# Robotic autonomous systems for unconstructed land reclamation and preparation

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**Abstract.** Today, a large portion of the world's land remains unused or has been abandoned after being previously abused unsustainably. These lands represent untapped potential for agricultural production, though reclaiming their productivity could prove to be very challenging. New technologies are being developed that offer potential solutions, such as automated robotic systems, which may replace some labor input. Automated robotic systems for key agricultural practices, such as sowing, irrigation, and harvesting requires the deployment of technological solutions, which depend on precision and efficiency. In principle, an automated system could significantly boost precision and efficiency in sowing seed, and with efficient watering/irrigation; however, we are limited with existing robotic systems. In addition to automating key agricultural practices that require precision, automated sensors with data collection technologies allow continuous monitoring of field conditions, and relay that information in real time. Continuous real time monitoring provides the basis for informed decisions and optimal resource use, and adaptive decision making, resulting in continual gains in land productivity. Under-utilized lands can become productive and sustainable by incorporating robotics and artificial intelligence into modern agriculture, increasing both productivity and sustainability.

## 1 Introduction

The worldwide agricultural industry is being confronted with extraordinary challenges—the intensity of which has not been seen before in the 21st century—at least since the industrial revolution. These challenges include shifting climates, reduced land, and unprecedented pressures to produce more food for a growing world population. Unsustainable practices and climate change have also helped in the decrease of the productivity in current farmland. Land use models, such as the Global Agroecological Zones (GAEZ) framework, estimates that around 160 million hectares of currently undeveloped land is suitable for production of major crops. At the same time, over 2 billion hectares are currently degraded. These changes can significantly threaten food security, which is especially concerning for vulnerable regions (e.g. Sub-Saharan Africa, portions of Asia). The depletion of the agroecosystem must encourage more creative solutions for reclamation, restoration, or management of land sustainability.

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In response to these challenges, robotic autonomous systems (RAS) have emerged as a transformative technology in contemporary agriculture. The use of AI, advanced sensors, and automation provide a new step toward the ability to recover and prepare underused or degraded areas with high precision and efficiency. Robotic systems can conduct the entire farming cycle from autonomous sowing, through irrigation, and into AI-based harvesting. Robotic systems are capable of carrying out complex tasks with little to no human operator involvement and should minimize resource loss plus waste. These systems will improve productivity, alleviating the labor shortage while bringing about better environmental outcomes associated with more precise and optimized use of inputs and chemicals.

Agricultural robotics have advanced quickly due to the progress made in machine learning, computer vision and navigation. The earliest automation developed for agriculture was focused on mechanizing equipment; however, current advancements have arrived at a point where autonomous agriculture can take place, merging with an adaptive level of autonomy that reacts to real-time conditions in the field environment, essentially enabling a fully autonomous agricultural environment. We review several current technologies which use AI and autonomous robotic systems to restore and prepare unstructured environments in terms of planting, watering and harvesting. This review also evaluates the viability of AI and robotic related techniques, based on the current technology literature, which could help yield significant benefits to agricultural workers. In combining agronomic science and robotic engineering, we hope to demonstrate the crucial role of automation in achieving sustainable land use and global food security.

## 2 Earth's Unploughed Lands

### 2.1 Unusable lands

#### *2.1.1 Introduction of Global Agroecological Zones (GAZE mode)*

GAEZ is a rigorous standard for evaluating agricultural land potential, integrating soil, topography and climate (temperature, precipitation, and actual evapotranspiration) and modelling the potential of land to grow specific crops at different management levels and inputs. To illustrate, Fig. 1. Average annual precipitation (mm) in 1981-2010 is shown.

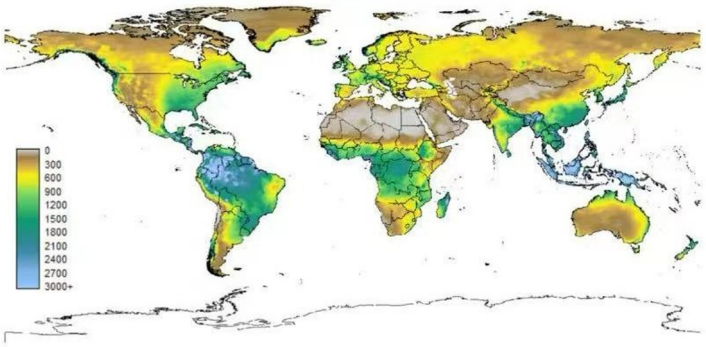


**Fig. 1.** Average annual precipitation (mm) in 1981-2010

*2.1.2 Findings of GAEZ mode*

The data has shown that around the world there are approximately 160 million hectares of land that is potentially suitable for the production of at least one major crop (wheat, soybeans, corn, etc.), but not presently being used as cropland. According to different regional soil data of Fig. 2. (Harmonized World Soil Database), the distribution of the undeveloped potential lands is very unequal [1]: Sub-Saharan Africa: the largest share, with around 735 million hectares of undeveloped potential lands, Latin America: about 573 million hectares, Eastern Europe: around 109 million hectares.

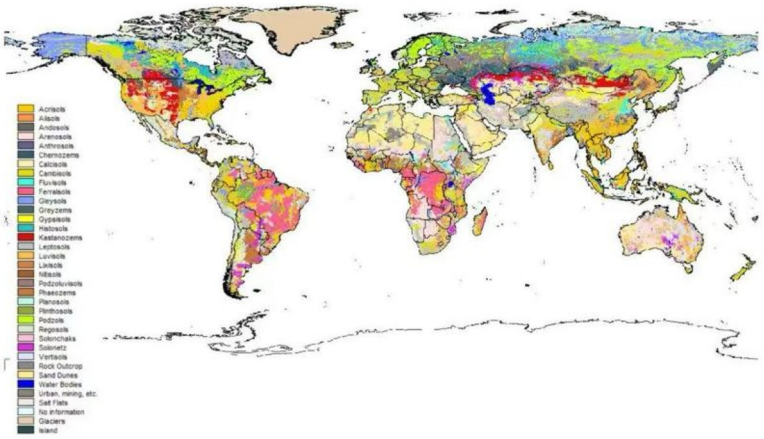


**Fig. 2.** Harmonized World Soil Database (HWSD)

### 2.2 Degraded land

Land degradation has emerged globally as one of the most significant environmental issues. The "Global Land Outlook" report released by the United Nations Convention to Combat Desertification (UNCCD) states that over 2 billion hectares of land experienced pivotal degradation worldwide, translating to over 15% of the total land outside of the ice caps on Earth. Degraded lands are typically reported as soil erosion, loss of soil fertility, loss of biodiversity, and loss of ecosystem functions. The causes of land degradation are closely related to human behavior including unsustainable agricultural degradation, overgrazing, deforestation, and climate change. Words are limited to describe how land degradation not only seriously threatens global food security and ecological resilience, but also aggravates poverty and social instability - with developing world regions in Africa and Asia being more adversely affected since they rely heavily on agriculture for their livelihoods. The international community is now actively advocating ecological restoration and sustainable land management that will help mitigate land degradation and restore land productivity and ecological functions.

## 3 Current development of agriculture by modern robot

### 3.1 Sowing

Farm seeding robot systems are among the key technologies in precision agriculture. Current solutions utilize machine vision, global navigation satellite systems (GNSS), the internet of

things (IoT), and artificial-intelligence-based decision support to execute verifiable, precise, and automated sowing decisions. This in turn substantially increases efficiencies and sustainability of inputs in all growth activities.

In terms of navigation and path planning, autonomous guidance systems employing RTK-GNSS systems allow the robots to achieve positioning accuracy within centimetres of true position, typically with an error of around ±2.5 cm [2]. These readers the familiar problems of overseeding and improper skips, which result from human operation and eliminates these problems to give a very consistent row to row and plant spacing. This precision sets up a strong basis for subsequent levels of automated field management.

Machine learning-based algorithms for machine vision systems will be integral to the seeding decision-making process. For example, robotic systems designed by researchers at the University of California, Davis, can detect and identify residue from previous crop stalks in real time. The robotic systems determine the best possible place (the optimal seed placement) to inject the seeds into the targeted area [3]. Other advanced methods include in-situ sensing of the soil. Robots can produce real-time maps of soil moisture, organic matter content, and soil compaction across the field with near-infrared (NIR) spectroscopy and electrical conductivity (EC) sensors. This will allow for dynamic adjustments to depth of planting and seeding density. Empirical studies reveal that variable rate seeding (VRS)—by increasing density in high-fertility areas and reducing density in adverse-fertility areas—has been reported as yielding a 5% to 10% increase in corn and soybean yields and nearly a 15% decrease in seed waste [4].

## 3.2 Irrigation

### *3.2.1 Sensor-Based Variable Rate Irrigation (VRI)*

Modern irrigation robots are equipped with high-resolution multispectral and thermal infrared sensors that monitor crop canopy temperature in real time, enabling the calculation of the Crop Water Stress Index (CWSI). Irrigation is triggered automatically when the CWS exceeds a threshold of 0.3, indicating mild to moderate water stress in the plants [5]. Research demonstrates that CWSI-based precision irrigation improves Irrigation Water Use Efficiency (IWUE) by 25% in cotton and 18% in maize compared to conventional scheduled irrigation, while maintaining or even slightly increasing crop yields [6].

### *3.2.2 In-Situ Soil Moisture Monitoring and Decision-Making*

Using Time-Domain Reflectometry (TDR) or Frequency-Domain Reflectometry (FDR) sensors, mobile robotic platforms perform grid-based (e.g., 10m × 10m) field measurements to create detailed 3D spatial variability maps of Soil Volumetric Water Content (VWC). The system dynamically adjusts irrigation timing and volume based on real-time moisture data at crop root zone depths—for instance, at 60 cm for maize. A field trial conducted by the University of California found that robotic irrigation systems using this approach reduced nitrogen loss caused by deep percolation by approximately 30% [7].

## 3.3 Harvesting

Harvesting robots are a revolutionary new technology for precision agriculture as they utilize computer vision, mechatronic systems, and artificial intelligence to enhance harvesting efficiency and alleviate labour shortages. Visibly, by employing multispectral imaging and

deep learning algorithms, these harvesting systems, can detect crop maturity with greater than 95% accuracy which mitigates pre-harvest losses [8].

Numerous studies illustrate the improvements in efficiency with robotic harvesters. In the case of apple harvesting, robotic apple harvesters developed by researchers from institutions including Washington State University have demonstrated a picking rate of 85–90% of mature fruit and damage rates of less than 5% of the total. In comparison, humans harvesting apples for both firm fruit and ease of harvesting achieved only half to two-thirds the efficiency (approximate 60–70% harvesting efficiency) under similar conditions. With exceptional high-value crops such as strawberries, robots such as those developed by Harvest CROO Robotics can achieve well over 50% faster harvesting rates per hour than humans. They are hoping to harvest well over 80% of the crop in a single pass while under structured growing conditions [9].

Further, robotic harvesters reduce reliance on seasonal labour and can reduce post-harvest losses. For example, in field trials conducted in California lettuce fields, data from autonomous lettuce harvesters showed a reduction in damage of approximately 30% compared to human harvesters, extending shelf-life and therefore food waste. By integrating light detection and ranging (LiDAR) sensors and inertial measurement units (IMUs), robots can operate in continuously changing light conditions and can maintain a position within 2 cm while harvesting [10].

## 4 Feasibility of artificial intelligence to change agriculture

### 4.1 Senor

AI systems utilize sensors and GPS technology to facilitate precision variable-rate applications. Researchers have found precision spraying systems to reduce herbicide use by 30-50% while effectively controlling weeds [11].

### 4.2 Solving problems

AI automation is able to assist in labor-intensive processes. Apple harvesting robots have reported pick rates of 85-90% on mature fruit and less than 5% damage to the fruit [12]. Automated weeding robots using computer vision reduce chemical use by 90% over traditional weeding systems [13].

### 4.3 Data analysis and collection

AI data collection and analysis allows for data-driven science-based decisions. Internet of Things (IoT) sensors, working in concert with machine learning algorithms, can identify when to plant with 92% accuracy, increasing yield by at least 10-15% [14]. Plants that use real-time monitoring and controls for soil properties such as moisture have documented use of 25% fewer irrigation water while maintaining proper plant health and development [15].

## 5 Conclusion

Globally, a large amount of underperforming or underutilized land still remains, and agricultural technologies continue to a better job at utilizing them. During the sowing stage, robotic systems are used achieving careful and effective sowing, relying on centimetres-level and variable rate seeding (VRS) technology resulting in improved yields of 5% to 10% for corn and soybean, as well as 15% of seed savings. During the irrigation stage multi-spectral

and thermal infrared sensors are used, and automatic irrigation is achieved, based on the crop water stress index (CWSI), improving water effectively by 25% for cotton and 18% for corn, reducing the loss of nitrogen by 30%. In the harvesting stage computer vision and AI utilized with improved operational precision for accuracy, speed, less damage and post-harvest losses. We look forward some creative technologies to improve agricultural effective globally, inspire a new generation of farmers, and produce much needed data for future researchers.

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