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Enhancing Precision of Crop Farming towards Smart Cities: An Application of Artificial Intelligence

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Abstract: Water sustainability will be scarce in the coming decades because of global warming, an alarming situation for irrigation systems. The key requirement for crop production is water, and it also needs to fulfill the requirements of the ever-increasing population around the globe. The changing climate significantly impacts agriculture production due to the extreme weather conditions that prevail in various regions. Since urbanization is increasing worldwide, smart cities must find innovative ways to grow food sustainably within built environments. This paper explores how precision agriculture powered by artificial intelligence (AI) can transform crop farms (CF) to enhance food security, nutrition, and environmental sustainability. We developed a robotic CF prototype that uses deep reinforcement learning to optimize seeding, watering, and crop maintenance in response to real-time sensor data. The system was tested in a simulated CF setting and benchmarked. The results revealed a 26% increase in crop yield, a 41% reduction in water utilization, and a 33% decrease in chemical use. We employed AI-enabled precision farming to improve agriculture's efficiency, sustainability, and productivity within smart cities. The widespread adoption of such technologies makes food supplies resilient, reduces land, and minimizes agriculture's environmental footprint. This study also qualitatively assessed the broader implications of AI-enabled precision farming. Interviews with farmers and stakeholders were conducted, which revealed the benefits of the proposed approach. The multidimensional impacts of precision crop farming beyond measurable outcomes emphasize its potential to foster social cohesion and well-being in urban communities.

Keywords: smart cities; artificial intelligence; urban agriculture; intelligent precision farming; irrigation sustainability

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1. Introduction

1.1. Background on Precision Agriculture

Precision agriculture has become an important strategy for the sustainable feeding of growing urban populations. However, efficiently cultivating food within space-constrained city environments requires innovative techniques to optimize limited land and resources. Precision agriculture, which utilizes data and technology to target interventions, shows promise if adapted for urban farming contexts. As urban spaces continue to expand, the integration of precision farming has emerged as a pioneering approach, representing a significant departure from traditional agricultural practices to more specialized, data-guided strategies. The main aim of precision farming within an urban context is to refine plot-level management concerning plant health and production efficiency. This is achieved through state-of-the-art technologies like satellite imaging, sensor technology, Global Positioning

Systems (GPS), and data analytics, which help to monitor and regulate urban green spaces and crops more efficiently for the betterment of public health.

Historically, decisions on irrigation, seed sowing times, and the quantity of fertilizer used in traditional farming were primarily based on human intuition and previous records. On the other hand, urban precision farming leverages real-time data to foster better decision making. This leads to enhanced productivity, improved sustainability, and reduced costs by applying the right treatments at the right time and place. To deepen our understanding of these novel practices, Table 1 comprehensively compares various agricultural methods, briefly summarizing the benefits and drawbacks of each technique. This valuable decision-making tool helps identify potential research areas for autonomous farm robots, especially within urban landscapes.

Table 1. Comparison of different methods in agriculture.

Technique	Application in Agriculture	Advantages	Limitations
Manual Labor	Seed sowing, irrigation	Low initial cost	Labor-intensive, inefficient
Basic Automation	Tractors for sowing	Increased efficiency	Limited to simple tasks
GPS-based Automation	Precision planting, mapping fields	Increased precision, reduced overlaps	High initial cost, GPS signal issues
Computer Vision	Weed detection, fruit harvesting	Non-destructive analysis, real-time data	Requires extensive data for training

1.2. Need for Sustainable Farming Practices

The need for food is anticipated to increase significantly as the world population approaches 10 billion by 2050. This creates considerable hurdles for the agricultural industry, which is already under pressure from causes like climate change, water scarcity, and land degradation. Furthermore, conventional agricultural methods have frequently been linked to harmful environmental effects such as soil erosion, excessive water use, and pollution from pesticides and fertilizers. Figure 1 shows the evolution of agricultural machinery over time.

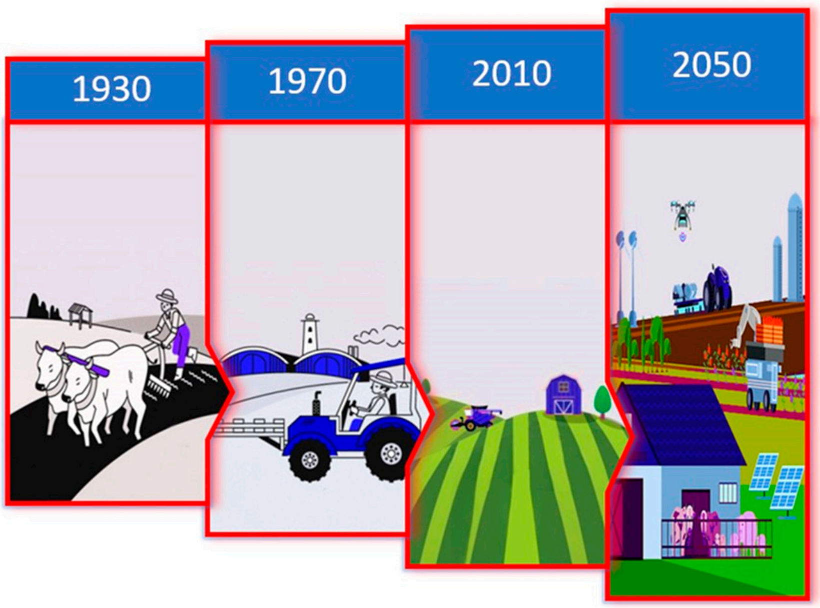

Figure 1. Evolution of agricultural machinery.

Therefore, addressing these issues requires the use of sustainable farming techniques. Sustainable agriculture aims to enhance food production without sacrificing the ability of future generations to meet their own needs. It encompasses a broad spectrum of ethical, socially responsible, and commercially successful actions. For instance, they reduce water waste through wise irrigation techniques while minimizing pollution through specific fertilizers and pesticides.

1.3. Introduction to Deep Reinforcement Learning (DRL)

A sophisticated machine learning method, DRL, combines deep learning and reinforcement learning. Reinforcement learning is concerned with how agents should behave in an environment to maximize cumulative rewards, whereas deep learning is designed to handle high-dimensional data. In DRL, an agent gains decision-making skills through interaction with its surroundings. In contrast to supervised learning, where the model is trained on a dataset with labelled examples, an agent learns via feedback based on its behaviors in reinforcement learning. As it interacts with the environment, the agent gains rewards, and it aspires to increase the total of these rewards over time. Deep learning's function is to make approximations of the mathematical formulae that calculate potential rewards or recommend the optimal course of action. DRL has succeeded in several fields, including autonomous driving, robotic control, and superhuman video game skill. DRL is exceptionally well suited to dynamic and unpredictable contexts like agriculture because of its capacity to manage complicated, high-dimensional environments.

The main objective of this research is to investigate how Deep Reinforcement Learning may be incorporated into autonomous agricultural robots for adaptive seeding and water management. Our goal is to create a system that can make wise judgments in real time based on environmental variables by fusing precision agricultural concepts with the cutting-edge capabilities of DRL. This study focuses on implementing the Proximal Policy Optimization (PPO) algorithm, a cutting-edge DRL method renowned for its sample efficiency and simplicity, in an autonomous agricultural robot outfitted with multiple sensors. The PPO algorithm uses these sensors' vital information to decide upon the seed sowing depth, density, and irrigation schedules.

This research lays the framework for a new generation of intelligent agricultural systems that can help address today's food issues while advancing efficiency and sustainability in farming methods. Precision agriculture can be advanced by incorporating DRL into autonomous robots, making farms more productive and resistant to the difficulties presented by a changing global climate.

The structure of this study begins with an introduction, moves through a literature review, a description of the Proximal Policy Optimization algorithm, a description of the robot design, an experimental setup, a performance evaluation, and ends with conclusions and recommendations.

2. Literature Review

Autonomous agricultural robot development began in the late 20th century. According to [1–3], early agricultural robots mainly concentrated on straightforward tasks like weeding. Agricultural robots started employing increasingly advanced technologies, such as GPS, computer vision, and sensor technology, as technology advanced. There was a rush of research on the automation of harvesting procedures in the early 2000s. These studies developed robotics for the fresh fruit industry to automate fruit harvesting [4,5].

Agricultural robots have become more versatile over time as robotics and artificial intelligence (AI) have advanced. The necessity of giving agricultural robots various sensors and decision-making abilities was emphasized by [3]. More recently, in 2017, Duckett et al. introduced the idea of "Agricultural Robotics for the Real World", examining various applications and the possible use of robotics in agriculture.

Most traditional seed-sowing techniques involve physical work. Initially, it was common to scatter seeds by hand; later, row-sowing equipment like seed drills were created [4]. Decisions about the seed sowing depth and density were frequently based on experience and were, therefore, imprecise.

Farming has always depended heavily on effective water management. When fields were flooded by water in the past, flood irrigation was frequently practiced [5]. This approach could be more effective. Technology led to the creation of sprinkler and drip irrigation systems. Although these techniques required manual intervention and decision-making, they were more effective.

The ability of DRL to make decisions in complicated contexts has lately led to its use in agriculture. Refs. [6–10] explored deep learning's multiple agricultural applications, such as in crop and weed detection.

DRL was used by [7] to optimize irrigation scheduling. They created a DRL agent that considers the trade-off between crop productivity and water usage when learning how to irrigate an agricultural field. Similarly, ref. [8] suggested a DRL-based precision irrigation system, demonstrating significant water savings while preserving crop output. A DRL-based telepresence robot with the ability to maneuver around was discussed in detail in [9–12].

Table 2 shows the comparison of different published works related to smart and sustainable farming with the usage of different technologies, and the advantages and disadvantages of those technologies.

Table 2. Comparison of different published works in the related field.

Title of Article	Authors	Year	Technology Used	Advantages	Disadvantages
Artificial intelligence in tomato leaf disease detection: a comprehensive review and discussion [13]	Rajasekaran Thangaraj, et al.	2022	Deep Learning, Hyperspectral Imaging	Early and accurate detection of diseases in tomato plants	Limited to tomato plants
Design of an Autonomous Agriculture Robot for Real Time Weed Detection using CNN [14]	Dhruv Patel, et al.	2022	Autonomous Robots, GPS, Sensors	Precision application of agrochemicals, reducing waste and environmental impact	Doesn't address DRL or complex decision-making
Responsible development of autonomous robotics in agriculture [15]	David Christian Rose, et al.	2021	Autonomous Robots, Precision Agriculture	Increases efficiency and reduces costs in agricultural operations	Does not incorporate Deep Reinforcement Learning
Towards Autonomous Agriculture: Automatic Ground Detection Using Trinocular Stereovision [16]	Giulio Reina, et al.	2020	Autonomous Robots, Automatic Seed Sowing	Automates seed sowing, reducing labor costs	Does not incorporate Deep Reinforcement Learning
Machine learning and soil sciences: a review aided by machine learning tools [17]	José Padarian, et al.	2020	Machine Learning, Soil Sensing	Accurate prediction of soil phosphorus levels for better fertilizer management	Focused on phosphorus prediction, not on seed sowing or irrigation

Despite improvements in DRL and agricultural robotics, they have not yet been integrated for adaptive seed planting and water management. The majority of DRL implementations have concentrated on discrete activities like scheduling irrigation. Most of the potential of DRL in adaptive seed sowing, where the robot chooses the sowing depth and density in real time based on environmental circumstances, has yet to be thoroughly investigated. Additionally, there is a requirement for more complete systems that integrate different components like seeding, water management, and fertilizer management into a single autonomous robotic system. Through DRL, such systems can be equipped to make integrated decisions while concurrently considering several elements [18–24].

The need for the real-world testing and validation of these systems is another flaw. Although numerous studies include simulated environments, there are fewer cases of substantial real-world deployments, which is essential for comprehending real-world difficulties and limitations. Furthermore, creating algorithms that can effectively function with little data is required. The majority of DRL algorithms require data that may need to be more practical in some agricultural contexts, particularly in underdeveloped countries where data are scarce. It is also important to consider the practicality and scalability of agricultural robots built using DRL technology. Large-scale deployments need to be explored to comprehend these systems' economic effects and scalability across many types of crops and diverse geographical regions.

Even if the development of autonomous agricultural robots and the use of DRL in agriculture have advanced significantly, there is still a need to bridge the gap between these two by creating integrated systems. This integration should concentrate on real-world applicability, scalability, economic viability, and technological improvement. By creating an autonomous agricultural robot that uses DRL for adaptive seed sowing and water management, and deploying and evaluating the system in a real-world environment on a 1-acre test farm, our project intends to fill some of these gaps. Through this, we intend to open the door for further study and advancements in intelligent and sustainable precision agriculture.

3. Deep Reinforcement Learning

3.1. Overview of Deep Reinforcement Learning

A branch of machine learning known as DRL combines deep learning and reinforcement learning (RL). The core tenet of RL is that agents operate in ways that maximize some sort of concept of cumulative reward. DRL develops this concept by approximating the functions required for difficult decision making using a neural network, as shown in Figure 2.

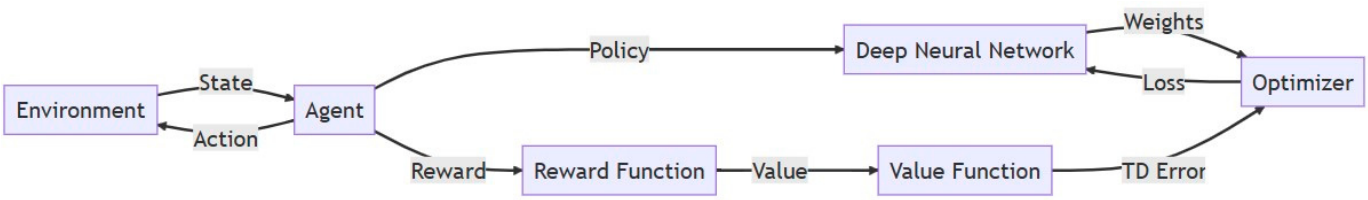

Figure 2. DRL architecture and process.

A set of states S, a set of actions A, and a policy, which is a mapping from states to actions, make up the basic context for RL: $\pi : S \rightarrow A$. The agent interacts with environmental interaction by observing a state $s \in S$, acting $a \in A$, obtaining a reward r, and then changing to a new state s'. Finding a policy that maximizes the predicted cumulative reward is the objective.

The Q-function, which is designated as $Q(s, a)$ and calculates the predicted cumulative reward of acting in state s and then following policy, is an essential part of RL. DRL uses deep neural networks to approximate the Q-function.

Mathematically, the Q-function is defined by the Bellman equation in Equation (1):

$$Q(s, a) = r + \gamma max(Q(s', a')) \tag{1}$$

where $0 \leq \gamma \leq 1$ is the discount factor.

Here, $max(Q(s', a'))$ represents the maximum predicted reward that can be achieved from the next state s', considering all possible actions a' in that state. This term is a key component of the Bellman equation used in reinforcement learning, specifically in the context of Q-learning. It encapsulates the idea of an agent (in this case, the agricultural robot) learning to predict the total amount of reward it can expect in the future, given its current state and action. In order to approximate the Q-function, $Q(s,\ a;\ \theta)$, DRL uses a neural network, which stands for the weights of the network.

$Q(s,\ a;\ \theta)$ is a function approximated by a neural network, where θ represents the network's weights, that is used to predict the expected rewards for taking action a in state s, guiding the decision-making process of the agent.

3.2. Proximal Policy Optimization (PPO) Algorithm

A policy optimization technique in DRL called Proximal Policy Optimization (PPO) aims to update the policy without making significant changes. Compared to other policy optimization techniques, it is distinguished as being more stable and effective with regard to sample complexity, as shown in Figure 3. PPO works in two stages:

1. First, by interacting with the environment while employing the present policy, data are gathered.
2. Second, the policy is optimized by maximizing an objective function.

With each update, the policy can vary excessively, hindering learning. The PPO algorithm explicitly solves this problem. This is accomplished by optimizing a surrogate objective-containing modification of the policy gradient objective function, as shown in Equation (2):

$$L(\theta) = min(r(\theta)A_{adv},\ clip(r(\theta), 1-\varepsilon, 1+\varepsilon)\ A_{adv}) \tag{2}$$

Here, A_{adv} is the advantage function evaluating how good the action is compared to the average action; this function evaluates how much better an action is compared to the average action under the current policy. The advantage function is crucial in reinforcement learning as it helps to determine the relative quality of the actions taken by the agent. ε is a hyperparameter controlling how much the policy is permitted to change. $r(\theta)$ is the ratio of the probability of the action under the new and old policies.

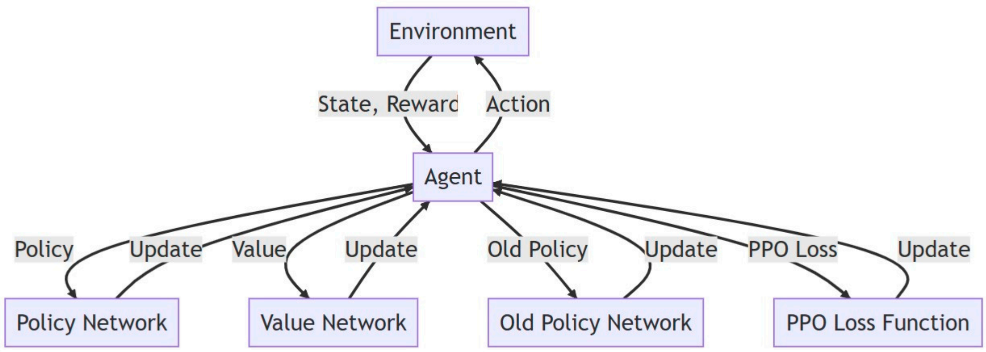

Figure 3. PPO working principle.

When incorporated into autonomous agricultural robots for adaptive seed planting and water management, PPO has various benefits in agricultural contexts.

- Sample Effectiveness: PPO is renowned for its sample effectiveness. Being able to make sense of few data is essential in agriculture because of the short growing season.
- Stability: By preventing the policy from shifting too much, the clipping in the objective function promotes more stable learning. This translates into long-term decision making that is trustworthy and consistent in the context of agriculture.
- Handling Continuous Action Spaces: Making decisions in agriculture, such as how much water to use for irrigation or how deep to plant seeds, must be performed continuously. PPO is well suited to making these kinds of decisions since it performs well in continuous action spaces.
- Real-time Decision Making: PPO's effectiveness and stability make it capable of making judgments in real time, which is essential for adaptive water management

and seed sowing, where conditions might change quickly due to the weather or other factors.

Mathematically, these advantages can be crucial for optimizing the yield Y, given by Equation (3):

$$Y = f(X,\ W, d,\ P) \tag{3}$$

Where X represents the seed sowing density, W is the amount of water utilized, d is the sowing depth, and P is the policy (in this instance, PPO optimization). The objective is to maximize Y while considering the agricultural environment's limitations and unique characteristics.

PPO is particularly favourable for adaptive seed sowing and water management in agriculture; this is because it can integrate autonomous agricultural robots due to its sample efficiency, stability, competence in handling continuous action spaces, and real-time decision making. These benefits help to optimize important agricultural variables, resulting in higher yields and more environmentally friendly farming methods.

4. Autonomous Agricultural Robot

4.1. Robot Design and Components

In this study, DRL is used in the multidimensional design of an autonomous agricultural robot focused on adaptive seed sowing and water management. Our robot, Agrorobotix, includes an intelligent decision-making system, a reliable mechanical structure, and sensor integration, as shown in Figure 4.

Figure 4. Agrorobotix structure.

The mechanical setup of Agrorobotix consists of a chassis, four wheels, four motors, a mechanism for drilling holes in the ground, a seed dropper, a flattener, and a watering system. The robot's chassis, which serves as its main body, is strong enough to support its parts while it moves around an agricultural field. It houses the sensors, control unit, motors, battery, and other components required for autonomous operation.

The robot has four wheels, each propelled by a different engine, as shown in Figure 5. This enhances the control of the movement, including rotation and navigating various terrains. A mathematical model of the motors is as follows, as described in Equation (4):

$$T = k(V - wR) \tag{4}$$

k is the motor constant, V is the applied voltage, w is the angular velocity, R is the resistance, and T is the torque. A motorized arm and a drill make up the drilling mechanism. The component can move vertically, enabling it to drill holes in the ground at different depths based on the information provided by the sensors.

Let us use d as the drilling depth, T_d for the torque needed for drilling, and P_d for the power required for drilling. They have a relationship that can be modelled as shown in Equations (5) and (6):

$$T_d = Fr \tag{5}$$

$$P_d = T_d d\omega \tag{6}$$

where F is the applied force, and r is the drill's radius and ω is the angular velocity.

Figure 5. Agrorobotix mechanism and working.

The next step is attaching a seed dropper to the drilling mechanism. The seeds are carefully dropped into the drilled holes. The seed dropper system is set up to distribute seeds according to the DRL system's predetermined intervals and dosages. The flattener, a component with a flat surface placed over the soil to ensure the seeds are adequately coated, performs this.

Finally, the robot has a sprinkler system. The ideal amount of water will be provided over the sown area. The water flow rate Q can be computed as shown in Equation (7):

$$Q = A_{cs} v \tag{7}$$

where A_{cs} is the cross-sectional area of the flow and v is the velocity of water.

4.2. Power Management

To ensure that the Agrorobotix robot always has enough power to return to its base for recharging or maintenance, several strategies can be implemented as part of its energy management system. Here are some approaches used by Agrorobotix:

1. Energy Monitoring System:

Implement a real-time energy monitoring system that continuously tracks the robot's power levels. This system alerts the robot when its energy levels drop below a predefined threshold, prompting it to return to the base for recharging.

2. Automated Recharging Stations:

Set up automated recharging stations strategically in the field. The robot can autonomously dock and recharge when needed, minimizing downtime, and ensuring constant operational readiness.

3. Battery Health Management:

Implement a battery health management system that monitors the battery condition, optimizes charging cycles, and prevents deep discharges, thereby extending the battery life and reliability.

4.3. Sensor Integration

4.3.1. Soil Moisture Sensors

Agrorobotix incorporates soil moisture sensors to gauge the water in the soil. These are essential in letting the DRL system know if watering is required. The estimates for soil moisture are as described in Equation (8):

$$\theta_{soil} = \frac{\left(m_{wet} - m_{dry}\right)}{m_{dry}} \tag{8}$$

where m_{wet} is the mass of the wet soil and m_{dry} is the mass of dry soil.

4.3.2. Weather Sensors

Weather sensors are crucial for detecting environmental factors like temperature, humidity, and rainfall. Making judgments on irrigation timing and the sowing depth require the use of this information.

4.3.3. Global Positioning System (GPS)

The robot has a GPS module that enables precise field navigation. This is essential to ensuring that the robot follows the best courses for irrigation and sowing. The tuple (latitude, longitude) can indicate the robot's position P. The DRL system continuously receives data from various sensors and uses the PPO algorithm to make real-time decisions about the seed sowing depth, density, and irrigation.

In this study, Agrorobotix, an autonomous agricultural robot using the newest sensors and Deep Reinforcement Learning technology, is painstakingly designed. Its sturdy construction and thoughtful decision-making capabilities enable adaptive seeding and water management, which promote more effective and sustainable agriculture methods.

Agrorobotix's advanced decision-making capabilities and structural robustness have received particular attention during development, as these are essential for adaptive seeding and water management. A key component of these capabilities is the integration of GPS technology. Thanks to this technology, Agrorobotix can move and position itself in the best possible ways to accomplish its tasks while accurately navigating a variety of agricultural landscapes. Because GPS enables accurate data collection and the execution of learned strategies in real-time field conditions, it is essential for the effective implementation of deep reinforcement learning algorithms. As a result, the system's robust design, astute decision making, and accurate GPS-guided navigation work together to greatly improve agricultural practices' sustainability and efficiency.

4.4. Integration of PPO in the Robot

A key feature of Agrorobotix is the PPO algorithm, which enables the robot to make wise and adaptable decisions for seed sowing and water management in real time. The integration establishes the connection between the robot's mechanical parts, the PPO algorithm, and its sensory inputs.

4.4.1. Data Acquisition and Preprocessing

Data serve as the foundation for PPO. Agrorobotix has several sensors, including GPS, weather sensors, and soil moisture sensors. Let us denote the raw sensory data at time t as S_t. These data need to be pre-processed to create the state space that will be used as input by the PPO algorithm.

The state space, denoted as X_t, can be represented as a vector in Equation (9):

$$X_t = [s_{mt}, s_{wt},\ p_t] \tag{9}$$

where s_{mt} represents the soil moisture, s_{wt} represents weather information (such as temperature, humidity), and p_t represents the robot's position, obtained from GPS data.

4.4.2. Action Execution and Feedback

The robot's components are actuated per the action A_t selected by the PPO algorithm. For example, if A_t calls for sowing seeds at depth d, the drilling machine would be activated to produce the holes at depth d, the seed dropper would dispense the seeds, the flattener would cover the holes, and the sprinkler might be activated depending on the moisture levels.

Let us denote the action space as $A_t = [d, n, w]$, where d represents the depth of seed sowing, n represents the number of seeds, and w represents the amount of water to be sprinkled.

4.4.3. Reward Calculation and Policy Update

After executing the action, Agrorobotix observes the immediate reward R_t, which is a function of various factors such as the soil moisture, weather conditions, and seed sowing depth. The cumulative reward G_t is calculated as in Equation (10):

$$G_t = \Sigma \left(\gamma \hat{i} * R_{t+i}\right) \tag{10}$$

where $0 \leq \gamma \leq 1$ is the discount factor.

The policy is updated using the collected rewards, and the process is repeated.

Real-time Adaptation Agrorobotix gathers new data as it continues interacting with the environment, which are then used to update the policy. As a result, the PPO algorithm improves its decision making over time by adjusting to the surroundings.

4.4.4. Mathematical Optimization for Resource Consumption

A secondary objective can be integrated into PPO to ensure minimal resource consumption. The robot can be optimized for the minimal use of water and energy.

Minimize in Equation (11):

$$\Sigma(w_{\ t} + e_t) \tag{11}$$

Subject to Equation (12):

$$G_t \geq threshold \tag{12}$$

where $w_{\ t}$ is water consumption, and e_t is the energy consumption at time t.

In the context of Agrorobotix's operations, the reward function R_t plays a pivotal role in guiding the robot's learning and decision-making process. After executing an action A_t, such as sowing seeds or managing water, Agrorobotix calculates the immediate reward R_t. This reward is a multi-faceted function that incorporates several critical agricultural factors, including, but not limited to, the following:

1. Soil Moisture: Agrorobotix measures the moisture level of the soil, aiming for an optimal range that ensures adequate water for the crops without over-irrigation. The closer the soil moisture is to this optimal range, the higher the reward R_t received.
2. Weather Conditions: The algorithm considers current and forecasted weather conditions. Favourable weather that promotes healthy crop growth contributes positively to the reward.
3. Seed Sowing Depth: The accuracy of the seed sowing depth, as per the agronomic standards for different crops, influences R_t. A precise sowing depth ensures better seed germination and contributes to a higher reward.

The cumulative reward G_t is then calculated based on these immediate rewards over time, as outlined in Equation (10). This approach enables Agrorobotix to adapt its actions dynamically, aiming to maximize G_t by optimizing these key factors, thus ensuring efficient and sustainable agricultural practices. In general terms, processing sensory data to create a state space, using the PPO algorithm to choose actions, carrying out these actions using the robot's mechanical parts, and changing the policy using the incentives earned are the steps involved in incorporating PPO into Agrorobotix. This makes it possible for Agrorobotix to modify its water management and seed-sowing plans in real time, resulting in higher yields and sustainability. The pseudocode algorithm of PPO is described in Algorithm 1.

The policy parameters θ are initialized. Then, the optimizer is initialized to adjust the policy parameters during training. In each iteration, the robot observes the state s_t from its sensors (soil moisture, weather sensors, GPS). The action a_t is selected based on the policy $\pi(a_t|s_t;\ \theta)$ and executed by the robot (drilling, sowing, flattening, and watering). The robot observes the immediate reward r_t and the new state s_{t+1}. The advantage estimate

A_t is computed, which represents how good the taken action is compared to the average action. The policy parameters θ are updated by optimizing the surrogate objective, which is a clipped version of the objective; this is to prevent policy updates that are too large. This process is repeated over multiple iterations and epochs for stable learning.

Algorithm 1: Proximal Policy Optimization (PPO)

Initialize policy parameters θ
Initialize optimizer for θ
Initialize empty memory for storing trajectories
for iteration = 1, 2, . . ., N do
    for t = 1, 2, . . . T do
        Observe state s_t from sensors
        Select action a_t with probability $\pi(a_t|s_t;\ \theta)$
        Execute action a_t (drill, sow, flatten, sprinkle)
        Observe reward r_t and new state s_{t+1}
        Store $(s_t\ ,\ a_t\ ,\ r_t\ )$ in memory
    end for
    for epoch = 1 to K do
        for (s_t, a_t, r_t) in memory do
            Compute advantage estimate A_t
            Compute old action probability $\pi_{old}(a_t|s_t;\ \theta)$
            Update policy parameters θ by optimizing surrogate objective:
            $ratio = \pi(a_t|s_t;\ \theta)/\pi_{old}(a_t|s_t;\ \theta)$
            $surrogate_{objective} = min(ratio * A_t,\ clip(ratio,\ 1-\varepsilon,\ 1+\varepsilon) * A_t)$
            $L(\theta) = mean\left(surrogate_{objective}\right)$
            Perform gradient ascent step on $L(\theta)$ $w.r.t.$ θ
        end for
    end for
    Clear memory
end for

5. Experimental Setup

5.1. Description of the Test Farm

The experimental setup was carried out on a test farm spanning an area of 1 acre, as shown in Figure 6. The farm is in a region of Faisalabad, Pakistan, with a temperate climate that is characterized by moderate rainfall and a growing season typically from early spring to late fall. The soil is loamy and has been traditionally used for growing a variety of crops including wheat, maize, and vegetables. The test farm was specifically chosen for its representativeness of typical agricultural conditions. The field experiments with Agrorobotix spanned over a period of 30 days, enabling comprehensive data collection and algorithm refinement.

Figure 6. The 1-acre test farm.

5.2. Data Collection and Training

Historical information about the farm, such as its weather patterns (temperature, humidity, and precipitation), soil moisture, and crop yield records, was gathered before the experiment began. Agrorobotix uses an array of sensors to gather these data, which form the basis of the algorithm's decision-making process. Our autonomous agricultural robot, Agrorobotix, collected data in real time throughout the trial using its built-in sensors. Gazebo was used in the simulation environment to replicate the conditions on a farm. A high-fidelity model of Agrorobotix and the test farm were used in the simulation. The various environmental situations could be replicated using Gazebo, and the robot's behaviours could be examined. Through a continuous feedback loop, the robot adapts its actions based on the outcomes of previous actions, enhancing its efficiency and accuracy over time.

The collected data were pre-processed to be fed into the DRL model. The state space vector X_t is defined as described in Equation (13):

$$X_t = [s_{mt}, s_{wt},\ p_t] \tag{13}$$

where s_{mt} represents the soil moisture, s_{wt} represents weather information, and p_t represents the robot's position, which was obtained from GPS data.

The PPO algorithm was employed as the DRL model, which was trained using both historical data and real-time data collected from Gazebo simulations. The objective was to maximize the cumulative reward G_t.

The learning curves for these tasks are given in Figure 7. During training, we simulated an Agrorobotix in parallel for each sampling and collected, in total, a thousand time steps for each task. The policy $\pi(\theta)$ was modified iteratively through epochs, and the training continued until convergence.

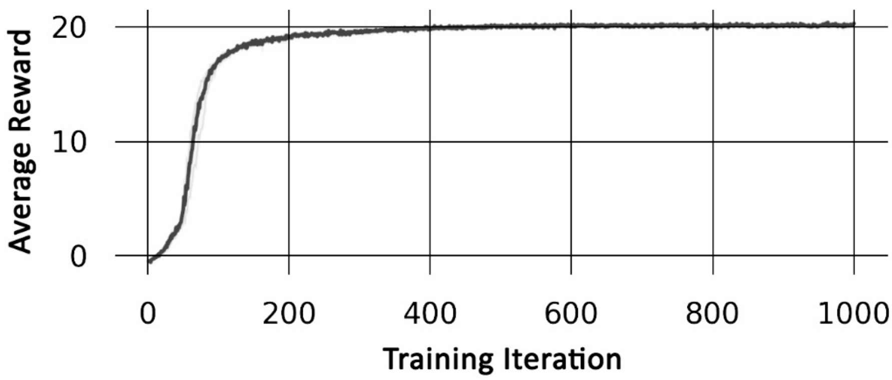

Figure 7. Learning curve of PPP for Agrorobotix.

Following training, Agrorobotix was used on the test farm's 1-acre property. Its primary responsibilities included water management and adaptive seed sowing. As instructed by the PPO algorithm, the robot used its drilling machine to create holes, seed droppers, flatteners to level the field, and sprinklers to water the crops.

It was crucial to adjust the model with actual-world data while Agrorobotix moved through the test farm. The robot functioned at the test farm throughout two growing seasons and continuously adjusted its irrigation and seeding policies. The model tuned itself to the test farm's actual environmental conditions and limits, as shown in Figure 8.

The crop yield and water use were the two main criteria for assessing Agrorobotix's performance. Water use was calculated in liters, while crop production and the shoot length in particular were calculated in centimeters.

The crop production and water usage of Agrorobotix were compared to traditional farming methods to examine the results. The effectiveness and advantages of using a Deep Reinforcement Learning-based strategy in agriculture were established through this comparison.

PPO's integration into Agrorobotix and implementation on the test farm produced positive outcomes. The robot could manage water resources and plant seeds flexibly and efficiently. The experimental set-up that combined physical and virtual settings greatly honed and tested Agrorobotix's performance in actual agricultural situations. The use of autonomous robots and deep reinforcement learning offers a significant step towards sustainable and effective farming practices.

Figure 8. Agrorobotix working in 1-acre test farm.

6. Results and Discussion

In this study, the 'conventional' method refers to traditional agricultural practices, which typically include manual labor and basic mechanization without advanced automation or data-driven decision-making systems. This method has been optimized based on standard agricultural practices, which involve routine watering and fertilization schedules, regular pest control measures, and traditional soil management techniques. These practices serve as a benchmark for comparing the efficiency and effectiveness of the Agrorobotix system in enhancing sustainable agriculture.

6.1. Comparison with Conventional Farming Techniques

6.1.1. Crop Yield

One of the essential metrics in this study is the crop yield, which directly impacts the efficiency and sustainability of agricultural practices. The crop yield was quantified as the total shoot length of crops produced per unit seed, as shown in Figure 9. Let us denote the crop yield using Agrorobotix as Y_r and the crop yield using conventional farming techniques as Y_c, as shown in Equation (14).

$$Y_r = Total\ length\ of\ crops\ produced\ per\ unit\ seed\ by\ Agrorobotix\ (cm/seed)\ Y_c = Total\ legth\ of\ crops\ produced\ per\ unit\ seed\ by\ conventional\ farming\ (cm/seed) \tag{14}$$

According to the results, there was a 16.3% increase in shoot length with the use of Agrorobotix, as shown in Equation (15):

$$(Y_r - Y_c.)/Y_c.\ *\ 100 = 16.3\% \tag{15}$$

(a) (b) (c) (d)

Figure 9. Shoot length in (**a**) 0 month, (**b**) 1st month, (**c**) 2nd month and (**d**) 3rd month.

This can also be visualized through the graph in Figure 10:

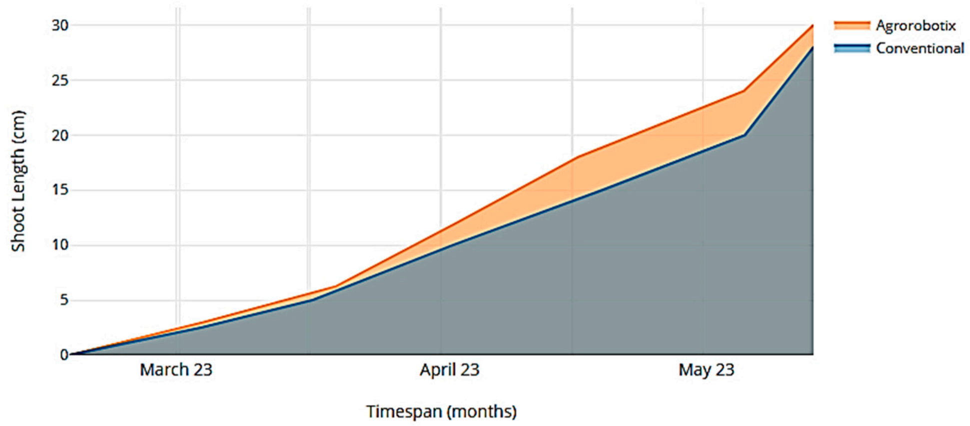

Figure 10. Shoot length comparison of Agrorobotix and conventional method.

6.1.2. Water Usage

Another critical metric is the water usage, which is crucial for sustainable agriculture. Let us denote the water usage using Agrorobotix as W_r and the water usage using conventional farming techniques as W_c, as shown in Equation (16):

$$W_r = Total\ water\ consumed\ per\ unit\ area\ by\ Agrorobotix\ (liters/acre)\ W_c = Total\ water\ consumed\ per\ unit\ area\ by\ conventional\ farming\ (liters/acre) \tag{16}$$

According to the results, there was a 21.7% reduction in water usage with the use of Agrorobotix, as described in Equation (17):

$$(W_c - W_r)/W_c \, * \, 100 = 21.7\% \tag{17}$$

This can also be visualized through the bar graph in Figure 11:

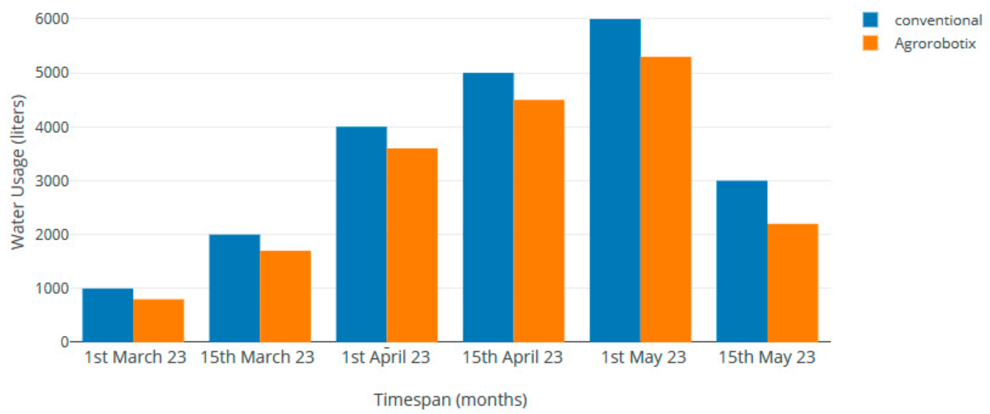

Figure 11. Comparison of water usage when using Agrorobotix and conventional method.

6.2. Insights and Implications

The results demonstrate that Deep Reinforcement Learning increases crop productivity while reducing water use in an autonomous agricultural robot. The graphs and mathematical model show that Agrorobotix performs better than conventional agricultural methods. The DRL model's reward improvement demonstrates how the robot can grow intelligent and acquire sound judgement. Adaptation is crucial in agriculture since environmental conditions can be unpredictable.

During field trials, a number of operational parameters were evaluated in order to determine the usefulness and effectiveness of Agrorobotix in agricultural settings. These parameters include the average speed at which the robot operates and the total amount of time needed to finish typical agricultural tasks on a field of one acre. Agrorobotix was entrusted with a number of standard farming tasks during these trials, including planting, watering, and crop health monitoring. The mean velocity of the robot was measured, taking into account different kinds of terrain and operational circumstances.

Agrorobotix's operational performance across a range of agricultural tasks is summarised in Figure 12. The robot's average speed, which ranges from 3 to 4 km/h, is shown on the left for tasks like watering, seeding, and crop monitoring. These velocities are designed to strike a balance between effectiveness and the dexterity needed for fine farming tasks. Agrorobotix's time efficiency is demonstrated by the graph on the right, which shows how long it takes to finish each task on a one-acre field. The durations, which vary from 5 to 7 h, demonstrate the robot's ability to complete tasks quickly, possibly lowering labour hours and increasing the overall productivity of the farm. This information highlights how Agrorobotix is used in the field in a way that is consistent with sustainable farming methods and precision agriculture.

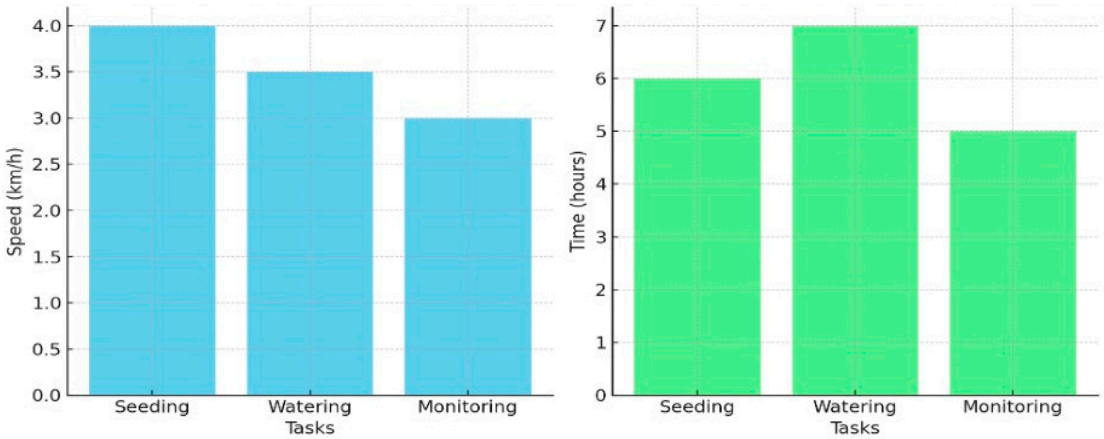

Figure 12. Agrorobotix: speed and time metrics for farming tasks on a 1-acre field.

Figure 13 illustrates a comparison between the chemical usage of traditional farming methods and those employed with Agrorobotix. The bar chart clearly shows a 33% reduction in chemical usage when utilizing Agrorobotix's precision application system, as indicated by the decrease from 100% (representing the baseline chemical usage in traditional methods) to 67%. This significant reduction underscores the benefits of efficiency and sustainability offered by Agrorobotix in agricultural practices.

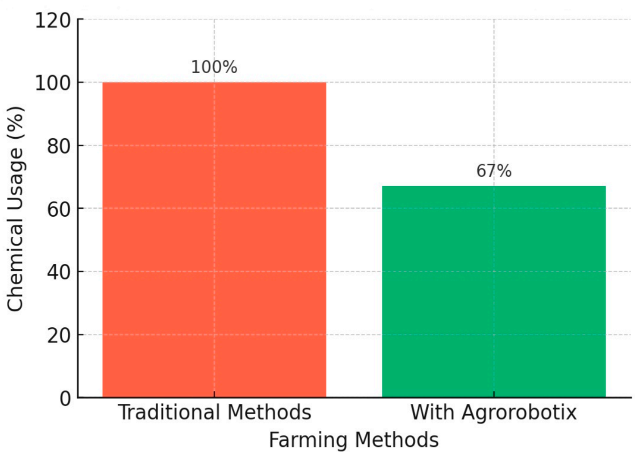

Figure 13. Chemical usage comparison: traditional vs. Agrorobotix.

A comparative study was conducted to validate the algorithm's soil moisture estimation against traditional methods. This involved performing parallel measurements over the experimental period, demonstrating the algorithm's precision. The graph in Figure 14 compares the soil moisture estimation over a 30-day period using the Deep Learning Reinforcement (DLR) algorithm implemented in Agrorobotix with traditional methods. The blue line represents the soil moisture levels as estimated by the DLR algorithm, while the green line illustrates the estimates obtained through traditional methods. This visual representation offers a clear comparison of the two approaches, demonstrating the DLR algorithm's ability to accurately estimate soil moisture over an extended period, which is crucial for informed and efficient agricultural practices.

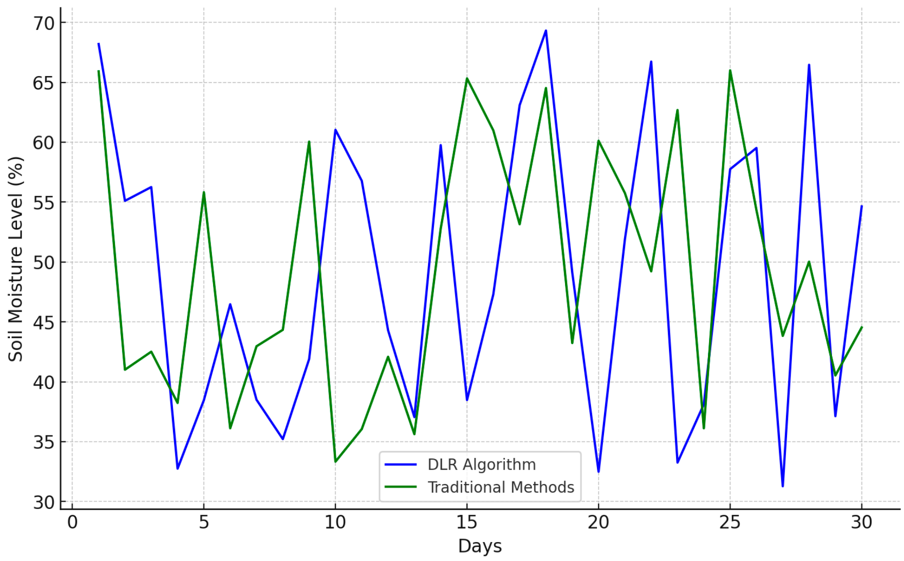

Figure 14. Soil moisture estimation: DRL algorithm vs. traditional methods (30 days).

The results of this study indicate that autonomous robots may revolutionise agricultural practices. Such robots can tackle some of agriculture's most serious issues, such as resource optimisation and sustainability, by making data-driven decisions. Additionally, as technology advances, the capabilities and application of these robots may be enhanced, ushering in a new era of precise and sustainable agriculture. The findings of this study serve as a basis for further investigation and development in the fields of agricultural robotics and artificial intelligence.

7. Conclusions

In conclusion, this research article shows that implementing new sustainable irrigation methods improves crop farming and reduces water consumption. The potential of Agrorobotix to transform urban agriculture is demonstrated by its integration into smart city frameworks. Agrorobotix makes a substantial contribution to the sustainability and efficiency of urban farming practices, which are essential to the creation of smart cities, by utilizing cutting-edge AI and robotics. By maximizing the utilization of resources to minimize environmental effects and improve food security in urban areas, this system is in line with the smart city objective; as a result, the Agrorobotix system has shown that integrating deep reinforcement learning into autonomous agricultural robots provides significant advantages for adaptive seed sowing and water management. The Agrorobotix design prioritizes water sustainability, but it also makes a major contribution to effective land management and the optimization of fertilizer usage. Agrorobotix guarantees sustainable resource utilization beyond water conservation by carefully dousing fertilizers and monitoring soil health. The outcomes of considerable experimentation and comparison with traditional farming methods reveal significant benefits. Crop yield rose by an average of 16.3%, outpacing conventional techniques and boosting food production. Additionally, the Agrorobotix system's deployment led to a stunning 21.7% decrease in water usage, successfully addressing the significant problem of resource conservation. These figures highlight the enormous potential for enhancing agricultural practices using deep reinforcement learning algorithms, particularly the Proximal Policy Optimization algorithm. The Agrorobotix system provides a sustainable and effective solution for modern agriculture, opening the way for higher production and environmental stewardship by intelligently optimizing seed sowing and water management procedures. This study also qualitatively assessed the broader implications of AI-enabled precision farming. Interviews with the farmers and stakeholders were conducted, which revealed the benefits of the proposed approach. Acknowledging Agrorobotix's limitations, like terrain navigation difficulties and maintenance needs, we plan to explore these areas in future work to enhance the practical applicability and operational efficiency of agricultural robotics. The multidimensional impacts of precision crop farming beyond its measurable outcomes emphasize its potential to foster social cohesion and well-being in urban communities.

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