyme-linked immunosorbent assays (ELISA) and polymerase chain reaction (PCR) are employed to detect and quantify specific pathogens. These methods are particularly effective in identifying and quantifying viruses, such as YMV, and fungal pathogens that impact yam productivity. By providing precise pathogen detection at the molecular level, these tools complement visual assessments and enhance the reliability of disease phenotyping [21].

Emerging technologies such as multispectral and hyperspectral imaging offer promising advancements in yam disease phenotyping. These imaging techniques capture detailed spectral data, distinguishing between healthy and diseased yam plants—often before visible symptoms appear. Such early detection capabilities can help breeders and researchers identify disease-resistant genotypes more efficiently and provide valuable insights into the progression of diseases under varying conditions [22].

Field trials and controlled environment studies remain essential for evaluating disease resistance in yam genotypes. These trials expose yam plants to natural or artificial disease pressures, allowing researchers to assess the performance of different genotypes under realistic or controlled conditions. The data generated from these studies are invaluable for identifying yam varieties with strong resistance to key diseases, such as anthracnose, YMV, and nematode infestations, and for informing breeding decisions [23].

Integrating these methods into yam breeding programs enhances the precision and efficiency of disease resistance evaluation. As yam breeding continues to evolve, the application of molecular and advanced imaging technologies alongside traditional methods holds significant potential to address the challenges posed by plant diseases.

3.9 Sustainable practices in yam farming: Conservation and organic agriculture

Sustainable yam farming is increasingly adopting principles of conservation and organic agriculture to enhance soil health, boost productivity, and promote environmental sustainability. These approaches not only address the challenges of soil degradation and climate change but also align with consumer demands for environmentally friendly farming practices.

Conservation agriculture focuses on three core principles: minimal soil disturbance, crop rotation, and maintaining soil cover. In yam cultivation, practices such as minimum tillage, mulching, and intercropping with legumes are being explored for their numerous benefits. Minimum tillage reduces soil disruption, preserving its structure and microbial activity. Mulching helps retain soil moisture, suppress weeds, and prevent erosion, while intercropping with legumes enriches soil fertility by fixing atmospheric nitrogen. Together, these practices improve soil health, reduce erosion, enhance water retention, and contribute to resilient yam production systems better adapted to climate variability [24].

Organic farming in yam production emphasizes natural inputs and ecological processes to manage soil fertility and pests. Techniques such as applying compost and green manures improve soil organic matter and nutrient content. Biological pest control agents, including beneficial microbes and natural predators, reduce the reliance on synthetic pesticides, minimizing environmental harm. Organic yam farming has gained traction due to its ability to support biodiversity, promote soil health, and meet the rising consumer demand for organic produce. Additionally, organic products often fetch premium prices in niche markets, providing economic incentives for farmers adopting this approach [10].

By integrating conservation and organic farming practices, yam farmers can build more sustainable and resilient production systems. These methods offer long-term benefits by maintaining soil productivity, reducing environmental impacts, and aligning with the evolving needs of both producers and consumers. As research continues to refine these practices, their adoption is expected to grow, ensuring a sustainable future for yam cultivation globally.

3.10 Integrated pest management (IPM)

Sustainable yam production requires integrated strategies that address pest and disease management, climate adaptation, and resource optimization. Biological control offers an eco-friendly alternative to chemical pesticides, using natural predators, parasitoids, and pathogens to manage pests and diseases. In yam farming, biocontrol agents such as *Trichoderma* spp. and *Bacillus thuringiensis* have been effective against soil-borne diseases and insect pests [17]. *Trichoderma* spp. enhances plant growth while suppressing pathogens such as *Fusarium* and *Pythium*, and *Bacillus thuringiensis* targets insect pests, reducing environmental contamination and resistance development associated with chemical pesticides. Scaling up these agents in yam farming could significantly improve yield and sustainability when combined with integrated pest management (IPM) strategies.

Cultural practices are fundamental to IPM in yam farming, offering cost-effective ways to disrupt pest and disease cycles. Techniques such as crop rotation, intercropping, and sanitation are crucial. Rotating yam with non-host crops like legumes reduces nematode infestations and pathogen build-up while improving soil fertility. Intercropping with crops such as maize or cassava diversifies the agroecosystem, reducing pest habitats and enhancing land-use efficiency. Field sanitation, including removing infected plant material, minimizes the spread of pathogens such as anthracnose and yam mosaic virus. These practices, when combined, enhance resilience against pest and disease pressures in yam farming systems.

The impact of climate change has necessitated strategies to enhance the resilience of yam crops to environmental stresses such as drought. Breeding programs are developing drought-tolerant varieties by incorporating genes that improve water stress resilience, ensuring stable yields in water-limited conditions. These efforts are complemented by efficient water management practices, including drip irrigation and rainwater harvesting. Drip irrigation delivers water directly to plant roots, optimizing water use, while rainwater harvesting ensures a reliable water supply during dry periods. Integrating drought-tolerant varieties with these practices ensures sustainable yam production under changing climatic conditions, securing food supplies and livelihoods for millions dependent on yam cultivation.

4. Post-harvest technologies

4.1 Storage techniques

Reducing post-harvest losses and maintaining the quality of yam tubers is critical for ensuring food security, improving market availability, and increasing farmer income. Yams are particularly susceptible to post-harvest deterioration due to their high moisture content, vulnerability to pests, and susceptibility to microbial infections. Therefore, improving post-harvest storage techniques has become a priority in yam production systems.

Innovative storage solutions, such as improved yam barns, have proven effective in minimizing losses. These structures are designed to provide better ventilation and protection from pests and environmental factors. Additionally, modern barns often incorporate temperature and humidity control systems, which help create optimal storage conditions to prevent tuber sprouting, rotting, and drying. Such controlled environments significantly extend the shelf life of yam tubers and preserve their nutritional and market value.

Another promising approach is the use of natural preservatives. These include botanical extracts, organic coatings, and other bio-based materials that create a protective barrier on yam tubers. Such treatments help prevent microbial growth and minimize spoilage, offering an environmentally friendly alternative to chemical preservatives.

Traditional methods such as intercropping systems and proper curing of tubers before storage also play a role in reducing post-harvest losses. Curing involves exposing harvested tubers to warm temperatures and high humidity for a specific period, which helps heal wounds and reduce water loss. This simple but effective technique is widely practiced and enhances the storage potential of yams.

Furthermore, capacity-building initiatives aimed at training farmers and stakeholders in proper handling, sorting, and storage practices are vital. Reducing

post-harvest losses requires a holistic approach that combines technical innovations with improved practices at all stages of the value chain.

By adopting these techniques, yam-producing regions can ensure a steady and high-quality yam supply throughout the year, reducing food waste and supporting livelihoods. Enhanced storage systems not only address food security challenges but also contribute to sustainable agricultural development in yam-producing regions [25].

4.2 Value addition

Value addition through processing yam into various products, such as flour, chips, starch, and other derivatives, is pivotal in enhancing market opportunities and increasing the economic value of the crop. Processing transforms yam into shelf-stable and high-value products that can be marketed both locally and internationally, thereby addressing key challenges such as post-harvest losses and market volatility. Technologies such as mechanical peelers, slicers, and solar or industrial dryers play a critical role in improving the efficiency and quality of yam-based products. For instance, yam flour, a widely demanded product, has a longer shelf life, ensuring year-round availability and reducing spoilage. Chips and starch, on the other hand, serve diverse industries, including food processing, pharmaceuticals, and textiles, creating multiple streams of economic benefits.

The adoption of yam processing technologies empowers smallholder farmers by enabling them to diversify their income sources and reduce their reliance on the sale of fresh tubers that are highly perishable. Processed yam products often attract premium prices in local and export markets, giving farmers and agro-processors access to more lucrative opportunities. Additionally, processing addresses consumer demands for convenience, quality, and value-added options, increasing the competitiveness of yam in both domestic and international markets.

In many yam-producing regions, post-harvest losses are a significant challenge due to inadequate storage and limited market access. Processing technologies offer a sustainable solution, allowing surplus harvests to be converted into durable and marketable forms. This not only stabilizes prices during peak production periods but also contributes to food security by ensuring the availability of yam products throughout the year. Furthermore, value addition fosters rural development and job creation, particularly in yam-processing hubs, where the establishment of small- and medium-sized enterprises stimulates economic growth.

Addressing these critical aspects, yam value addition underscores its potential as a driver of agricultural transformation, rural empowerment, and sustainable economic development. With increasing investment in processing technologies and supportive policies, yam-producing regions can maximize the crop's potential while ensuring long-term benefits for farmers, processors, and consumers alike [19].

5. Conclusion

Technological advancements and innovations are revolutionizing yam agriculture, offering solutions to many of the challenges farmers face. These innovations, from traditional breeding techniques to modern biotechnologies and digital tools, enhance productivity, sustainability, and resilience in yam farming. Continued research and development and adopting these technologies will play a crucial role in ensuring food security and improving livelihoods in yam-growing regions.

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Section 3

Simulation Models and Adaptation Options in Climate Change

Effect of Salt Stress on Growth, Nodulation and Antioxidant Responses of *Medicago sativa* (Alfalfa) Inoculated with Indigenous Strains

Oukacha Amri, Laila Aberchane, Hakima Lounis, Rachid Fghire, Khouzaima el Biari, Abdeslem Talbi, Mustapha Faghire and Khadijattou Taoufiq

Abstract

Alfalfa is vital legume forage in the Mediterranean, but its production and nitrogen-fixing activity are hindered by salt stress. This study evaluated the effectiveness of the indigenous rhizobia strain Rhol3, alone or combined with non-rhizobia strain LNR57 (Rhol3-LNR57), in improving salinity tolerance in three alfalfa varieties: Moroccan (Morr), American (United States), and Australian (Aust). Rhol3 was isolated from *M. sativa* nodules in Marrakech, and LNR57 (*Enterobacter* sp.) from legume nodules in Tata-Akka. Seedlings inoculated with Rhol3 or Rhol3-LNR57 were grown under control (0 mM NaCl) and salt stress (100 mM NaCl) conditions. Salinity had no adverse effects on biomass or nodulation in plants inoculated with Rhol3 or Rhol3-LNR57. Antioxidant enzyme activity (SOD, PO, PPO, CAT) and total phenol content increased under salinity, while H₂O₂ and MDA levels remained stable. These responses suggest that inoculation with Rhol3 or Rhol3-LNR57 alleviates salt stress by enhancing nodulation and antioxidant defenses, maintaining low oxidative damage. This highlights the potential of these strains to mitigate salinity effects and improve growth and productivity in alfalfa under stress conditions.

Keywords: Rhol3, Rhol3-LNR57, symbiosis, salt stress, antioxidant responses, *Medicago sativa*

1. Introduction

Alfalfa (*Medicago sativa* L.) is a high-quality forage crop widely grown throughout the world. Alfalfa is a perennial, outcrossing, and autotetraploid species, widely grown as a forage legume for hay, pasture and silage [1, 2]. Due to its outcrossing

nature, most alfalfa cultivars are synthetic populations with complicated genetic background [3]. The ecological interest in alfalfa relies on its ability to fix atmospheric nitrogen in symbiosis with rhizobia inside nodules, which allows the reduction or avoidance of N fertilizer application [4–6]. In the rhizobia-legume symbiotic process, host plants provide carbon compounds derived from photosynthesis to support activity and development of rhizobia. In return, rhizobial symbiosis improves plant growth by providing fixed nitrogen and amelioration nutritional status, and by enhancing their defense against pathogens and their adaptation to various environmental stresses [7].

Salinity recorded in many regions in the world constitutes a major environmental factor limiting plant growth and productivity of alfalfa. Salinity stress affects negatively many physiological processes in plants such as photosynthesis, mineral nutrition and protein content [8–10], and carbon metabolism in nodules of legumes which decreases the activity of nitrogenase and thereby the fixation of nitrogen [11–13]. The negative effect of salinity is mainly due to osmotic, ionic and oxidative stress. Osmotic stress decreases soil water availability to plants, and impedes the plant's absorption of water. Ionic stress disrupts mineral homeostasis, while oxidative stress causes the release of reactive oxygen species (ROS), which inhibit cell growth and disturb plant metabolism [9, 14]. Several studies have shown that rhizobia symbiosis improved the salt tolerance of alfalfa plants by mediating a series of molecular and physiological processes, such as enhancing the activity of antioxidative defense to remove ROS molecules [15].

Thus the objective of this study is to examine the effect of inoculation by indigenous rhizobia on some agro-physiological traits of *Medicago sativa* L. under salinity conditions. Biomass production, nodulation, total phenol content, the activities of peroxidase (PO), polyphenol oxidase (PPO), superoxide dismutase (SOD) and catalase (CAT) were evaluated as well as the content of MDA and H₂O₂.

We hypothesized that the rhizobia strain Rhol3 and non-rhizobia strain LNR57, both isolated from the root nodules of alfalfa, and legumes, respectively, grown in salt-affected soils might improve the alfalfa salt tolerance by affecting its physiological, morphological and biochemical processes during stress response.

2. Materials and methods

2.1 Biological material and experimental treatments

This study was carried out under greenhouse conditions, at the Faculty of Science, Ibnou Zohr University, Agadir. Three alfalfa (*M. sativa*) varieties, Moroccan variety (Morr), American variety (United States), and Australian variety (Aust), were inoculated with *Rhizobium* strains Rhol3 and co-inoculated with Rhol3 and non-rhizobial strains LNR57 identified as *Enterobacter* sp. Rhol3 strains were isolated and purified, as described by El Khalloufi et al. [16], from roots nodules of *M. sativa* plants collected from Marrakech regions, while LNR57 strains were isolated and purified, as described by Taoufiq et al. [17], from roots nodules of legumes plants collected from Tata-Akka regions in South of Morocco.

Commercial seeds of Moroccan variety (Morr), American variety (United States) and Australian variety (Aust) were surface disinfected with NaClO (5%) for 5 min, washed with sterile distilled water and germinated on the surface of filter paper soaked with sterile distilled water. The germination was conducted in the dark

at 25°C for 3 days. The young seedlings were transplanted (ten per pot) into 20 cm diameter and 30 cm height pots containing sand and peat at a 2:1 ratio, respectively, and previously sterilized. The pots (10 plants) were arranged in a simple randomized design and each pot was considered as one replicate with three pots per treatment per population. Each seedling was inoculated with 1 ml of RhoI3 or a mixture of RhoI3 and LNR57 that were applied directly to the roots. The inoculums were grown in Yeast Extract Mannitol (YEM) medium with a density of 109 mL^{-1} . The pots were initially irrigated with nutrient solution [18] supplied with 2 mM of urea during the first week of culture every three days. Then, the pots were irrigated with N-free nutrient solution [18]. Three weeks after transplantation, plants were subjected to two saline treatments: 0 and 100 mM NaCl added to the nutrient solution. After 3 days of the second nutrient irrigation, the plants were irrigated with distilled water to leach the salts. The cycle was then repeated. After six weeks of salt treatment, the plants were harvested and the roots were thoroughly washed with distilled water. The samples were used for the different analyses or frozen and stored at -80° .

2.2 Quantification of the dry biomass (DW)

For dry weight (DW) measurement, shoots, roots and nodules were separated and dried at 80°C for 48 h. Then, DW was weighed.

2.3 Determination of malondialdehyde (MDA) content of the plants

The thiobarbituric acid (TBA) method was applied to measure the MDA content as result of lipid oxidation [19]. TBA reacts with MDA to give a red fluorescent adduct with maximum absorbance at 532 nm. The content of lipid peroxide in the samples could be estimated after colorimetry. Thus, fresh nodules or leaves (100 mg) were individually crushed and homogenized in 0.5 ml of 0.1 trichloroacetic acid (TCA) (10%), then mixed with 0.5 ml of acetone and centrifuged at 8000 rpm for 15 min. Then, 1 ml of phosphoric acid (H_3PO_4) and 1 ml of thiobarbituric acid (0.6%) were added to 500 μl of the supernatant. The mixture was heated to 95°C , for 30 min, with agitation and then cooled into an ice bath. Then, 1.5 ml of 1-butanol was added to the mixture. The supernatant was recuperated after centrifugation at 8000 rpm for 15 min and its absorbance was determined at 532 nm. The concentration of MDA (μmol of MDA per g of fresh weight) was calculated using an extinction coefficient of $155 \text{ Mm}^{-1} \text{ cm}^{-1}$.

2.4 Determination of hydrogen peroxide (H_2O_2) content

Hydrogen peroxide was spectrophotometrically measured following the protocol of Velikova et al. [20]. Fresh leaf and nodule tissues (100 mg) were crushed and homogenized in the ice bath (or 4°C) with 2 ml trichloroacetic acid (20%) (TCA). The homogenate was centrifuged at 15000 rpm for 15 min., and the supernatant (0.5 ml) was added to 0.5 ml 10 mM potassium phosphate buffer (pH 7.0) and 1 ml of potassium iodide (1 M). The absorbance of the supernatant was measured at 390 nm after 1 h of incubation at the obscurity. The amount of H_2O_2 was expressed as μmol of H_2O_2 per g fresh weight in Ref. to a standard range established under the same conditions with known concentrations of H_2O_2 .

2.5 Determination of the total phenol content

The content of phenolic compounds in the leaf extracts was measured using the Folin-Ciocalteu's method [21]. Total phenols were extracted by crushing and homogenizing 100 mg of fresh samples in 1.5 ml of methanol solution (80%) at 4°C. The mixture was centrifuged at 13000 rpm for 10 min at 4°C. The supernatant samples (0.5 ml) were transferred into 5 ml tubes, and the reaction mixture was prepared by combining 1 ml of 95% ethanol, 2.5 ml of distilled water, and 0.25 ml of Folin-Ciocalteu reagent. After 5 minutes of incubation, 1 ml of 20% sodium carbonate (Na_2CO_3) solution was added. The mixture was immediately vortexed, then incubated in the dark at 40°C for 1 hour. Finally, the absorbance was measured at 760 nm. A mixture of 7% Na_2CO_3 solution, 1:10 diluted Folin-Ciocalteu reagent, and the extracting solution instead of plant extract was used as blank. Solutions of gallic acid were used to prepare the standard curves [22]. Results were expressed as μg gallic acid/mg leaves or nodules dry weight.

2.6 Preparation of extracts and enzyme assays for peroxidase (PO), polyphenol oxidase (PPO) and superoxide dismutase (SOD)

The antioxidant potential of plant extracts was assessed using the method of Tejera et al. [23]. The extracts were prepared by crushing and homogenizing leaves or nodules samples (100 mg) (in cold mortar) with 1.5 ml of phosphate buffer (0.1 M, pH 7.0) containing 5% of polyvinylpyrrolidone (PVP). The mixture was vigorously shaken, and the tubes were centrifuged at 12000 rpm for 30 and the supernatant was used to determine the activities of the enzymes. Peroxidase (PO) activity was measured on the basis of determination of kinetic formation of tetraguaiacol at 470 nm. The PO activity was determined at 30°C by mixing 100 μl of the enzymatic extract, 300 μl of guaiacol (20 mM), and 2 ml of phosphate buffer (0.1 M, pH 6). Then, 200 μl H_2O_2 was added to trigger the reaction [24].

The activity of POD was assayed by adding an aliquot of the tissue extract (100 μl) to 500 μl of catechol (1.6%) in phosphate buffer (0.1 M, pH 6) for 3 min at room temperature. The absorbance was read at 410 nm [24]. PO and PPO activities were expressed as the amount of enzyme that oxide 1 μmol of guaiacol or catechol per mg of protein per min.

The SOD activity was determined by colorimetric method at 560 nm. SOD was assayed on the basis of its ability to inhibit the photochemical reduction of nitro blue tetrazolium by O^{2-} , generated in the reaction by photo-reduction of riboflavin, according to the method of Iordachescu and Dumitru [25].

2.7 CAT content

Catalase activity (μmol H_2O_2 /mg Prot/min) was measured following the method of Gong et al. [26]. Leaf, root or nodule fresh segments (100 mg) were homogenized in 5 ml of Tris-HCl (pH 8.5) containing 2 mM EDTA and 10% polyvinylpyrrolidone (p/v). The homogenate was centrifuged at 16000 rpm for 14 min at 4°C, and the supernatant was immediately used for the following enzyme assays. The CAT activity was determined by monitoring the decomposition of H_2O_2 substrate at 415 nm [27, 28]. The reaction mixture consisted of the enzyme extract and 2 ml of tampon Tris-HC 150 mM pH 6.8 containing 5 mM H_2O_2 , and the reaction was stopped by the addition of 0.25 ml of 20% titanium tetrachloride after 10 min at 20°C. A blank was prepared by adding 0.25 ml of tétrachlorure de titane (20%) in time zero to stop the enzymatic reaction.

2.8 Statistical analysis

The experimental layout was a completely randomized design. The growth values were means of six replicates per treatment. Three replicates were used for the other parameters. All results were subjected to a three-way analysis of variance. The means were compared with the least significant difference (LSD) test using CoStat.

3. Results

3.1 Plant biomass

The results represented in the **Figure 1A** and **B** showed that salinity did not affect dry weight of shoots and roots of Morr, United States and Aust of *M. sativa* inoculated with Rho13 or their combination Rho13-LNR57. In general, a leger increase of dry weight, was observed, for the three varieties of *M. sativa* inoculated with Rho13-LNR57 in comparison to Rho13, under salinity.

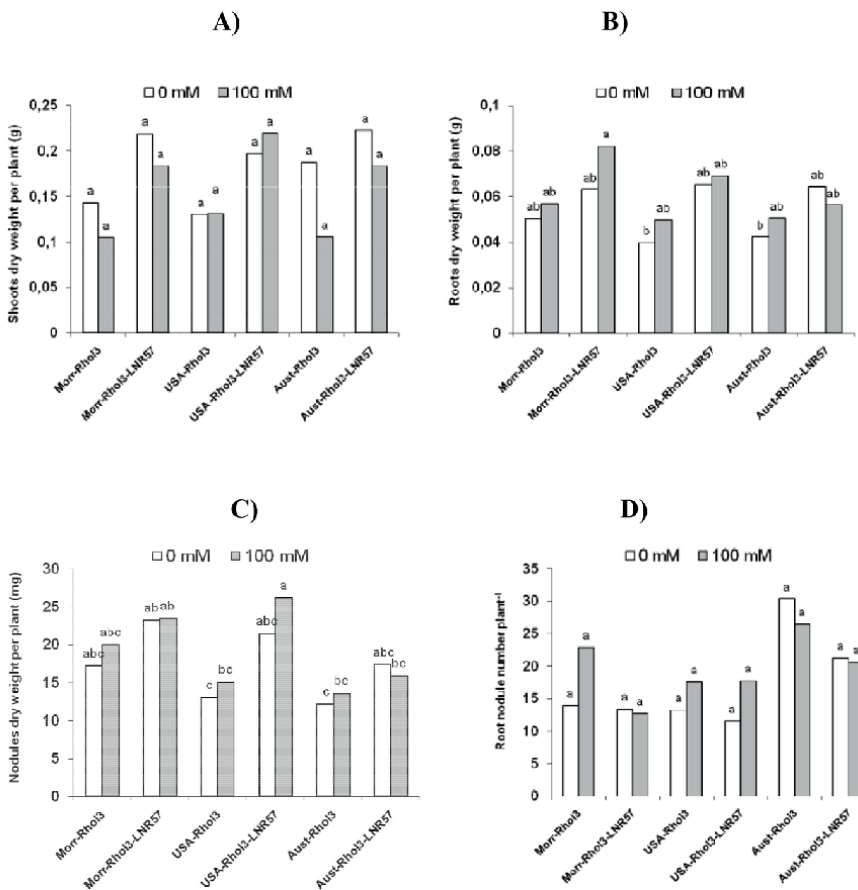


Figure 1. Effects of salt treatment on shoot dry weight (A) roots dry weight (B) nodules dry weight (C) and nodules number (D) of *M. sativa* inoculated with Rho13 or Rho13-LNR57 bacterial strains. Bars with no common letter are significantly different as determined by LSD ($p \leq 0.05$).

3.2 Rhizobial symbiosis

Rhizobial symbiosis, evaluated by dry weight and the number of nodules, was not affected by salinity in all symbiotic associations (**Figure 1C and D**). The higher dry weight of nodules was observed in USA-rho13-LNR57 with 25 mg/plant, while we recorded 30 nodules/plant as the higher number of the nodules in the roots of Aust-Rho13.

3.3 Antioxidant enzymatic activities

The results (**Figures 2 and 3**) indicated that salinity did not affect the amount of SOD, POD, PPO and CAT in leaves and roots of the majority of the symbiotic associations. By contrast, SOD and POD activities in leaves were markedly increased under salinity treatments in United States and Aust inoculated with Rho13-LNR57. While, a significant increase of PPO activity in leaves and roots, under salinity, was observed in Morr inoculated with Rho13 and Rho13-LNR57 and in the activity of CAT in United States inoculated with Rho13. CAT activity was markedly increased under salinity treatments in nodules of the two varieties Morr and United States inoculated with single inoculation and dual inoculation (**Figure 4**). While no increase in the activity of SOD, POD and PPO, under salt stress, was recorded except for the symbiotic association

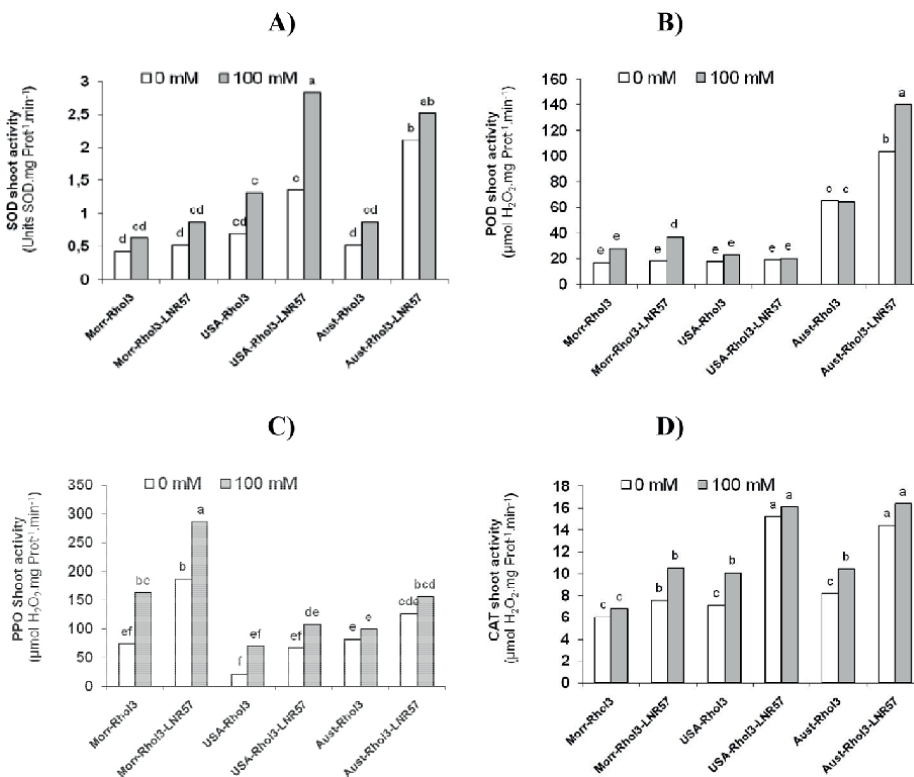


Figure 2. Effects of salt treatment on content of antioxidative enzymes in leaves of *M. sativa* inoculated with Rho13 or Rho13-LNR57 bacterial strains. Superoxide dismutases (SOD) (A), Peroxidase (POD) (B), Polyphenoloxidase (PPO) (C) and Catalase (CAT) (D). Bars with no common letter are significantly different as determined by LSD ($p \leq 0.05$).

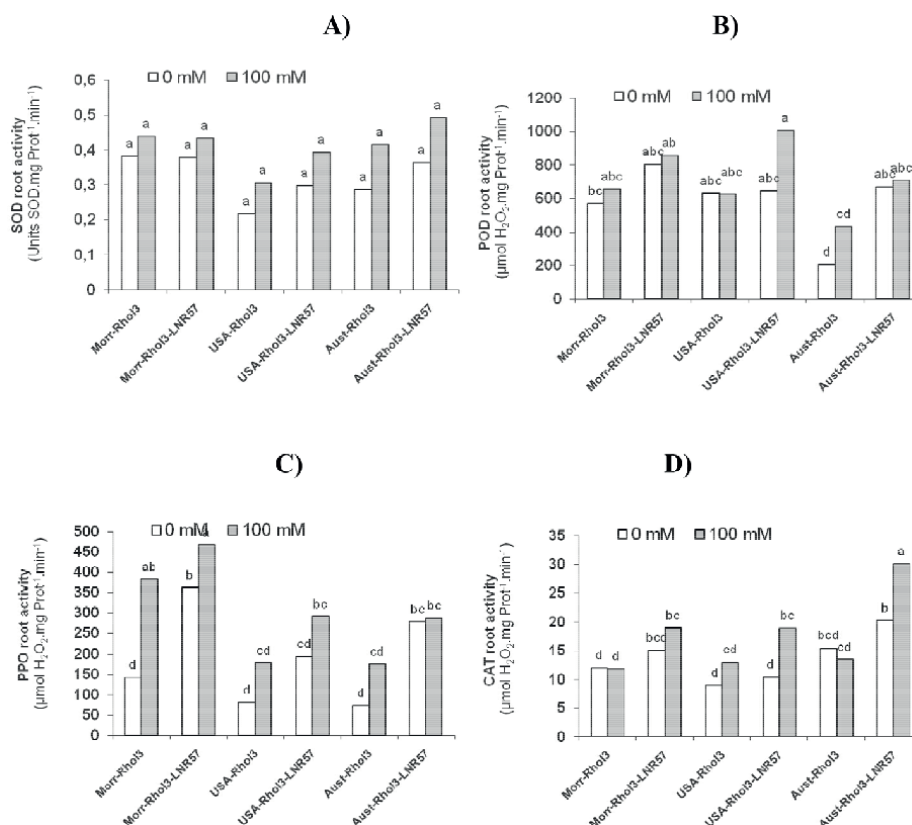


Figure 3. Effects of salt treatment on content of antioxidative enzymes in roots of *M. sativa* inoculated with *Rho13* or *Rho13-LNR57* bacterial strains. Superoxide dismutases (SOD) (A), Peroxidase (POD) (B), Polyphenoloxidase (PPO) (C) and Catalase (CAT) (D). Bars with no common letter are significantly different as determined by LSD ($p \leq 0.05$).

USA-Rho13 where we observed an increase in the activity of POD under salinity conditions. The activity of CAT and PPO was more pronounced in the nodules than in the shoot and root tissues, while POD activity was more important in roots, in contrast, no significant difference was observed in SOD activity in the different tissues tested.

3.4 Lipid peroxidation

The obtained results showed that salinity did not affect the amount of MDA in the nodules and roots of all symbiotic associations. Also, the amount of MDA was not affected, by salinity, in leaves of the three varieties of *M. sativa* inoculated by Rho13. By contrast, salinity increase significantly the amount of MDA in leaves of Morr, United States and Aust inoculated with Rho13-LNR57; MDA values are higher in the roots than in the shoot and nodules tissues (Table 1).

3.5 Total phenol content

The absorbance values of total phenol content are shown in Table 1. The results showed that the content of total phenol was more pronounced in leaves compared to

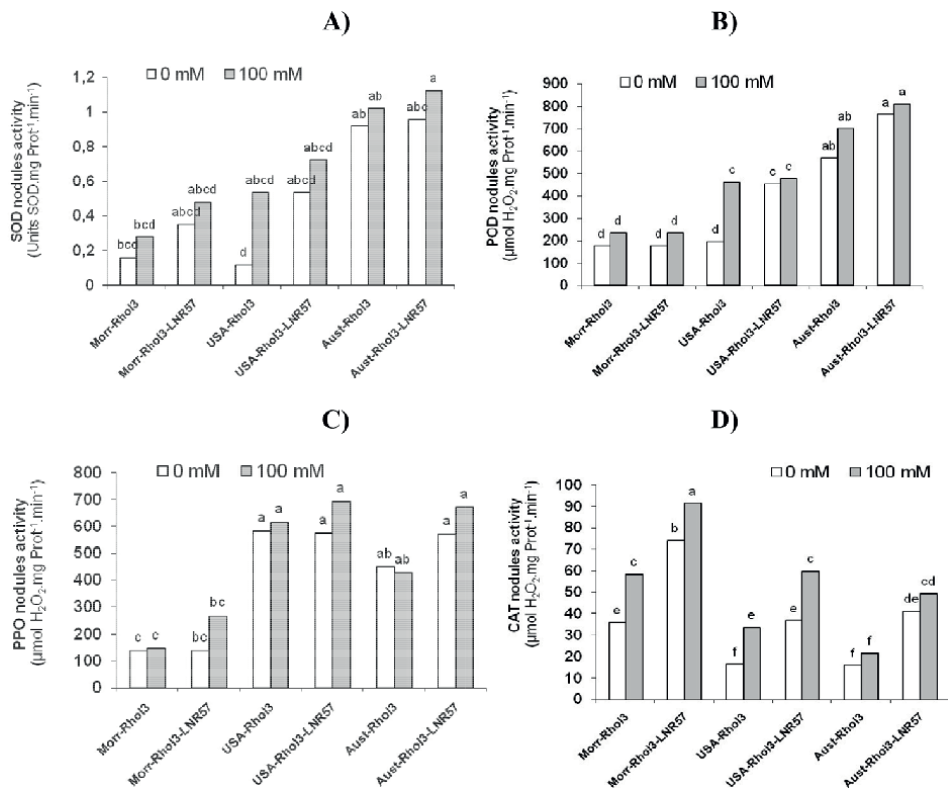


Figure 4. Effects of salt treatment on content of antioxidative enzymes in nodules of *M. sativa* inoculated with *Rho13* or *Rho13-LNR57* bacterial strains. Superoxide dismutases (SOD) (A), Peroxidase (POD) (B), Polyphenoloxidase (PPO) (C) and Catalase (CAT) (D). Bars with no common letter are significantly different as determined by LSD ($p \leq 0.05$).

the roots and nodules. In leaves the amount of total phenol content was increased significantly by salinity in Morr-Rho13-LN57 and Aust inoculated with single and dual inoculation. While salinity stress increased the amount of nodules of total phenolic compounds significantly in only the Morr-Rho13-LN57 symbiotic association. By contrast, salt treatment did not increase the roots total phenolic compounds in all the symbiotic associations.

3.6 Hydrogen peroxide content (H_2O_2)

To evaluate the oxidative stress level in the plants, we quantified the plants content of hydrogen peroxide. The results (Table 1) showed that salinity did not affect the content of H_2O_2 in all the symbiotic associations of *M. sativa*, which means that inoculation by *Rho13* or *Rho13-LNR57* has reduced oxidative stress under salt conditions.

4. Discussion

As reported by many authors, salinity affects the growth of *M. sativa* by affecting many physiological processes, which lead to several disturbances such as a decrease

	Genotypes	strains	Leaves			Roots			Nodules	
			0 mM	100 mM	0 mM	0 mM	100 mM	0 mM	100 mM	100 mM
H ₂ O ₂ content (μmol g ⁻¹ MF ⁻¹)	Morr	Rhol3	40,27 fg	48,34 efg	17,08 cd	22,15 bcd	18,60 b	23,79 ab		
		Rhol3-LN57	56,34 efg	63,65 def	39,12 abc	48,32 a	35,50 a	32,04 ab		
	United States	Rhol3	41,32 fg	35,10 g	24,35 bcd	29,60 abcd	21,81 ab	17,56 b		
		Rhol3-LN57	97,78 a	91,17 ab	40,38 ab	31,40 abcd	33,40 a	35,04 a		
Phenol content (mg acide gallique g.MF ⁻¹)	Aust	Rhol3	78,30 bc	66,89 cde	12,19 d	20,75 bcd	23,50 ab	26,56 ab		
		Rhol3-LN57	76,51 bcd	67,38 cde	31,69 abcd	36,18 abcd	24,88 ab	27,09 ab		
	Morr	Rhol3	218,23 c	181,93 c	57,11 c	141,79 abc	169,43 bc	177,73 bc		
		Rhol3-LN57	341,67 b	497,79 a	149,26 abc	199,73 ab	277,42 b	367,39 a		
MDA content (μmol MDA gMF ⁻¹)	United States	Rhol3	309,76 b	316,28 b	158,57 abc	180,15 abc	133,52 c	203,59 bc		
		Rhol3-LN57	430,23 a	432,78 a	219,50 a	204,79 a	130,45 c	136,43 c		
	Aust	Rhol3	149,59 c	300,37 b	86,21 bc	89,72 bc	98,90 c	168,25 bc		
		Rhol3-LN57	322,54 b	432,19 a	92,88 bc	154,54 abc	142,31 c	148,83 c		
	Morr	Rhol3	0,035 d	0,062 cd	0,265 bc	0,344 ab	0,042 abc	0,053 ab		
		Rhol3-LN57	0,043 cd	0,121 b	0,366 ab	0,391 ab	0,064 a	0,059 a		
	United States	Rhol3	0,033 d	0,036 d	0,034 d	0,031 d	0,022 c	0,020 c		
		Rhol3-LN57	0,071 c	0,136 ab	0,073 d	0,109 d	0,043 abc	0,034 abc		
	Aust	Rhol3	0,032 d	0,029 d	0,218 c	0,275 bc	0,023 bc	0,050 abc		
		Rhol3-LN57	0,116 b	0,159 a	0,300 abc	0,405 a	0,036 abc	0,040 abc		

Table 1.
 Effect of salt treatment on content of hydrogen peroxide (H₂O₂), phenol and malondialdehyde (MDA), in leaves, roots and nodules of *M. sativa* inoculated with Rhol3 or Rhol3-LN57 bacterial strains. Means followed by the same letter within a column are not significantly different ($P \leq 0.05$) using the least significant difference (LSD) test.

in relative water content, a perturbation of membrane permeability, a decrease in nutrients concentrations and protein concentration [8–10]. In general, salinity can affect plants by causing osmotic, ionic, and/or oxidative stress, which has a negative impact on crop growth and productivity [14, 29].

Rhizobial symbiosis could play important roles in the maintenance of plant and soil health under different stressed conditions. Alleviation of salt stress by rhizobia has been reported in *Medicago sativa* [30] and other legumes such as *Phaseolus vulgaris* [11, 31, 32]. In this study, we assessed the effects of indigenous rhizobial strain Rho13 or its combination with non-rhizobial strain LNR57 (Rho13-LNR57) on three varieties of alfalfa under salt stress. The results showed that salinity did not affect the growth and nodulation of the three varieties of alfalfa, which indicate an efficient rhizobial symbiosis and synergetic effects between Rho13 and LNR57. It has been reported that inoculation by rhizobia maintains high nitrogen fixation attributes, including the weight and the number of nodules, allowing additional uptake and assimilation of nitrogen, which leads to the enhancement of the growth under salinity stress [33–36]. Thus, nodulated legumes are more tolerant to adverse environmental conditions than plants receiving mineral nitrogen [35, 37, 38]. Wang et al. [39] suggested an enhancement of photosynthesis as a strategy to meet the additional energy needs for active nitrogen fixation for dealing with salinity stress. Also, rhizobial strains may have contributed to nutrient mobilization from soil minerals, thereby improving plants nutrient status, which in turn allows the host plant to form the nodules and fosters N fixation by rhizobia [40]. In addition, rhizobia can also increase root length, surface area, and root number under salinity, which facilitates the uptake of water and minerals and enhances growth [41, 42].

H_2O_2 at high concentration is the most stable ROS in the cells that can diffuse very rapidly across the subcellular membrane, which leads to peroxidation of their fatty acids and the production of malondialdehyde (MDA) [43]. The presence of MDA in a cell has a toxic effect on both DNA and proteins [44, 45]. Our results indicated that salinity did not affect the amount of H_2O_2 and MDA in roots and nodules of symbiotic associations despite the fact that nodules are prone to high levels of ROS due to the high respiration rate necessary to supply the energy required by the nitrogen reduction process [46]. These results were correlated to an enhancement of the amount of PPO, SOD and CAT under salinity stress. Similar results were found in *Rhizobium*-alfalfa symbiosis [30], and maize inoculated with *Bacillus aquimaris* DY-3 [47]. The CATs and SODs enzymes are the most efficient antioxidant enzymes, their combined action converts the potentially dangerous superoxide radical (O_2^-) and hydrogen peroxide (H_2O_2) to water (H_2O) and molecular oxygen (O_2), which averts cellular damage [48]. While PPO detoxifies H_2O_2 by catalyzing the oxidation of phenolic compounds, mainly flavonoids, and phenylpropanoids, into highly reactive quinines [49]. Wang et al. [15] suggested that nodulation enhances the amount of antioxidant enzymes and upregulates proteins involved in many processes such as cell wall degradation, biotic and abiotic stress, protein degradation, receptor, kinase signaling, and storage proteins in the alfalfa roots, under salt stress. The results have shown also that induction of SOD, PO, PPO and CAT was more observed in the nodules and roots than in the shoots tissue, may be because the nodules and roots are the first to encounter excess salinity, or because alfalfa roots were more sensitives to salt stress than shoots. The same results were reported by Wang et al. [15], where an enhancement of antioxidative enzyme was observed in the roots of alfalfa under salt stress. At the same time, salinity increased total phenol, mainly in leaves, compared to the roots and nodules. Similar responses have

been observed in roots of *Pisum sativum*—rhizobia symbiosis [33]. Ashraf et al. [50] have shown a positive correlation between the content of leaves in polyphenols and plant growth of wheat under salt stress conditions. The capacity of polyphenols to detoxify ROS has been attributed to their ability to act as hydrogen donors and reducing agents, which protect membranes by neutralizing lipid radicals [51, 52].

5. Conclusion

Our finding revealed that salinity did not affect the growth and nodulation of alfalfa inoculated with Rho13 or Rho3-LNR57, which suggests a positive protective role of these inoculums against salt stress. Inoculation by the indigenous rhizobia and its combination may alleviate the deleterious effects of salt stress and stimulate plant growth, principally by enhancing nodulation, the antioxidant enzymes and total phenol and thereby reducing cell membrane damage as indicated by low amount of MDA. Thus, these indigenous strains may be a promising biological technology to improve the tolerance of alfalfa to salinity.

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Conflict of interest

The authors declare that they have no conflicts of interest whatsoever.

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Perspective Chapter: Characterize the Impact of Climate Change and Its Variability on Agricultural Crops by Use of Crop Simulation Models

Naveen Kalra

Abstract

Rising trend in temperature and carbon dioxide concentration is noticed over the globe. In tropical and sub-tropical regions, inter-and intra- climatic variability is quite high. There is a need to characterize climatic variability through growth and yield of crops. Occurrence of extreme climatic/episodic events have increased in the last couple of decades. Crop growth models, such as WTGROWS (Wheat Growth Simulator), DSSAT (Decision Support System for Agrotechnology Transfer) and InfoCrop (for crops in tropical and sub-tropical regions) have been developed and successfully used for land use planning, resource management, agri-production estimates and evaluating climate change impacts. Interaction effect amongst changes in temperature, rainfall, radiation and carbon dioxide concentration have been evaluated for crops and cropping systems, and thus identifying options for agri-sustainability. DSSAT model is widely used over the globe for vulnerability assessment and suggesting suitable mitigation and adaptation strategies for agri-sustainability. Pest damage mechanisms coupled with InfoCrop model; for simulating the effect of pests on growth and yield of crops especially rice and wheat have been evaluated. There is a strong need to link the socio-economic database layers with bio-physical aspects to evaluate the impact of the climate change. Most of the research results are based on point scale, so there is a need to evaluate the impact on regional scale, where the extent of spatial and temporal course of variability in the bio-physical and socio-economic aspects to be taken. There is also a need to include the inter-sectoral interaction for evaluating the impact of climate change.

Keywords: climate change, climatic variability, agri-crops (wheat, rice, maize), DSSAT, InfoCrop, WTGROWS, vulnerability assessment, mitigation and adaptation strategies

1. Introduction

Major agri-sustainability concerns, in particular for tropical and sub-tropical regions and stressed agri-production environments, are emerging with the course of intensive cultivation. Most of the concerns are indicated below:

- Crops' productivity decline/stagnation trends in majority of the agro-ecological zones
- Reduced partial factor productivity in inputs viz. nutrients, water, pesticides
- Deteriorating soil health (physical, chemical and biological attributes,)
- Newer emerging insects and pests with agri-ecosystems
- Frequency of occurrence of extreme/episodic climatic events have increased over the last couple of decades
- Global climate change
- Inter- and Intra- climatic variability, more significant in tropical and sub-tropical regions
- Increased soil-air-water pollution due to crops' intensification, industrial pressure, population rise and other drivers of rapid land use and cover change

1.1 Climate change and its variability

Global climate change is a major concern for the society and mankind [1–5]. Agriculture and allied sectors are directly and indirectly affected with climate change, its variability and extreme climatic/episodic events. Climatic elements viz. temperature, carbon dioxide concentration, precipitation, solar radiation are the major factors affecting the agricultural productivity. Aerosols, UV-B radiation, tropospheric ozone, GHGs are major atmospheric pollutants contributing to climate change.

Generally, temperature change, variation in rainfall and solar radiation are seasonal, caused by geographical location and topography. In the last 100 years global surface temperatures have risen. In all parts of the world, mean maximum temperature has risen by 0.6°C and mean minimum temperature has decreased by 0.1°C. Attempting to predict the degree of temperature increase spatially and temporally is tedious and uncertain.

It is worthwhile to understand the inter-seasonal and inter-annual climatic variability in different agro-ecological regions of globe. From the historic weather datasets over a specific location, we can understand the variability and gradual trend in climate change pick up. India comprises of numerous and diverse agro-ecological regions, and the impact of inter-seasonal and inter-annual climate variability is contrastingly different for crops and cropping systems. Quantification of inter-seasonal climatic variability has been carried out with the help of conventional statistical procedures, but it is worthwhile to evaluate in terms of growth and yield response of crops and cropping systems through use of crop simulation models [5, 6].

Inter-seasonal and intra-annual climatic variability is large in tropical and sub-tropical regions [5]. Global climate change is a small but gradual change taking place over the years, whereas some times the extreme climatic events are confused with the climate change. Probability of occurrence of these events has increased in the recent past. There is a need to characterize the climatic variability through growth and yield response of crops over different production environments [7, 8]. The trend of change is spatially and seasonally variant, i.e. at some locations and in some seasons, the warming is noticed, whereas at the other locations/seasons cooling was observed. The growth rate for these climatic parameters is also spatially and temporally variant.

1.2 Crop simulation models

Crop growth models, in particular mechanistic and dynamic, if properly calibrated and validated, are strong tools for assessing growth and yield of crops/cropping system. Use of crop models can directly/indirectly covers interaction amongst biotic/abiotic attributes, subsequently could include plant/soil processes and predict growth and yield, water use and nutrients uptake of crops and cropping systems. Models have been used in past for yield forecasting, irrigation scheduling, nutrients management, carbon sequestration, cultivars' designs/choice, defining suitable agronomic practices, climatic variability characterization and climate change studies.

Crop simulation tools (viz. WTGROWS, InfoCrop, DSSAT etc.) have been developed and have successfully demonstrated through modifications in phenological development, water and nutrients requirement, assimilation and partitioning behavior, source-sink relationship and yield formation [9–13].

Technical coefficients, as generated through quantification of inter-annual climatic variability through growth and yield of important crops, thereafter linked with regional climate change scenarios for assessing the impact for defining the vulnerable regions [10, 14, 15]. Simulation models can be used for identifying vulnerable regions of climate change, defining suitable mitigation and adaptation options for sustaining agricultural productivity and also safe guarding the environment [16].

Keeping the imperatives in view, the present study was planned to evaluate the impact of climate change and its variability on growth and yield of crops/cropping systems in diverse production environments with the following objectives:

2. Objectives

Characterize the impact of climate change and its variability on growth and yields of crops through use of crop simulation models viz. DSSAT, InfoCrop and WTGROWS;

Identify suitable agronomic and inputs management options for agri-sustenance under extreme climatic and episodic events;

Evaluate vulnerability assessment, identifying suitable mitigation and adaptation options to meet the challenges of climate change concerns for agri-sustenance.

3. Methods

In the present paper, I have used well calibrated and validated models viz. DSSAT, InfoCrop, WTGROWS, for predicting growth and yield of crops and cropping

systems, in diverse production environments (mostly in India, Bangladesh), by also incorporating various biotic and abiotic stresses. The models have been primarily used for evaluating plant growth and soil processes for crops in relation with climate change, its variability, extreme climatic/episodic events and degraded lands. Use of simulation tools for water and nutrients management, yield losses associated with insects/pests, soil-air-water pollutants management for sustainable agriculture have been attempted and demonstrated. Characterizing vulnerability assessment, suitable mitigation and adaptation strategies in growing regions were used through use of simulation models.

The major steps involved, in general, for evaluating the impact of climate change and its variability on crops/cropping systems are as below:

- Development of crop growth models, including components of soil, water, plant, atmosphere inter-continuum, with well designed flow charts.
- Calibration of crop models for solo crops and cropping systems cropping systems through conducted on-farm trials over various locations and production environments. Field experiments to be carried out on knowledge gaps.
- Validation of models for performance evaluation in independent set of experiments with crops grown under various biotic/abiotic stresses and production environments.
- Application of crop simulation models have successfully been demonstrated in the recent past for on-farm water and nutrients management, yield forecasting, climatic variability characterization, climate change impacts evaluation, vulnerability assessment, suggesting suitable mitigation and adaptation strategies, state of soil health over time, deriving optimum sowing window and cultivars/crops introduction/suitability over location, yield forecasting by linking satellite data with crop simulation model.
- Creation of agri-informatics layers for characterizing soil (physical, chemical and biological), water (surface and ground water availability and quality), crops/cropping systems characters (genetic, physiological and phenological coefficients), agronomic management options followed over regions, crops/cropping system acreage and productivity estimates, climate variability/climate change surfaces and subsequent use of crop simulation models for sustained agri-management over representative regions of target areas.
- Identifying vulnerable regions for crops/cropping systems through use of crop models and conduction of field experiments and preparing the vulnerability maps through use of GIS and have been successfully reported by researchers.
- InfoCrop model has been successfully employed for GHGs emission from important crops and cropping systems, still there is a need to further develop the sub-routine to include diverse agri-production environments.
- Suggesting suitable mitigation options to check GHGs emissions and control the environment and define suitable adaptation strategies for sustaining the agricultural production under climate change scenarios and extreme episodic/climatic events

4. Result and discussion

4.1 Crops' growth and yield estimates through use of crop growth models

Temperature and rainfall effect the morphology, physiology and phenology of plants whereas change in CO₂ effects plant morphology, photosynthesis and transpiration. Since environmental control, especially of CO₂, is very difficult and expensive; there have been only a few studies all over the world, a similar facility has been developed at our Center and used for quantifying the CO₂ response on agricultural important crops in the region. Combinations of radiation-temperature-CO₂ interaction have been tried for important crops and cropping systems in calibrating and validating the crop models and hence used for climate change studies [17–19].

Wheat growth simulator (WTGROWS), developed at IARI, New Delhi, has been extensively tested for different agro-environments, successfully used for identifying suitable agronomic, inputs (water, nutrients) and resources management, forecasting of wheat yields and climate change/variability studies for vulnerability assessment, identifying mitigation options and adaptation strategies for meeting the challenges of climate change [9, 14].

Using WTGROWS, a strong linear decline in wheat yield was noticed, in Indo-Gangetic Plains, with the increase in January temperature, for every degree increase in mean temperature, grain yield decreased by 428 kg/ha [20]. Inter-seasonal climatic variability analysis carried out through yield response of wheat indicated that impact of the variability was lowest for Kota and highest for Solapur. Inter-seasonal climatic variability characterized through growth and yield response under different production environments, which clearly indicate the use of crop model as an indicator of climatic variability/change. Simulating with WTGROWS indicated optimal sowing date in wheat advanced by 5–8 days per degree rise in temperature (one of the major adaptation strategies) [14, 21–23]. Field/control chamber based multi-disciplinary research results, covering soil-water-plant-insects and pests-atmospheric continuum processes were used to develop dynamic/mechanistic crop growth models. These models, after thorough validation (viz. WTGROWS, InfoCrop and DSSAT) have been successfully employed for evaluating soil and crop processes and subsequent evaluating growth and yield response of crops in relation to climate change. By using these models, differential response of reduced crops yields to rising temperatures was noticed at locations. Interaction of delta change in CO₂ and temperature was significant, as noticed through growth and yield response of crops [24].

The impact in crops was more pronounced in relatively warmer regions, which became highly adverse under limited supply of water and nutrients. Shifts in the productivity centers northward for major crops, in relation to temperature rise and enhanced CO₂ concentration, were noticed.

Using WTGROWS, InfoCrop and DSSAT, the impact of aerosol (atmospheric brown cloud) was evaluated on rice, wheat and sugarcane, and radiation reduction was compensated with the enhancement in duration of the crops due to cooling and marginal reduction in yield of crops was noticed [9, 12, 25, 26].

Seasonal temperature dependence of yield of crops (wheat, barley, gram and mustard) were established for northern region of the country by compiling the historic datasets on meteorological sub-divisional scales [20]. Reduction in yield associated with increase in temperature was characterized for these important crops for northern region during *rabi* (winter) season. The reduction factor per degree rise

in temperature, on an average, were 4.26, 2.77, 0.32 and 1.32, q/ha for wheat, barley, gram and mustard, respectively.

The effect of sowing at different dates on the yield of wheat was simulated for different locations [3, 9, 14]. Places having higher potential yields of wheat had greater reduction in yield per day delay in sowing from the optimal date. A few locations (north-eastern locations) showed a small yield reduction with delayed sowing. With the temperature rise, the adjustments in the date of sowing to have the similar weather conditions can be ensured, but it can imbalance the cropping system schedule, which is important for developing countries where intensive cultivation is practiced on small and marginal lands.

The interaction effects of CO₂, radiation and temperature can also be best studied though the use of crop growth simulation models, and has been used for identifying optimal window of climate change for sustenance [11, 21].

InfoCane was developed for simulating growth and yield of sugarcane and subsequently evaluating the climate change impact in three contrasting production environments of India. The model was tested in the farmers' fields for suggesting resource management options and evaluating the impact of temperature rise, carbon dioxide increase and rainfall changes in the contrasting environments [27].

Crop-weed competition will be affected depending upon their photosynthetic pathway. Since, most crops are C₃ and most weeds are C₄ plants, increased CO₂ would favor crops over weeds reducing needs for weed control. The accompanied temperature increase may further alter the competition depending upon the threshold ambient temperatures.

DSSAT model is detailed, soil and crops processes based, widely used by researchers over the globe. The model comprises of several crops (cereals, pulses, oilseeds, fiber, vegetables, fruits (strawberry- recently introduced), has capabilities of analyzing for climate change, seasonal, cropping-system and many many others. Well designed files for soils, crops, weather, cultivars etc). The model has been successfully employed for productivity estimates, natural resources management, climate change and its variability analysis and widely documented in diverse production environments ([13, 17, 18, 28] for rice), ([15, 19, 29] for wheat), ([30, 31] for corn). Being a model developer, WTGROWS, InfoCrop, InfoCane MungGro [32], Tea crop [33]), I feel DSSAT is very effective tool from training purpose as well further use for several applications. There is a strong need to understand the well designed files structure for inputs, calibration, parametrization, validation, sensitivity, applications and interpretation (graphics and statistics analysis). Researchers have to be cautious in handling this model, so training of the capabilities is very much needed, which is easy and may be within 3–5 one can get training for its effective use. Till date, DSSAT model has N and P routines, but there is a need to calibrate for contrasting production environments. Scope of other important fruit crops viz. blueberries, strawberries (although developed but needs to be parametrized for different agro-ecologies) exists, and at present we are developing at University of Waterloo (Systems Design Engineering Department).

There is a need to initiate the modeling works related to agro-forestry, lot of field trials have been conducted in the past, but on qualitative basis, with most of the agro-economic trials. Since DSSAT covers numerous crops, perennial trees and grasses, the DSSAT team take this initiative through international network of inter-disciplinary team of researchers and students.

We have started model development work with *Pinus Roxburghii* at Forest Research Institute, Dehradun, India. PhenoPine is a very simple model, semi-mechanistic and

dynamic and was tested for climate change impact analysis in the regions of Western Himalayas, India [34]. At present I am based at University of Waterloo, Ontario, Canada, may explore the possibility of initiative the work in my region.

The prime question of handling multi-nutrients interaction component for integrated nutrients management, to be addressed at the terminal stage of the run or use of technical coefficients generator or may be use of AI tools, as sub-routine added in the DSSAT model (?). There is a need to strengthen population dynamics (for insects, microbes) for IPM capabilities, otherwise most of us are using the population attribute as forcing variable over time in the model (say InfoCrop, DSSAT).

There is a strong need to address integrated assessment modeling (IAM) for inter- and Intra Sectors, as well the prime component of Land Use and Land Cover Change through an Inter-national Network, which can become an Advanced Center for Climate Change Impact Analysis over the globe, which subsequently will aid IPCC, UNEP, UNFCCC for subsequent planning and management.

4.2 Soil health

There are concerns world over about sustainability arising due to decreasing soil productivity. Today the management of soil is, therefore, very important for development as we are crossing the threshold of new land available for cultivation. Soil and climate change are inter-related. Changes in temperature and precipitation can influence soil water-content, runoff, erosion, salinization, biodiversity, soil processes and organic carbon and nitrogen content. Changes in soil water induced by global climate change may affect all soil processes and ultimately the crop growth. It may lead to modifications in soil physical, chemical, biological and phyco-chemical characteristics. Rise in sea level associated with increased temperature may lead to salt-water ingress in the coastal lands turning them unsuitable for conventional agriculture.

Organic matter content, which is quite low in most tropical and sub-tropical regions. SOM content is an indicator of soil health, through soil structure, soil moisture retention, release and transmission characteristics, nutrients availability through soil biological health and soil nutrients availability through favored soil microbial activities. Increase in atmospheric CO₂ concentration may compensate for increased decomposition of soil organic matter but the net balance would depend upon the carbon inputs and losses. There are reports that residues of crops under elevated CO₂ concentration have higher C:N ratio, and this may reduce their rate of decomposition in soils leading to an increment in ecosystem carbon stock. This feature is effectively handled in InfoCrop and DSSAT models. Increase of soil temperature by 1°C may help in increased mineralization but N-availability for crop growth may still decrease due to increased gaseous losses through processes such as volatilization. These changes may further compound the direct effect of temperature and CO₂ on crop growth and yield. All these effects, however, would be highly region specific, depending upon the magnitude of climatic change, basic soil properties and current climatic conditions.

Soil quality (or health) index has been developed through selected soil physical, physico-chemical, chemical and biological attributes, through assigning weights for subsequently evolving SH(Q)I, for subsequent use in irrigation/tillage/nutrients/problem soils management for sustained agricultural production. SQI can be used for land capability/suitability classification for crops' choices, options for inputs/agro-nomic management [35]. In most of the developing countries, numerous set of soil test values are available, but not effectively utilized for soil and crop management for

sustenance. There is a scope to develop methodology appropriate use of STV, through evolving application based SQIs (for water, nutrients, tillage, crops management).

Soil is considered to be one of the most important sources and sinks of greenhouse gases, thus directly influencing climate change and indirectly through the production and consumption of ammonia (NH₃), nitrogen oxides (NO_x) and carbon monoxide (CO). It contributes about 20% to the total emission of carbon dioxide through soil respiration and root respiration, 12% of methane and 60% of anthropogenic nitrous oxide emissions. GHGs emission inventory for crops and cropping systems based on technical coefficients generator have been reported in literature. The emission is based on crops/cultivars, crop growth stage, water/nutrients availability, soil environment (physical, chemical and biological), climatic elements (temperature, rainfall, radiation, CO₂ concentration), models have been developed by integrating these attributes [36–38]. InfoCrop model has been developed on this important aspect and successfully demonstrated for rice-wheat cropping systems [13]. Mitigation options to reduce the gaseous losses have been identified and included in some of the models, like InfoCrop [39]. However, there is a need to develop sub-routine for emission estimates and management for crops, livestock and industries and effluents/solid wastes, which could be linked with popular models like DSSAT.

4.3 Aerosols and solid particulate matters in the atmosphere

Specific aerosol event of direct radiation reduction during January–March, 1999, in all parts of India, did not show register in crops' yields as evidenced from the records [25, 40]. This might be due to modifications in the coupled weather conditions, which compensated for the slight reduction in yields of wheat, rice and sugarcane (runs through use of WTGROWS for wheat, rice and sugarcane for DSSAT) due to reduced radiation amounts alone. Moreover, this specific event is very less probabilistic. The researchers till now have looked at the impacts of haze in the region's climate and agriculture in a very preliminary way (UNEP panel on Asian Brown Cloud, subsequently named as Atmospheric Brown Cloud).

More refined work on climate modeling and development of crop models to take care of various scenarios of this emerging science is needed to get conclusive information. The effect of reduced solar radiation on yield of irrigated wheat at New Delhi environment (by using WTGROWS), which clearly indicated the reduction in the grain yield to the tune of 5% with 15–20% reduction in the radiation. The response may be different in rainfed and water limited environments.

4.4 Insects-pests and diseases

Incidence of pest and diseases is most severe in tropical regions due to favorable climate/weather conditions, multiple cropping and availability of alternate pests throughout the year. Accordingly in the south Asia, pests and diseases deleteriously affecting the crop yields are prevalent. Climate indicators are the causative agents in determining the population fluctuations of pests. They influence plant disease establishment, progression and severity. In fact, a clear understanding of population dynamics as influenced by abiotic and biotic parameters of environment is of much help in pest forecasting and to formulate control measures [10, 41, 42].

Development of diseases and pests is strongly dependent upon the temperature and humidity [41]. Any change in them, depending upon their base value, can

significantly alter the scenario, which ultimately may result in yield loss. Any small change in temperature can result in changed virulence as well as appearance of new pests in a region. Likewise, crop-weed competition may be affected depending upon their growth behavior [43].

Climate is changing which will definitely affect population density and period of activity of pests. However simultaneously crop management practices and land use and cover changes have also influenced pest fauna of crops. Population models can also be used for delineating pest hot spots by using GIS. Further the linkage of population models with climate change scenarios can help in visualizing changes in pest hot spots.

InfoCrop model, a generic crop growth simulation model developed at IARI, New Delhi, India, has been coupled with different pest damage mechanisms such as germination reduction, stand reduction, light stealing, assimilation rate reduction, assimilate sapping, tissue consumption and turgor reduction [10, 41, 42]. This classification of pests is based on physiological basis of their damage. All the insects, diseases, nematodes and weeds can be covered under one or more of these categories. One pest can have more than one damage mechanisms depending upon the number of plant physiological processes it affects. The InfoCrop has been validated for stem borer, leaf folder, bacterial leaf blight and weed effects in rice, and for stem borer, leaf rust and weed damage in wheat. The validated model was then used to establish economic injury levels and also to formulate isocost curves for the pests, which can be used for rationalizing pesticide use on crops. Gradual climate warming will lead to changes in the composition of pest fauna in different areas. The high population growth rate of many species will ensure changes in pest distribution.

4.5 Inter-sectoral interaction for agri-impact analysis

The impact of the climate change on various sectors such as energy, transport, water (ground, surface and sea) in terms of quality and quantity, forest will also directly or indirectly affect the agricultural production/activity. It is not only the agriculture, which might be influenced by global warming, but the human health may also get affected. Outbreaks of number of diseases, including dengue fever, bubonic plague, cholera and malaria have been linked to climatic variability. The climatic change has triggered the shift and expansion of the population of vectors and hosts to different geographic regions. It can also directly effect the distribution and abundance of pathogens themselves, thereby increasing the prevalence of disease in humans, animals and plants. There is a need to initiate inter-sector impact evaluation of the climate change.

4.6 Danger of errors propagation in assessing the agricultural impacts

How much will be the magnitude of climate change, where and in what time frame remains uncertain. All IPCC scenarios, nevertheless, project an increase of CO₂, temperature and sea level during this century. There is a need for future climate change scenarios with higher resolution (temporal and spatial), for subsequent use in evaluating the impact on agriculture.

On the basis of historic climatic analysis, in India there is a mixed trend in temperature change; some of the locations show increase whereas some of them are showing decrease in temperature. Similar trend is being noticed in various seasons.

Extrapolation of the point results of the impacts, as obtained through use of simulation models, to a larger scale may bring in more errors, if the spatial and temporal variability in the socio-economic and bio-physical aspects are not included.

5. Conclusion

Inter- and intra-seasonal climatic variability is significant, mostly in tropical and sub-tropical regions and have pronounced effects on growth and yield of crops. Extreme climatic/episodic events have increased in the last couple of decades, and there is a strong need for identifying options for agri-sustenance. Crop growth models, such as WTGROWS, DSSAT, InfoCrop have been developed, and extensively used in different parts of the world, for yield forecast, inputs' and agro-management options for sustenance, impact analysis of climate change and its variability. Simulation results with major crops as wheat, rice, maize, mung-bean indicated decreased yield with rise in temperature from 1 to 3 degree celcius. Decreased yield was primarily due to reduction in crop growth duration with rise in temperature.

Simulation results could clearly demonstrate radiation-temperature-carbon dioxide interaction effect on growth and yield of crops. Shift of productivity centres northward was noticed in India for wheat with 2 degree celcius rise and 425 ppm CO₂ concentration (on the basis of WTGROWS runs). Simulation models could clearly delineate the vulnerability regions for crops with temperature rise. InfoCrop model could predict GHGs emission for rice and wheat crops with temperature and CO₂ concentration increase, as well could clearly identify suitable mitigation options for emission reduction. DSSAT model could successfully identify mitigation strategies and adaptation options for agri-sustenance, through choice of crops, altered date of sowing to enter into favorable environment and appropriate water and nitrogen management. Most of the climate change impact studies are point based, and there is a need to link the crop growth models with the relational database layers through remote sensing and GIS platform to subsequently understand the agricultural production on regional scales. We need to identify agronomic and inputs management options to sequester soil organic carbon, and also evolve methods to enhance water and nutrients' use efficiency. The crop-pest-weather interaction and socio-economic components in the climate change impact evaluation are relatively weaker in most of existing crop models. Socio-economic aspects needs to be introduced with the bio-physical layers to develop crop models for assessing the impact of climate change on agriculture on regional scales.

6. Research needs

- Evaluating climatic variability through growth and yield of crops and cropping systems, develop options for sustenance under extreme climatic events
- To link the future climate change scenarios with the agricultural system for evaluating the impact and suggesting suitable options for sustenance
- Soil health service for representative agri-production environments in relation various bio-physical and socio-economic attributes, with special reference to zero/minimum tillage, organic farming

- Characterizing drivers of rapid land use and cover change, design appropriate land use options for sustenance, through use of remote sensing, GIS, AI and simulation models
- On-Farm water management, with special reference to conjunctive water use for agricultural purpose
- Integrated Nutrients Management
- To develop efficient and effective on-farm water management practices
- To develop BMPs (best management practices), including resource conservation technologies for sustaining the agricultural production under crop intensification, human interventions, resources degradation, climate change and extreme events situations
- To develop on-line agro-met advisory services (synoptic hours, short-term, medium-range weather forecast, long-term)
- Sub-routines development for integrated pest management, population dynamics modules for insects and pests, microbes, integrated nutrients management, air pollutants (aerosols, UV-B and ozone mediation), GHGs emission, carbon sequestration fishery/livestocks, bio-physical aspects
- Integrated assessment modeling (inter-and intra-sectors) for meeting challenges of climate change and extreme climatic events
- Developing methodologies for linking satellite signatures, machine learning/AI and GIS with crop models for yield forecasting, crops' condition assessment
- Most of the studies are point based, but for climate change impacts evaluation, there is a need to integrate bio-physical and socio-economic aspects relational layers with the crop models for realistic estimates.

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Risk Averse Smallholder Agri-Food System: Exploring Climate Change Adaptation Options to Inform Planning and Policy in Ghana

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Abstract

The Ghanaian agriculture sector is highly vulnerable to climate change and variability due to its dependence on rainfall. Resilience must therefore be built into its food systems to reduce the vulnerability of smallholder farmers. Implementation of climate information services and climate-smart agriculture has become an urgent intervention by both governments and donor communities. However, climate information services and climate-smart agriculture technologies have been implemented independently, which limits the impact of the technologies. The bundling of climate-smart agriculture (CSA) and climate information services (CIS) is critical to achieving household food security. This paper discusses the climate risk profile of Ghana and the implementation of climate-smart agriculture (CSA) and climate information services (CIS) for smallholder farmers. Specifically, the chapter discusses digital platforms available to smallholder farmers and agricultural extension agents, analyzes governance arrangements, and assesses their potential in scaling up CIS and CSA innovations. The paper also emphasizes the opportunities for bundling CSA and CIS to enhance the uptake of smart innovations. This chapter also captures agriculture and climate change policies by state and non-state actors in Ghana's food systems as well as illustrates the constraints and makes recommendations to advance decision-making in policy formulation. Given the fact that CIS and CSA align with most sustainable development goals, such as poverty reduction and food security, this paper presents significant implications that could inform climate policy in sub-Saharan Africa, particularly Ghana.

Keywords: agriculture risk, climate change, food security, sub-Saharan Africa, digital tools

1. Introduction

Climate change is a major problem in developing countries largely dependent on rainfed agriculture [1]. It is causing noticeable effects such as flooding, erratic rainfall patterns, droughts, and lower crop productivity [2]. The results of these effects are increased food insecurity and poverty, which threaten the livelihoods of smallholder farmers who constitute the majority of the population [3].

The adverse effect of climate change on food security has led to smallholders undertaking unsustainable farming practices. Such unsustainable farming practices have destroyed natural resources, caused land degradation, and polluted water bodies. Agricultural innovations that improve the adaptive capacity of agricultural production systems and the resilience of farmers are required to ensure the food and livelihood security of farming communities.

Adaptation has been identified as an important strategy for the global response to climate change, particularly following the Paris Agreement. The Paris Agreement promotes global adaptation goals and a mandate for all parties to undertake and assess adaptation progress [4]. Adaptation and mitigation planning and future commitments in National Adaptation Plans (NAPs) and Nationally Determined Contributions (NDCs) are informed largely by documentation of progress [5]. In developing countries, where cascading climate risks could influence the Sustainable Development Goals (SDGs), the deployment of adaptation measures is urgent [6]. Adaptation is even more important in the most vulnerable countries, such as Ghana, where climate-sensitive sectors such as agriculture play a central role in economic development [7]. Ghana's vulnerability to climate change is worsened yearly due to its increased reliance on agriculture [8], and the sector is vulnerable due to its reliance on rainfall [9]. Agriculture employs about 45% of the total workforce, leading to 20% of gross domestic production [10] and supporting food security. Only about 2% of the total agricultural land area is under irrigation [11]. Projected climatic conditions indicate a decrease in optimal suitability for most crops in Ghana. The leading agricultural food commodities by harvest area consist of cassava, maize, groundnuts, and sorghum [12]. A general decrease in crop yield due to climate change effects (e.g., maize yields have reduced between 5 and 25%) has been reported in Ghana [12].

An analysis of Ghana's climate change and agriculture situation showed that agricultural production will be affected significantly by temperature increases and variations in rainfall amounts and distribution, as well as extreme climatic events such as droughts [12]. The temperature situation in Ghana is expected to increase to 1.02°C (2040), 1.5°C (2060), and 1.8°C (2080) [11]. Rainfall events are also projected to become more erratic and unpredictable, with late-onset and early cessation reported [12]. This has necessitated the search for solutions to moderate the effects of climate change in Ghana. Building resilience to climate change in the agriculture sector in Ghana requires an understanding of climate risk. Smallholder farmers respond to climate risks such as dry spells and erratic rainfall by employing various farming practices to curb or reduce the food and nutrition security needs of households.

An important step toward improving the ability to manage climate-related hazards is the adoption of climate-smart agriculture (CSA) and the timely availability and usage of climate information services [12]. Climate-smart agriculture (CSA) and climate information services (CIS) are being disseminated as adaptation approaches to

change agriculture systems to sustain food security [10]. However, CSA and CIS have been presented as individual interventions. The bundling of CSA and CIS to address the climate-driven needs of smallholder farmers in Ghana is critical to achieving household food security. Evidence on mainstreaming climate information services in agricultural systems in Ghana is limited [13], despite its potential to promote adaptation to climate change [14]. Limited research has been conducted on climate information services [11, 15], including barriers to adoption as well as bundling of CSA and CIS. For instance, Ref. [14] reported on several structural barriers (e.g., gender norms and patriarchal values) to acquiring climate information services. Ref. [12] revealed that access to and desire to pay for climate information services in Ghana were influenced by both individual and environmental-specific factors, including drought and farm experience, as well as food insecurity. This paper provides insight into Ghana's adaptation options and demonstrates the significance of bundling CSA and CIS to sustainable food production under the current climate stress environment as well as the policy environment to drive these interventions.

2. Approach to the study

A systematic approach was used to identify and synthesize climate change adaptation options important to Ghana's agri-food systems. The mixed method approach combines several steps to identify the adaptation options relevant to the food system. As shown in **Figure 1**, a stepwise approach was used to map adaptation options. These options should have been reported in the Ghanaian agriculture and food system. The steps consist of sourcing information on the CSA and CIS profiles of Ghana and reviewing climate-smart village information in Ghana. Besides, more adaptation options were identified through a literature review of peer-reviewed papers and gray literature. This was undertaken through online searches by using relevant search terms and from the repository of the Food and Agriculture Organization (FAO). Scopus and Web of Science databases were searched for peer-reviewed publications that are relevant to the adaptation options in Ghana.

3. Prioritization matrix of climate smartness in Ghana

The identification and prioritization of adaptation options are key prerequisites to collective ownership and adoption. Participatory Action Research (PAR) was employed by stakeholders in undertaking the prioritization process [16].

Collaborations are built through the prioritization of CSA-CIS technologies that allow farmers to achieve enhanced benefits and reduce potential losses [16].

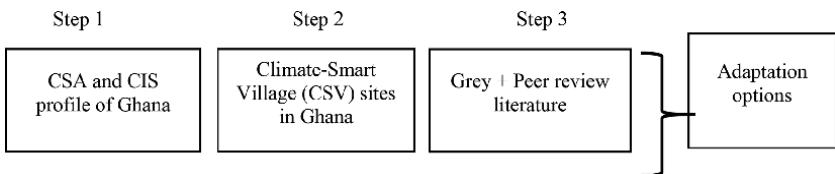


Figure 1.
Steps for identification of adaptation options.

Climate smartness			Women friendliness					
Productivity	Adaptation	Mitigation	Lower associated drugery	Availability	Accessibility	Affordability	Socio-cultural acceptability	Lower implementation requirements
One-health achievement								
Reduces pest load	Addresses nutrient depletion	Addresses soil water adequacy	Addresses soil-water pollution	Promotes crop-livestock integration	Lower GHG emissions	Address public health issues	Preserves biodiversity	
End-user friendliness								
Technical feasibility			Lower associated cost (Cost-effectiveness)					
Male		Female			Male		Female	
Source: Ref. [47].								

Table 1.
Criteria for CSA-CIS prioritization.

Both experts and practitioners are needed to undertake collective prioritization of CSA-CIS technologies in different agroecological zones [17].

The implementation of climate-related projects, particularly those with adaptation options, requires technology prioritization for effective upscaling. Prioritization is sometimes done with much emphasis on commodity value chains and/or regional blocks [17], which can limit its application and response to climate risk. Identification of technologies and subsequent prioritization exercises should be undertaken by all actors in the agriculture value chain [17]. The effective uptake and utilization of CSA-CIS practices are based on the co-prioritization of practices fit for different agroecological zones [18]. Co-prioritization allows the proposed interventions to meet certain criteria in the intervention communities. The process of co-prioritization of technologies involves the identification of enablers that will propel the acceptance and use by beneficiaries. The quest for inclusive prioritization that meets the needs of diverse end users led to a classification of four thematic areas, including (1) Climate Smartness, (2) Gender and Social Inclusion (GSI), (3) Contribution to One-Health, and (4) End-User Friendliness (**Table 1**) [17]. Climate smartness consists of three indicators, namely (i) productivity, (ii) adaptation, and (iii) mitigation. Gender and Social Inclusion (GSI) comprised of 4 indicators, which are (i) labor requirement, (ii) youth involvement, (iii) lower costs, and (iv) women friendliness. Women's friendliness is defined by technologies with fewer labor requirements (drudgery), easy access and affordability, and technologies that meet the socio-cultural needs of women [17]. Regarding One-Health, the indicators used were reducing pest load, addressing nutrient depletion, increasing soil water adequacy, and addressing soil water pollution. The analysis of the results is carried out by using a Likert scale (5-point) defined as 1 (very low importance), 2 (low importance), 3 (medium importance), 4 (high importance), and 5 (very high importance). Extensive prioritization could lead to demand-led technologies with the potential of scaling through demonstrations at the community level [18].

4. The case of climate information services in Ghana

Climate information services are the generation and dissemination of climate data, information, and knowledge, which is needed for policy and planning [19]. Climate-related risk and vulnerability have been lowered by the implementation of climate information services [20]. The quality of CIS is important in determining decisions around the livelihoods of smallholder farmers. It allows end users to make informed decisions toward disaster risk management, which is important for national development [19]. Climate information services have become critical because of the need to reduce the vulnerability of smallholder farmers, which has made the CIS delivery very significant. This is essential since smallholder farmers are the majority in sub-Saharan Africa, including Ghana. CIS provides intermediaries such as extension officers, scientists, and actors in the policy space with the requisite know-how in supporting beneficiaries to adapt to climate-related risk. Quality information is a basic requirement for pre- and post-planting decision-making. Farmers have to make decisions regarding the type of crop to plant, land preparation, planting, transplanting, fertilizer and pesticide application, harvesting, and post-harvest activities [21], which require quality CIS. In Ghana, like other sub-Saharan countries, CIS has been used to make decision by farmers. **Table 2** below presents examples of the use of climate information services in decision-making.

Type of CIS	Information needs	Category of farmers			
		Young men	Young women	Elderly men	Elderly women
Seasonal forecast	Type of crop and the variety of seed to select			✓	✓
	Land size and number of farmland to cultivate			✓	✓
	When to plow	✓	✓		
Daily-weekly forecast	Sowing of seeds or transplanting of seedlings	✓		✓	
	When to apply fertilizer and other agrochemicals	✓		✓	
	When to weed	✓	✓	✓	✓
	When to start harvesting	✓	✓	✓	✓
	Marketing and processing				✓
Legend		Applicable to specific category of farmers			

Adopted from: Ref. [21].

Table 2.
Climate information needs of smallholder farmers.

The access and adoption of CIS in Ghana have been challenged by low literacy levels, poor quality information, inadequate funding sources, poor infrastructure development, and cultural norms. This is irrespective of its importance to smallholder farmers [13]. Information delivery in Ghana is undertaken using informal channels as an important means of interaction among smallholders. Climate information services are mainly provided by agricultural extension agents and other tools such as workshops and social networks using participatory approaches [22]. Normally in many farming communities, farmer teachers or lead farmers have received capacitation to be able to share information in public places such as market centers, churches, mosques, lorry stations, and community centers. Mostly CIS information received by a community leader is shared with other members of the community [23]. This poses a great challenge to the financial models of institutions and individuals involved in providing CIS through the utilization of ICT platforms. CIS is deemed as belonging to the general population, and it should be made available to all end users to enhance their adaptation capacity to climate risk. Production and delivery of climate information services are associated with costs emanating from data collections, weather models, Internet data, and telecommunication networks. Therefore, CIS delivery comes in the form of quasi-public goods with some excludability as users pay for CIS to enable the recovery of costs [24]. The inclination of end users to pay for CIS has sparked around using ICT as a medium for dissemination. Many smallholder farmers are not willing to pay the cost of CIS delivery through ICT channels [25]. CIS disseminated through the radio and televisions provided for free are not tailored to the specific needs of farmers. Farmers who rely on such sources for free do not get the full complement of the information and may use conventional methods in weather forecasting to undertake their farm operations (Table 3) [24].

Currently, many farmers prefer ICTs that deliver climate information services using interactive platforms so that they can follow up on the information by asking

Category of CIS financiers	Funding mechanism
Government financing	Free provision by GMet and GTV through tax and sometimes product levies
Financing by agri-input companies	Provides embedded services by including the cost of CIS as part of the contract farming
Commercial output buyers	Makes CIS freely available but incorporates the cost as part of the contract farming
Farmer-based association, e.g., Cocolink	Membership fees, donor subsidies, government subsidies, and contracts
Direct payment	Direct fees paid through farmers' call credit or airtime, e.g., Esoko
Funded projects	Donor contracts information providers to deliver CIS freely to target groups of farmers
Contract sale	Farmers' subscription is paid by insurance companies or agribusinesses
Business advertisement on CIS platforms	Advertisement of agricultural products linked to the provision of CIS
Minimum payment under public-private partnership	Subsidized payment is made by farmers under a project compared to those who are not part of any project

Source: Ref. [21].

Table 3.
Financing of CIS with ICTs to farmers in Ghana.

questions and sharing their experiences [26]. This indicates the importance of interactive platforms (ICTs) in CIS delivery. Mobile phones especially have supported farmers in communicating CIS to their colleagues despite the limitation in accessing climate information services. This has enhanced interaction and strengthened the interpersonal relationships among smallholder farmers. The spirit of community ownership has been enhanced through the strong person-to-person communication of CIS. According to Ref. [27], this promotes the spirit of openness and strengthens the bond in rural communities by allowing information flow between families and intermediaries among smallholder farmers as mobile phones also complement informal ways of communication. Hence qualities such as sincerity, transparency, inclusiveness, and open sharing of information are enhanced. Also, complementary roles are explored by intermediaries who use ICTs to provide CIS by exploring other digital channels and informal mediums of communication [28]. It is clear that the use of ICTs to deliver CIS has increased farmers' access to CIS and therefore helps in building their resilience to climate shocks and vulnerability. This position has been supported by Ref. [18], who observed that the combined use of ICT and informal communication helps to increase farmers' access to CIS.

5. Bundling climate-smart agriculture and climate information services

One of the major pathways to scale CIS and CSA technologies to target end users to create impact is through scaling through intermediary organizations such as small and medium agribusinesses, input providers, and producer associations who help to reach higher numbers and create greater impact [29]. The augmented promotion of CSA in Ghana was achieved following the ratification of the United Nations Framework

Convention on Climate Change in 1995 [30]. Following the ratification, Ghana's Parliament adopted the Kyoto Protocol in 2002 and subsequently developed the current National Climate Change Policy [31]. Climate-smart agriculture has now been included in the agricultural development policy of Ghana through a concerted effort by both state and non-state actors [32]. The successful implementation will enable end users to achieve enhanced productivity and income and also reduce their carbon footprint. Nevertheless, CSA and CIS have been disseminated independently, thereby reducing the benefit of promoting solutions holistically [33]. Recently, bundling CSA and CIS has arisen as an effective approach for the deployment and uptake of CSA and CIS technologies. Last-mile farmers are effectively reached through the bundling of CIS-CSA practices [34].

Bundling CSA with CIS to assist smallholder farmers make informed decisions in farm management activities is a great strategy to achieve CSA adoption at scale [35]. However, CSA and CIS are provided individually to beneficiaries, thereby limiting the impact of the technology. The current dissemination pathway for CSA and CIS makes bundling more significant as the tool for dissemination is tilting toward digital agro-climate advisories [36]. Bundling integrates Knowledge Products (KP; CIS, CSA), consumables (C; certified seed, fertilizer, chemical inputs), Financial services (FS), and Physical Services (PS; mechanization, milling, solar) as illustrated in **Figure 2**. The integrated manner of bundling CSA and CIS strengthened the potential impact the technology will have and improved the scalability of the project.

The decision for an end-user to integrate CSA and CIS technologies is based on the information available to them. Depending on the farmer's condition, farm experience, and environment, they required support in deciding combinations of practices that best fit them. Such combinations should provide them with the greatest positive response in terms of resilience to climate risk [37]. The integration of options (bundling) enhances farm products through optimization. It improves complementarity and manages trade-offs when it is integrated with a varied set of practices to the maximum benefit of the smallholder farmer [38]. Bundling demand-driven CSA and CIS is helpful in settings where productivity is stressed by biotic and abiotic factors and rudimentary practices [39]. The bundling of CSA and CIS will capacitate users to make informed decisions. Making informed decisions tends to reduce the failure of their productive system, leading to high adoption and improved yields and food security [37]. A study conducted in Ethiopia showed an increase in crop productivity of farmers who received climate information on crop type, water and disease management, and other agronomic practices [38].

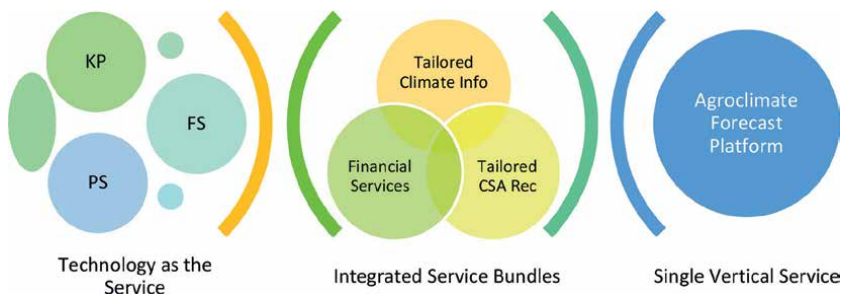


Figure 2. Bundling of innovations. Credit: Alliance Bioversity and CIAT. Source: Ref. [37].

6. Climate change policy trajectory in Ghana

Worsening climate effects are one of the greatest threats to the contribution of the agricultural sector to improving farmers' living conditions. As a signatory to international organs like the United Nations Framework Convention on Climate Change (UNFCCC), several actions have been undertaken to address challenges underpinning the agriculture sector, including climate situations. The National Climate Change Policy (NCCP) is Ghana's joined efforts to deal with climate issues [40]. It is essential to properly harmonize the policies or actions in order to enhance the benefits and work together for the sustenance of the developmental agenda of the country. With effective harmonizations, the vulnerability of the general population will be greatly reduced. The sustenance of national priorities underpins the development of the policies with the potential for sustainable national development. The NCCP offers a clear roadmap for addressing climate change events in the context of the country's social and economic development. The National Climate Change Policy (NCCP) also highlights the chances offered by climate change in connecting to the advantages of the green economy. The NCCP policy has five (5) priority areas, namely (i) agriculture and food security; (ii) disaster preparedness and response; (iii) natural resource management; (iv) equitable social development; and (v) energy, industrial, and infrastructural development [40].

The policy areas are divided into 10 programs. The programs are intended to deal with fundamental issues of climate change in Ghana. The 10 areas consist of developing systems that address climate-resilient agriculture and food security, climate-resilient infrastructure, improving the resilience of vulnerable communities to climate risks, scaling up carbon sinks, improving the management and resilience of terrestrial, aquatic, and marine ecosystems, addressing climate change impacts on human health, reducing climate change impacts on access to water and sanitation, addressing climate change issues related to gender, tackling issues of climate change and migration, and reducing greenhouse gas emissions [40].

Another key policy is the Climate Smart Agriculture Investment Plan of Ghana (CSAIP). The CSAIP develops actions for climate-resilient agriculture by assessing the National Climate Change Policy and the National Climate Smart Agriculture Food and Security Action Plan [41]. The CSAIP advocates for nine (9) action areas toward building resilient agriculture and food security systems [42]. A study has shown that the nine priority CSA actions have the potential to increase yield by at least 20% and up to 59% for sustainable fisheries and aquaculture compared to conventional systems without these actions [41]. For example, in a situation where the CSA actions were not implemented, cocoa is projected to lose 3% by 2030 and up to 5–7% by 2050; cereals were generally projected to lose 4–6% over the next 40 years. Maize yield is projected to decline by 8–11% over the next 10 years [41]. The cereal and legume integration action has shown great promise across the country [43]. The CSA action on root, tuber, and livestock integration has built on the predicted resilience of crops like cassava and yam. It has also counterbalanced some potential damage to the livestock industry, such as cows and cattle. The water harvesting and irrigation action is suitable for harnessing the resilience of rice and has boosted rice production in some parts of the country. However, there are bottlenecks to the effective implementation of these policies. The NCCP, for example, is closely linked to the implementation of climate-smart agriculture activities. Policy gaps and distortions have limited the effectiveness of CSAIP actions. Key constraining factors include (i) lack of cross-sectoral and interagency collaboration, (ii) misalignment of policies,

(iii) policy distortions, (iv) weak institutional capacity (inadequate access to farmer information and capacity-building), and (v) donor unwillingness to support investments (policies focused on damage control). These factors pose a threat to the success of interventions as well as affect the context of the policy. Policy implementation is affected by a frail partnership between government and non-governmental agencies and sectors. A lot of the policies outline CSA goals but fall short of assigning clear roles and responsibilities and the target beneficiaries. There is little coherence among sectoral policy documents and approaches as well as competition and weak collaboration between sectors and ministries rather than strong coalitions to facilitate shared goals [44]. This limits the ministry directly responsible for CSA and CIS dissemination to farmers, the Ministry of Food and Agriculture (MoFA), and other key stakeholders [32]. Also, strong institutional capacity is needed to achieve Ghana's national climate-smart goals. Stakeholders, including MoFA, have constantly emphasized the need for investment in capacity-building as a prerequisite for coordination and implementation of climate change action. There is inadequate training and technical capacity-building for staff [45]. This has led to a weak alignment of policy frameworks needed to achieve coherence between policies and establish coordinated efforts across sectors and departments. In particular, the Ghana Environmental Protection Agency (EPA), which serves as the focal point for climate change and is mandated to lead capacity-building programs and establish appropriate mechanisms to ensure collaboration among climate-related sectors, lacks financial support for cross-sectoral planning. Another obstacle is the mitigation-oriented nature of some interventions. Most international donors focus on mitigation measures, and most are unwilling to fund adaptation-focused programs. Adaptation is critical because it allows resource-poor smallholder farmers to adjust their farm management and livelihood decisions to increase resilience to climate change. Policies, particularly in the wildlife and forestry sectors, are heavily focused on mitigation. While it is clear that the focus on climate change mitigation is driven by international funding structures, some important national processes and interests promote this focus. These include the deliberate framing of the climate change problem, the active participation of environmental stakeholders in particular in shaping climate policy, and the interest of governmental and non-governmental actors in funding mitigation activities. While mitigation is important, there are increasing calls at the national level to focus efforts on preparing smallholder farmers to reduce their vulnerability to climate-related risk for improved productivity.

7. Discussions

Innovations in agriculture that have the capacity and potential to improve the resilience of production systems are urgently needed to curb rising food insecurity and the deteriorating livelihoods of farming communities [4]. Worldwide adaptation has been reported to be a proven measure for responding to climate change and climate-associated risk [6]. Adaptation is significant in sub-Saharan Africa, including Ghana, where agriculture, which is the mainstay of the people, is highly dependent on rainfall. Despite this recognition, adaptation measures are not effectively employed to reduce climate risk at the community level. Climate-smart agriculture and climate information services are significant means of managing the effects of climate variability. It has been established in this review that CSA and CIS have been implemented independently but not as bundled products. The fact that climate-smart

agriculture and climate information services have been provided independently poses a great gap in creating the impact expected of these technologies. It is anticipated that when the technologies are bundled and presented to end users or beneficiaries as a single product, it enhances its adoption and results in greater impact [21]. The integrated application of CSA and CIS technologies may have become a challenge in Ghana mainly because of the inadequate capacity, resources, and social norms that serve as barriers to effective implementation. In this context, prioritization is a necessity to generate demand-driven technologies for effective upscaling. The product of effective prioritization takes into consideration indicators such as climate smartness, gender, and social inclusion; the economic potential of the technology; and the potential of the technology to address one-health issue [26]. The resultant product of this process will likely meet the aspirations of end users. A lot of technical know-how and resources are also required for the effective implementation of bundled CSA-CIS products in Ghana. The fact that many smallholder farmers do not have access to climate information mainly due to gender norms and infrastructure challenges influences the combined application of CSA and CIS technologies. In many situations, the majority of smallholder farmers want the government to provide CIS information to them for free. This attitude of end users may significantly affect the optimization of the technologies. Optimization will enhance farm outcomes, which will be better achieved through the integration of demand-driven technologies.

Developing policies that ensure issues of climate change are addressed is a significant step to achieving food security. The review identifies several policies such as the National Climate Change Policy, the Climate Smart Agriculture Investment Plan of Ghana, and the Climate Smart Agriculture and Food Security Action Plan. These policies address climate change issues from different fronts and are meant to enhance the resilience of the population, including farmers, against climate change [38]. Despite some successes of the policies in addressing the vulnerability of smallholder farmers in Ghana, their implementation has faced some grievous bottlenecks, particularly a lack of investment and ineffective coordination. Proper coordination among implementing institutions with clearly defined roles as well as improving resource allocation for the policy implementation is highly recommended for greater impact on Ghanaian farmers. The establishment of roles, synergies, trade-offs, and compromises among stakeholders, particularly government institutions, will be a critical step in implementing and improving the effectiveness of existing climate change policies, particularly taking the nation's limited budget and resources into consideration. Better coordination among government agencies, or even a single entity responsible for coordination between the government and the private sector, could increase the currently limited private sector engagement in Ghanaian climate change programs. Improved institutional capacity would prepare ministries to realign existing policy frameworks necessary to achieve coherence between policies and establish coordinated efforts across departments, ministries, and farmers. Efforts must be taken to reorient climate change-focused policies toward climate adaptation and productivity gains. This will have a disproportionately positive impact on climate-vulnerable households, national food security, and the agricultural economy.

8. Policy implications

Inadequate investment in the implementation of climate-smart agriculture and climate information services is a barrier to the adoption of the innovations. Pursuing

climate-smart innovation in Ghana will require support from the government, non-governmental organizations, civil society organizations, as well as international bodies. These will require a strong policy environment that incentivizes the donor agencies to invest more in climate change adaptation and mitigation measures for resilient agri-food systems. This support is particularly important since funding climate change activities is donor-driven in Ghana. Thus, the need to strengthen the components of finance and institutions to deliver more investment in climate adaptation and mitigation sectors. Regional institutions are also providing support, but more funding is needed to support science and technology to develop innovations that make the agricultural sector more resilient and climate-proof. The climate-smart agriculture investment plan will need to be aligned with the climate change priorities of regional bodies and institutions. Low transfer and dissemination of science, technology, and research results, water management systems, and poor tracking of pests and diseases are affecting the success of climate change interventions. Extension and information-sharing systems are critical in the fight against climate change because they enable centralized reporting that supports mitigation measures, such as early warning systems and advisories for pest outbreaks or the detection of animal disease outbreaks and their early containment. The extension services of the Ministry of Food and Agriculture require improvement in terms of capacity strengthening and funding to enhance their access to improve technologies. The ability of state institutions like meteorological agencies to provide timely and reliable weather forecasts to reduce the vulnerability of end users should be among the policy strategies of the country. Though the implementation of climate change interventions has brought some degree of respite to farmers, more actions are needed to ensure a resilient agri-food system. Because effective adoption of climate-smart practices requires some knowledge and skills, enhancing farmer education and access to extension services should be among the policy measures that could facilitate adoption.

9. Conclusion

The agriculture sector of the Ghanaian economy, like many other countries in sub-Saharan Africa, largely controls the growth and development of the economy. The health of the economies is determined by the strength of the agriculture sector. The source of raw materials for the industrial sector is generated by the agriculture sector, making industrialization largely dependent on agriculture. The agriculture sector also serves as the main source of foreign exchange earnings for the country, making the sector very important for economic growth and development. The transformation of the Ghanaian economy could be facilitated with rapid and robust development of the agriculture sector. This paper demonstrates that the agriculture sector could be improved with smart implementation of climate-smart agriculture (CSA) and climate information services (CIS). These technical innovations have the potential to enhance the resilience of the agri-food systems by reducing the vulnerability of farmers to climate risk. The adoption of these technologies remains low, and often the technologies are implemented independently. Low levels of education and capacity among smallholder farmers and limited access and diffusion of information on CSA are critical challenges militating against the adoption of the technologies. Similarly, limited access to inputs and smart equipment constrained the adoption of CSA options. Action is required toward capacity strengthening of end users, including farmers and extension officers, building reliable input-credit systems and subsidies,

and supply of smart mechanization equipment to remove the barriers militating against the adoption of CSA technologies. More importantly, this review demonstrates that providing CSA and CIS innovations in an integrated manner (bundling) is an ideal scaling mechanism for higher adoption. The integrated deployment of CSA options with other enablers (bundling) such as consumables (inputs such as seed and agro-chemicals) with financial services (credit) and mechanization services offers a great benefit to end users.

The complementarity of CSA and CIS innovations raises some critical questions that require further diagnosis, including how to bundle CIS and CSA in an integrated manner and how to add other agriculture products and services for effective scaling. Also, there is the need to determine the business model that could facilitate ease of implementation of the bundle and encourage private sector participation. Also, additional areas that require further research may include the use of digital platforms to disseminate CIS information and the financial model that can support sustainable deployment to farmers in a way that maximizes their benefit.

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Conflict of interest

The authors declare no conflict of interest.

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This book covers a wide range of applications of technologies (including robotics and artificial intelligence), innovation, models and approaches to enhance the productivity of the agricultural system. The book also focuses on managing the environment and climate change related to agriculture. The book is structured into three sections: 1. *Modeling and Decision Support Systems for the Advancement of Agriculture*; 2. *Advanced Technologies and Innovations in Agriculture*; and 3. *Simulation Models and Adaptation Options in Climate Change*. Ten chapters are included in the aforementioned sections to provide information on applying comprehensive agricultural technologies and innovations.

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