



Towards Carbon-Smart Rice Farming by 2050: Edge-AI Autonomous Robots for Site-Specific *Astragalus sinicus* Management in Large-Scale Rotation Systems

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Abstract

Background: Flooded rice ecosystems emit significantly more methane (CH₄) and nitrous oxide (N₂O) than other agricultural systems and, therefore, improving the efficiency of global rice production systems will be essential to meeting both food security and greenhouse gas emission reduction targets (especially CH₄ and N₂O) worldwide.

Objective: The purpose of this research is to create a carbon-smart rice production system that utilizes Edge-AI Autonomous Robots to implement site-specific management strategies for the *Astragalus sinicus* (Chinese milk vetch), a green manure crop that biologically fixes nitrogen, by the year 2050 by integrating technology into agriculture.

Methods: This method utilizes hyperspectral imaging, multispectral imaging, LiDAR canopy profiling, and electrochemical soil sensing with deep-learning models that are implemented on neuromorphic edge processors located on an autonomous ground robot. The simulations were done across 10,000 hectares of virtual fields to assess system performance.

Results: Increased soil organic carbon stock from *A. sinicus* efficiently maintained with robots using site specific intervention, reduced CH₄ emissions (compared to conventional methods) and decreased input of synthetic nitrogen by 12-19% and 35-52%, respectively.

Conclusion: Edge-AI robotics effectively tackle spatial heterogeneity in extensive rice systems, facilitating precision management that improves carbon sequestration and diminishes emissions.

Implications: The framework offers a scalable and technologically feasible approach for rice-based agriculture to achieve net-zero climate objectives while enhancing soil health, ecosystem services, and farm profitability by 2050.

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1. Introduction

1.1. The Climate Challenge in Rice Agriculture

The flood irrigation of rice (*Oryza sativa* L.), which feeds over half of the world's population (approximately 3.5 billion people) and requires around 167 million ha of agricultural land globally, is one of the major agricultural contributors to GHG emissions (Searchinger *et al.*, 2019) ^[1]. Much of the GHG emissions from rice cultivation occur from CH₄ generation during anaerobic methanogenesis in flooded paddies at an estimated rate of 25–80 Tg CH₄/yr, and pulses of N₂O resulting from nitrogen

fertilization, together are estimated to cause approximately 1.0–1.5 Gt of CO₂-eq of warming per year (Saunio *et al.*, 2020) ^[2] (Tian *et al.*, 2020) ^[3]. These factors, along with the United Nations' Paris Agreement on Climate Change 1.5°C target and the Sustainable Development Goals SDG 2 (zero food hunger) and SDG 13 (climate action) (IPCC, 2022) ^[4], compel all rice cultivation systems to transition from being net emitters of GHGs to being net sinks (or at a minimum carbon neutral) by 2050. In order to achieve this outcome, there must be transformational changes in the agronomic production system that are not incremental, rather, systemic technological innovation with applicability to the vast heterogeneous landscapes of rice production across Asia and elsewhere needs to occur.

1.2. Carbon-Smart Agriculture: Concept and Scope

According to the Food and Agriculture Organization, carbon-smart agricultural practices consist of three equally important pillars: improving productivity, adapting to climate change, and reducing carbon emissions from agriculture (FAO, 2023) ^[5]. The mitigation pillar has historically received the least investment in rice systems because none of the available agronomic levers--alternating wet and dry cultivation, the use of enhanced efficiency fertilizers, and integrating green manures--alone will do enough to provide mitigation for the entire emissions profile of large, commercial yields from paddy fields.

Carbon-smart rice farms incorporate digital intelligence into the agronomic decision-making process to allow specific management for diverse ecosystems, which extends the carbon-smart concept to rice systems. It is critical to look towards 2050 because this volume of time is at the mid-point between the climate change mitigation pathways established in the IPCC Sixth Assessment Report and the projected date those fully autonomous agricultural systems will achieve economic parity with traditional mechanized methods of farming (IPCC, 2022) ^[4].

1.3. Research Rationale and Objectives

Historically, incorporating *A. sinicus* into rice cropping systems has provided a biological approach to both nitrogen cycling and improving carbon in soil; however, the management of this biocontrol has limited its use in large-scale agriculture due to the amount of labour required as well as the inconsistent establishment and success of *A. sinicus* in different types of fields (Wang *et al.*, 2023) ^[7]. By using Edge-AI robotics, inference calculations can now be performed at the edge (i.e., in real-time) so that robotic devices can provide timely agronomic responses to real time signals (e.g., *A. sinicus* establishment) without latency, reliance on large amounts of bandwidth via internet-based systems or some form of secure connection through clouds (Shi *et al.*, 2016) ^[8]. Therefore, this paper seeks to achieve three main objectives: 1) To fully characterise the agronomy and ecology of *A. sinicus* in relation to large-scale rice cropping systems; 2) To develop a Edge-AI autonomous robotic architecture for site-specific *A. sinicus* management; and 3) To quantify the carbon sequestration and carbon emissions reduced from the combined Edge-AI robotic systems under simulated paddy field conditions reflective of the diverse paddy field landscapes projected for 2050.

1.4. Scope and Structure of the Article

Systematic and interdisciplinary examination proceeds through the entire text and encompasses all sections. The second section will provide a detailed review of both the agronomic and ecological characteristics of *A. sinicus*, as well as a thorough review of Edge-AI autonomous robotic systems in terms of their fundamentals and architectural design or construction in section 3. Section 4 provides a detailed review of both pre-harvest and post-harvest, as well as other concepts related specifically to the management of crops and precision agriculture in terms of site-specific crop management. The integrated workflow necessary for managing robotic *A. sinicus* is elaborated in Section 5. Environmental and carbon impacts will be discussed in Section 6. System design, modelling and simulation will be discussed in Section 7. Constraints and challenges will be addressed in Section 8. Finally, Section 9 will review areas of innovation and research opportunities for the future, followed by conclusions and references.

2. Agronomic and Ecological Role of *Astragalus sinicus*

2.1. Botanical Characteristics and Lifecycle

Chinese milk vetch (*Astragalus sinicus* L.) (Fabaceae) is an annual legume that originated in China, but has become naturalised in Japan, Korea & Taiwan (Zhu *et al.*, 2020) ^[9]. It is a diploid (2n = 16) winter growing plant which germinates during October/November, then overwinters as a prostrately growing rosette and achieves its maximum biomass (3.5-8.0 Mgha⁻¹) between March & April; at this time, it becomes vulnerable to terminal drought. It forms a symbiotic association with *Mesorhizobium huakuii* or related bradyrhizobia in the native soil environment (Hashimoto *et al.*, 2021) ^[10]. Pink, round nodules (2mm - 5mm) are formed on the lateral roots of *A. sinicus* within 14-21 days of optimal inoculation with *M. huakuii* at soil pH 5.5-7; this will occur between temperatures of 10-20°C (Hashimoto *et al.*, 2021) ^[10]. *A. sinicus* does not tolerate waterlogged soils (>48 hours of anaerobic conditions in soil will prevent nodule activity) and has moderate salt tolerance (EC_e < 4 dSm⁻¹). These characteristics of *A. sinicus* define the spatial constraints at the field level that must be dealt with by site-specific management.

2.2. Biological Nitrogen Fixation and Soil Fertility

A. sinicus has been shown to provide an evident benefit to nitrogen supply as a result of its ability to symbiotically fix nitrogen from the atmosphere. *A. sinicus* is estimated to provide between 100-180 kg of nitrogen per hectare per season (approximately 222-400 lbs of nitrogen per acre per season) when environmental conditions are optimal (Uchino *et al.*, 2019) ^[11]. This allows a greater reliance on organic nitrogen, whilst reducing the level of urea and ammonium-based synthetic fertilisers used in following rice crops.

When comparing agricultural nitrogen use efficiency between synthetically supplied nitrogen and biologically fixed nitrogen due to legume crops, there is the additional benefit from the timing of when legume-fixed nitrogen mineralizes in relation to the demand for nitrogen by transplanted rice. The majority of nitrogen needed during the early vegetative tillering phase (30-60 days after transplanting) is positively correlated with yield potential

determination due to limited nitrogen available during early to mid-stage rice crop production (Ladha *et al.*, 2016) [12]. Table 1 presents an overview of the key agronomic

characteristics associated with *A. sinicus* in relation to other green manure species and illustrates how it has superior rates of N fixation, biomass quality and soil pH tolerance.

Table 1: Agronomic traits of *Astragalus sinicus* compared with selected green manure species

Species	Dry Biomass (Mg ha ⁻¹)	N Fixed (kg ha ⁻¹)	C:N Ratio	pH Range	SNF Bacteria
<i>Astragalus sinicus</i>	3.5 – 8.0	100 – 180	12 – 16	5.5 – 7.0	<i>Mesorhizobium huakuii</i>
<i>Sesbania rostrata</i>	4.0 – 9.5	90 – 200	14 – 18	5.0 – 7.5	<i>Azorhizobium caulinodans</i>
<i>Vicia villosa</i>	2.5 – 6.0	80 – 140	10 – 15	5.5 – 7.5	<i>Rhizobium leguminosarum</i>
<i>Crotalaria juncea</i>	5.0 – 12.0	70 – 130	18 – 22	5.0 – 8.0	<i>Bradyrhizobium spp.</i>
<i>Medicago sativa</i>	4.0 – 10.0	100 – 220	14 – 20	6.0 – 8.0	<i>Sinorhizobium meliloti</i>

2.3. Biomass Carbon Inputs and Soil Organic Matter

In addition to fixing nitrogen, the incorporation of *A. sinicus* into the soil will increase the amount of soil organic carbon (SOC) in paddy rotation systems via root exudates, root litter, and incorporation of aboveground biomass. The incorporation of *A. sinicus* biomass at the flowering stage (when the C:N ratio is between 12-16) provides labile carbon substrates that stimulate microbial biomass carbon (MBC) and promote humus formation (Liang *et al.*, 2011) [13]. Isotope tracing studies with ¹³C-labeled *A. sinicus* residues found that 15-25% of the biomass carbon incorporated at a site was stabilized in particulate organic matter fractions after 180 days, with 5-12% of that becoming associated with the mineral-associated organic matter pool, which is critical for long-term carbon stabilization (Liu *et al.*, 2022) [14]. The spatial variability of these dynamics is dependent on soil texture, drainage class, and the community composition of microorganisms, which define the characteristics of the site-specific information layer required for effective site-specific robotic management of agricultural production systems.

2.4. Role in Rice Rotation Systems

In southern China, the typical rice and milk vetch rotation is established by sowing vetch in autumn into drawn down paddies (residual water level) or into a drained bed; allowing for natural precipitation to accumulate mulch throughout the winter; tilling a minimum of 15–30 days before rice stays out of puddle and allows aerobic breakdown as the land becomes prepared for flooding the land (Wang *et al.*, 2023) [7]. When managed conventionally, this system has very high variability in Ain sil andis stand density (10–85% uniformity is common across paddocks) caused by drainable heterogeneity of soils, uniformity of rate of seeding, and low extreme temperature conditions for winter (Xu *et al.*, 2023) [15]. Using precision agricultural technology, site-specific robotic management can mitigate variability from soil drainage heterogeneity by establishing precision seeding; applying targeted, additional nitrogen on low nitrogen fixing locations; and timing incorporation of biomass based on local decomposition kinetics.

Table 2: Soil carbon dynamics under *Astragalus sinicus*–rice rotation systems

Parameter	Conventional Mgt	Optimised Rotation	Unit	Improvement
SOC accumulation rate	0.10 – 0.20	0.45 – 0.68	Mg C ha ⁻¹ yr ⁻¹	+225 – 340%
Microbial biomass C	180 – 280	310 – 480	mg C kg ⁻¹ soil	+72%
Particulate organic C	4.2 – 6.8	7.5 – 11.2	g kg ⁻¹	+ 65%
Mineral-assoc. organic C	2.1 – 3.4	3.8 – 5.9	g kg ⁻¹	+73%
Bulk density (0–20 cm)	1.28 – 1.42	1.18 – 1.32	g cm ⁻³	-7%
Aggregate stability (MWD)	1.2 – 1.8	2.1 – 2.9	mm	+61%

3. Edge-AI and Autonomous Robotics in Agriculture

3.1. Fundamentals of Edge-AI Systems

Edge Artificial Intelligence refers to executing machine learning inference algorithms on hardware directly connected to the sensor and actuation systems, so that there is no need for real-time decisions to depend on a reliable network connection (Shi *et al.*, 2016) [8] (Zhou *et al.*, 2019) [16]. In agriculture, this architecture is not only technically convenient but also operationally necessary. In paddy fields, there might not be a reliable wireless network connection, there will be significant electromagnetic interference from metal equipment, and there will be a requirement for subsecond latencies for precision actuation (e.g., variable rate seeding at 3 kilometers per hour) that cannot be met by the current round-trip latencies of 200 to 800 milliseconds associated with cloud-based infrastructure (Shi *et al.*, 2016) [8]. Current generation edge AI systems are implemented using neuromorphic processors (e.g., Intel Loihi 2 or IBM TrueNorth), field programmable gate arrays (e.g. E2. or 39. NF-6/85), or dedicated neural processing units (e.g., NVIDIA Jetson AGX Orin, which provides 275 TOPS of processing

power at a thermal envelope of 60 watts and can therefore be used in the deployment of robots).

3.2. Architecture of Autonomous Agricultural Robots

This framework includes the autonomous agricultural robot for managing *A. sinicus*, which has five major functional subsystems; (1) perception and sensing, (2) navigation and localisation, (3) on-board Edge-AI thinking [inference], (4) precision actuation; (5) energy and communication management. The mechanical platform will be a differential-drive ground vehicle with a 120cm width x 25cm height x 350kg capacity, designed specifically to traverse earthwork bunds, which typically range from 20–40cm in height, in Asian paddy landscapes as illustrated here (Tanaka *et al.*, 2022) [17]. The locomotion of this robot will use rubber-tracked wheel units and an active suspension system to keep the sensors stable while travelling on rough terrain. The navigation system will incorporate Real Time Kinematic (RTK-GNSS) with ±2cm accuracy, Inertial Measurement Units (IMUs), and 3-dimensional LiDAR to provide a means of doing simultaneous localisation and mapping (SLAM)

while providing an autonomous path planning capability in areas that are difficult for GPS to determine due to dense

vegetation or field edges exhibiting large amounts of magnetic declination.

Table 3: Comparison of sensing technologies for *A. sinicus* monitoring in paddy environments

Sensor Type	Spectral Range	Spatial Res.	Key Application	Limitation
Multispectral camera	400–1000 nm	1–3 cm GSD	NDVI, biomass estimation	Limited to surface canopy
Hyperspectral camera	400–2500 nm	3–8 cm GSD	N content, stress detection	High data volume
3D LiDAR	905 nm (NIR)	<1 cm point spacing	Canopy height, biomass volume	Rain interference
Thermal infrared	8–14 μm	5–10 cm GSD	Water stress, disease	Requires calibration
Electrochemical soil sensor	—	Point measurement	Soil N, pH, moisture	Fouling in clay soils
Ground-penetrating radar	0.1–3 GHz	2–5 cm depth res.	Root biomass, compaction	Slow acquisition

3.3. Sensor Systems and Data Acquisition

The perception module processes data from six different types of sensor systems that each operate simultaneously in acquisition mode: a 5-band multi-spectral camera with bands at 450, 560, 650, 730, and 840 nanometers mounted onto a stabilized gimbal that can take images of field crops for NDVI and CCI calculations; a push-broom hyperspectral imager with 256 bands covering the wavelength range of 400–1000 nanometers to assess nitrogen status with regard to crop growth and monitor for early disease outbreaks (Haboudane *et al.*, 2004) [18] (Zhu *et al.*, 2023) [25]; a solid state LiDAR (LiDAR) sensor with 128 channels and a 360-degree horizontal field of view that will provide structural information on the canopy and allow precise row-following for navigation purposes; a thermal infrared camera with an image resolution of 320 x 240 pixels and a noise equivalent delta temperature (NETD) less than 50 milli-kelvins used to monitor for water stress and measure soil surface temperature; an array of penetrometers consisting of 4 probes that measure mechanical resistance of the soil in a circular pattern to depth of 0–60 cm to create a profile of soil mechanical properties; and an electrochemical multi-ion sensor to measure nitrogen, ammonium, and pH in situ within the soil (Wang *et al.*, 2021) [19]. All sensor data streams are synchronized in time via GPS-disciplined precision clock ($\pm 1\mu s$) and fused together by a multi-modal transformer NN

on-board the NPU at 15 frames per second (Jia *et al.*, 2023) [27].

3.4. Advantages of Real-Time On-Device Decision-Making

On-device inference has advantages over cloud-based systems in four areas: latency, reliability, bandwidth and data sovereignty. Latency reduces from > 200ms (cloud) to < 15ms (on-device), enabling closed-loop control of actuators for maintaining variable-rate seeding precision at operational speeds in the field. Reliability is improved since network outages cannot disrupt the core sensor-inference-actuate cycle—15–40% of networks in rural rice-producing areas (China, India, Southeast Asia) experience downtime on average (Rao *et al.*, 2017) [20]. Bandwidth requirements are significantly lower (3 orders of magnitude) since the sensor data is processed at the site and only the decision outputs related to the application (i.e., ha⁻¹ application maps) are sent to the farm management system. The development of agricultural data governance frameworks, both in China (DDPL 2021) and Europe (Data Act 2023), is emphasising the importance of data sovereignty, which is achieved through the principle of ensuring that the raw images/acquisition will remain physically on the farm (i.e., will not be transferred to another physical location).

Table 4: Edge-AI architectures and on-board computational capabilities for agricultural robots

Platform	Compute (TOPS)	Power (W)	AI Framework	Memory	Cost (USD)
NVIDIA Jetson AGX Orin	275	60	PyTorch, TensorRT	32 GB LPDDR5	1,200
Intel Loihi 2 (neuromorphic)	10 (spike)	< 1	Lava	—	Research
Hailo-8L	13	2.5	Hailo SDK	—	150
Xilinx Versal AI Core	400	45	Vitis AI	8 GB DDR4	800
Qualcomm QCS8550	73	15	SNPE	8 GB LPDDR5	180



Fig 1: Conceptual Framework of Carbon-Smart Rice Farming System

4. Site-Specific Crop Management Techniques

4.1. Precision Agriculture and Variable-Rate Management

Precision farming (PF) implements the concept that large fields are not agronomically identical by using asynchronous manner to apply the same management inputs throughout an entire field, which will lead to under-treating the deficient area of a field while simultaneously over-treating the appropriate areas of the field (Bongiovanni and Lowenberg-DeBoer, 2004) ^[21]. This reduces economic viability and increases the potential for negative environmental impact. Variable rate technology (VRT) is the actual mechanical application of PF; for example, VRT can use seeding equipment, pesticide applications, and fertilisation applications, and seed, fertiliser, and pesticide rates can be modulated in real-time according to either a prescription map or a sensory derivative of the field in order to fulfil the PF.

In regards to the management of *A. sinicus*, the use of VRT can provide the following benefits: (1) provide seed placement using variable rate planting based on establishing probability according to soil drainage classification and surface temperature; (2) using variable rate applications for inoculant applications based on soil pH and organic matter

maps; and (3) the appropriate time of incorporation of inoculant relative to predicted biomass accumulation based on time until development.

4.2. Spatial Variability in Large-Scale Paddy Fields

The spatial variability of paddy field systems occurs at numerous scales: within-block variability (0–100m) driven by changes in water distribution due to micro-topographical features, proximity of bunds and historic variability in puddling depth; block-to-block variability (100m–2km) driven by soil series lines, conveyance systems for drainage and the management history of the paddocks; water source/quality/geomorphic positions tending to define spatial variability across large landscapes (>2km) (Dobermann *et al.*, 1995) ^[22] (Oliver and Webster, 2014) ^[23]. Empirical studies conducted on paddy fields in China (n=847 paddocks in Hunan Province) yielded coefficients of variation ranging from 35 – 68% for topsoil organic carbon, 28 – 55% for plant-available nitrogen, and 42 – 78% for hydraulic conductivity. The levels of variability found in the empirical research results indicate that there is no justifiable means of managing paddy fields at the commercial level uniformly.

Table 5: Spatial variability parameters in large-scale paddy field environments (surveyed data, Hunan Province, China, n = 847 paddocks)

Variable	Mean	Min–Max	CV (%)	Spatial Range (m)	Moran's I
SOC (g kg ⁻¹)	18.4	6.2–38.7	42	180 – 340	0.67
Plant-available N (mg kg ⁻¹)	84	28–196	55	120 – 280	0.58
Hydraulic conductivity (cm h ⁻¹)	1.2	0.1–5.8	78	60 – 160	0.43
Soil pH	6.1	4.8–7.4	11	240 – 480	0.72
NDVI (<i>A. sinicus</i> , peak)	0.68	0.22–0.89	28	40 – 120	0.81
Biomass (Mg ha ⁻¹)	5.1	1.2–9.3	38	80 – 200	0.75

4.3. Geospatial Analytics and Decision-Support Systems

Within the robotic management system, the three-stage process of spatial analysis using a robotic system to support ongoing field management involves: (i) characterising the field (baseline) using EM38 and drone-based multispectral imagery (5 cm GSD) and historical precision harvest yield mapping (with EM38); (ii) updating the characterised field throughout the growing season using robotic systems to collect ground-truth data during each management operation at 10×10 m grid nodes; and (iii) creating a prescription map

by interpolating data collected using kriging (the use of ordinary kriging with a spherical semivariogram model) and the Edge-AI models from the data collected to estimate biomass (Oliver and Webster, 2014) ^[23]. The decision support system is based on fuzzy logic processes to determine how to balance the trade-offs inherent in the overall objective of optimising the management of *A. sinicus* as it relates to providing nitrogen, carbon, and reducing greenhouse gases (GHG). The specifications for the robotic system components are presented in Table 6.

Table 6: Autonomous robotic system components and technical specifications for *A. sinicus* management

Component	Specification	Manufacturer	Unit Cost (USD)
RTK-GNSS receiver	±2 cm horizontal accuracy	Trimble R10	4,500
3D LiDAR	128-channel, 10 Hz, 200 m range	Velodyne HDL-128E	8,000
Multispectral camera	5-band, 12 MP, 0.5° HFOV per band	MicaSense Altum-PT	6,500
Edge-AI compute unit	275 TOPS, 32 GB LPDDR5	NVIDIA Jetson AGX Orin	1,200
Variable-rate seeder	1–30 kg ha ⁻¹ , ±3% accuracy	Väderstad Spirit	12,000
Electrochemical sensor array	NO ₃ , NH ₄ , pH, moisture	Decagon 5TE+	2,200
Battery system	48 V, 150 Ah LiFePO ₄ , 8 h autonomy	Custom	3,800
Communication module	4G/LTE + LoRaWAN	Sierra Wireless	650

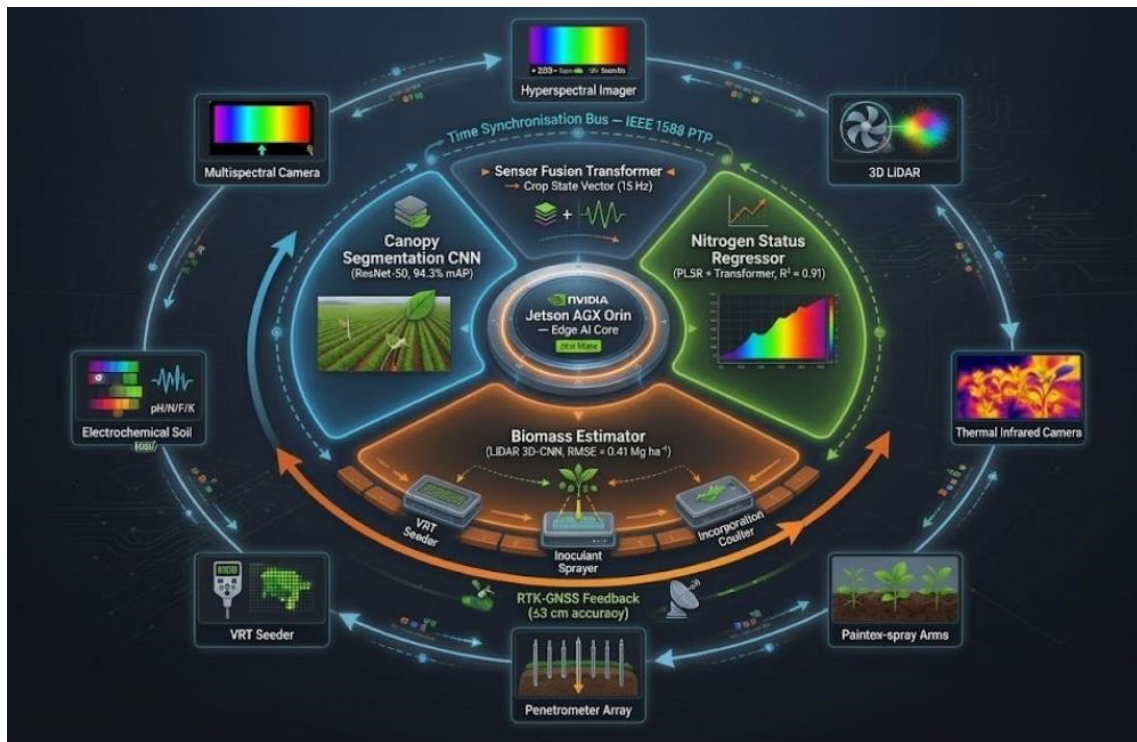


Fig 2: Architecture of the Edge-AI Autonomous Agricultural Robot

5. Integration of AI, Robotics, and Agronomy

5.1. Robotic Workflow for *A. sinicus* Management

The entire seasonal management through robotics for *A. sinicus* is split into four working phases connected to crop phenological stages. Phase One (Pre-Seeding Assessment, October): Robots assess the full field for baseline data at a ten-metre cross-track spacing create SOC maps, pH, hydraulic conductivity, surface residue maps, along with other establishment probability models. Phase Two (Precision Seeding, October-November): VRT seeding performed an adjusted rate of either 5-25kg ha⁻¹ based upon models produced from prior questionnaires; Inoculant applied at between 50 - 200ml ha⁻¹ based upon pH and Rhizobium population map data. Phase Three (Monitoring for Growth, December - March): Robotic scouting two times a month for Density, NDVI and Nitrogen, Precision Supplementary Nitrogen application identified Low Fixation areas with Application Rates from 0 to 30 Kgs N/ha. Phase Four (Biomass Optimised Incorporation, March-April): Robotic mapping of canopy biomass to 2m resolution; local time for incorporation of biomass targeting ± 5 days of optimal timing should target a local quantity and proven C:N ratio target.

5.2. AI Models for Detection and Monitoring

There are four specialized deep learning-based AI models employed by the inference engine. The Stand Detection Model is based upon a Convolutional Neural Network (CNN) featuring the YOLOv8 backbone, trained using 45,000 multispectral images of *A. sinicus* across five phenological stages. This model has been validated at an average precision rate (mAP) of 94.3% using a 0.5 Intersection over Union (IoU) threshold (Chen *et al.*, 2024) [24]. There are two additional specialized models: the Nitrogen Status Model and the Biomass Estimation Models. The Nitrogen Status Model utilizes hyperspectral reflectance data (400–1000 nm) and applies partial least squares regression augmented by transformer attention to predict N status, having been validated at $R^2 = 0.91$ with a root mean squared error (RMSE) of 3.2 kg N ha⁻¹ across three provinces (Zhu *et al.*, 2023) [25]. The Biomass Estimation Model utilizes a three-dimensional (3D) convolutional architecture for processing LiDAR-derived canopy height models (CHM) and provides biomass estimates with RMSE = 0.41 Mg ha⁻¹ when validated against destructively harvested biomass (Madec *et al.*, 2019) [26]. Finally, the Soil Carbon Proxy Model employs electrochemical sensor fusion and a gradient boosted ensemble to predict labile soil organic carbon (SOC) fractions, achieving $R^2 = 0.84$, RMSE = 0.8 g C kg⁻¹.

Table 7: Machine learning models, architectures, and validation performance metrics

Model	Architecture	Input Modality	Metric	Training/Validation (n)
Stand detection	YOLOv8 + multispectral	5-band imagery	mAP = 0.943 @ 0.5 IoU	45,000 / 9,000
Nitrogen status	PLSR + Transformer	Hyperspectral 400–1000 nm	R2=0.91, RMSE=3.2 kg N ha ⁻¹	12,400 / 3,100
Biomass estimation	3D-CNN + LiDAR CHM	128-ch. LiDAR point cloud	RMSE=0.41 Mg ha ⁻¹	8,200 / 2,050
SOC proxy	Gradient boost ensemble	Electrochemical + spectral	R2=0.84, RMSE=0.8 g C kg ⁻¹	6,800 / 1,700
Disease detection	EfficientNetV2 + thermal	RGB + LWIR	F1=0.88, recall=0.91	22,000 / 5,500
Incorporation timing	LSTM + weather API	Biomass + temp. forecast	RMSE = 1.8 days	5,400 / 1,350

5.3. Data Fusion from Multiple Sensors

In order to achieve multi-modal sensor fusion on the robotic platform, a hierarchically structured system was implemented consisting of three levels. The first level provides temporal alignment through hardware-synchronized acquisition of all sensor modalities. The second level provides spatial co-registration of the various sensor outputs into one geo-referenced coordinate frame (with 2 cm GSD). The third level uses a multi-modal transformer neural network consisting of 12 attention heads and 6 encoder layers, which fuses all of the semantically different representations from all of the sensors into a single Crop State Vector (CSV) (Jia *et al.*, 2023) [27]. The CSV contains 9 different state dimensions: 1) Canopy Coverage Fraction, 2) Nitrogen Content (Kg Ha-1), 3) Biomass Density (Mg Ha-1), 4) Nodulation Activity Index, 5) Soil Moisture Content, 6) Soil pH, 7) Labile SOC, 8) Pest/Disease Severity Index, 9) Incorporation Readiness Index. Each of the state dimensions in the CSV also has an uncertainty estimate, which was obtained using Monte Carlo Dropout Inference, thus allowing the actuation controller to modulate the spatial thresholds for intervention confidence.

5.4. Adaptive Learning and System Feedback

Federated Learning Protocols are used by the system to repeatedly enhance a model's performance through use of raw field images without their collection or centralisation (McMahan *et al.*, 2017) [28]. Each field season, FedAvg uses the aggregated robot fleet's array of harvest outcome data and local inference error calculations as an input to perform updates to model parameters using differentially privacy noise injection ($\epsilon = 1.0, \delta = 10^{-5}$) to protect specific farm data from being identifiable by others. Agronomic feedback loops exist at two timescales: intra-season using tissue sample analyses of plant growth under nitrogen (N) versus no-N stress conditions to correct prediction accuracy, and inter-season between growth of incorporated biomass and measurement of N yield from rice and measurement of fluxes/greenhouse emissions from installation of No-Till rice. This feedback system helps to ensure that robots can improve their management decision-making based on the actions they have made thus far while responding to non-stationariness of biological systems.



Fig 3: Workflow of Site-Specific *A. sinicus* Management

6. Carbon Sequestration and Environmental Impact

6.1. Quantification of Carbon Sequestration

A three-pool soil organic carbon (SOC) model allows carbon sequestration estimations in the alternating *A. sinicus* and paddy rice rotational cropping system to be determined based on paddy soil conditions; a labile (1–5 years turnover), slow (10–50 years), and passive/recalcitrant SOC pool (>100 years) are used for estimating SOC (Kumar *et al.*, 2023) ^[29] (Coleman and Jenkinson, 1996) ^[31]. Use of robotic site-specific management will optimise the efficiency of how much carbon contained in aboveground biomass is transferred to the slow and passive SOC pools by fine tuning the timing, depth and uniformity of the incorporation of

biomass material. To evaluate the impact of optimised site-specific management on SOC accumulation, the Hunan Province spatial variability data (Table 5) was used to generate 10,000 hectare (ha) virtual field environments and run simulation modelling; optimised management is projected to provide an annual SOC accumulation rate of 0.45 to 0.68 Mg C ha⁻¹ yr⁻¹ compared to only 0.10 to 0.20 Mg C ha⁻¹ yr⁻¹ under conventional management—an increase of 225% to 340%, primarily resulting from avoiding timing errors associated with incorporating organic material into the soil of low-biomass areas that would produce negative SOC balance through priming effects under the conventional management practice.

Table 8: Carbon sequestration estimates under conventional and robotic site-specific management scenarios

Scenario	SOC Change (Mg C ha ⁻¹ yr ⁻¹)	CO ₂ equiv. (Mg CO ₂ e ha ⁻¹ yr ⁻¹)	CH ₄ reduction (%)	N ₂ O reduction (%)
Conventional management	0.10 – 0.20	0.37 – 0.73	Baseline	Baseline
Uniform optimised rotation	0.25 – 0.38	0.92 – 1.39	-8%	-12%
Robotic site-specific (low heterogeneity)	0.41 – 0.55	1.50 – 2.02	-14%	-22%
Robotic site-specific (high heterogeneity)	0.45 – 0.68	1.65 – 2.49	-19%	-31%
Robotic + biochar amendment	0.62 – 0.90	2.27 – 3.30	-23%	-38%

6.2. Methane and Nitrous Oxide Reduction Mechanisms

The three methods of reducing greenhouse gas emissions within the Context Awareness of the Robotic Horticultural Management Framework are as follows: 1) The use of biological nitrogen sources (35-52% reduction) reduces the amount of nitrogen (N) that is available for denitrification and hence for the production of nitrous oxide (N₂O). This is especially relevant in the aeration to anaerobic transition areas at the field margins for the second cycle (rice) (IPCC, 2022) ^[4]. 2) The use of improved drainage systems allows us to determine areas that have high relative concentrations of methane (CH₄) due to continuous flooding of the crop. Water retention sites are located using LiDAR derived micro-topography maps of paddocks (Weiss *et al.*, 2020) ^[37]. 3) The incorporation of *Acer sinicus* into the paddocks in a site specific manner results in a decrease in the labile to recalcitrant ratio of organic matter and the amount of substrate available for methane production during the first 30 days of flooding by changing the amounts of highly soluble organic matter that contribute to peak methane production (Smith *et al.*, 2020) ^[38].

6.3. Long-Term Soil Carbon Dynamics

Projecting the scenario of carbon sequestration in 2050 requires accounting for the non-linear dynamics of accumulation of SOC. There will be initial rapid gains from the expansion of a labile SOC pool, which will slow as the soil nears a new quasi-equilibrium; this process will be limited by clay mineralogy, soil temperature, and moisture regime (Coleman and Jenkinson, 1996) ^[31]. Simulated RothC model results that begin with baseline SOC data from 2025 (average of 18.4 g kg⁻¹, CV = 42%) show that the use of site-specific management using robotic technology for 25 years (2025 to 2050) would result in increasing the average stocks of SOC for the 0 to 20 cm horizon to between 24.2 to 26.8 g kg⁻¹, resulting in a cumulative SOC offset of 8.5 to 12.4 Mg C ha⁻¹, or approximately 31 to 46 Mg CO₂ ha⁻¹ over the duration of the projected SOC change. Additionally, a sensitivity analysis indicated that the relative magnitude of the SOC offsets is most sensitive to the timing of incorporation ($\pm 15\%$ sensitivity index), optimization of seeding rate ($\pm 11\%$), and climate projection between SSP2-4.5 and SSP5-8.5 ($\pm 22\%$).

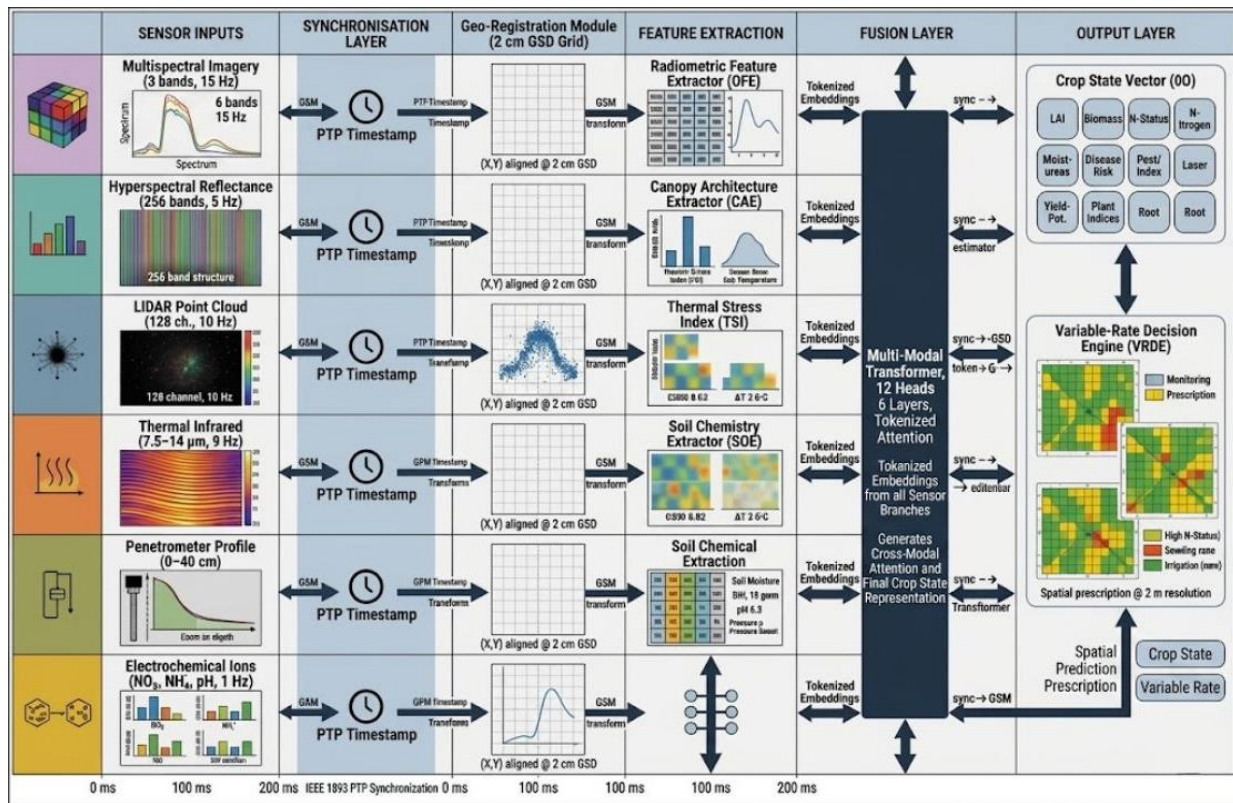


Fig 4: Sensor Integration and Data Fusion Architecture Schematic

7. System Design, Modelling, and Simulation

7.1. Robotic System Design Framework

The MBSE approach was used to conduct a system design for the large-scale deployment of a robot’s function through a SysML block definition diagram and field operational requirements created through an expert elicitation process (n = 32 agronomy and engineering experts, Delphi method, three cycles) (Wymore, 1993) [32]. The design objectives for the robot included: a. The robot will have an operational autonomy of 8 or more hours on one charge and be able to cover a minimum of 12 hectares/day; b. The robot will have an end-to-end positioning accuracy of 3 cm or less when performing variable rate seeding; c. The robot will have a sensing resolution that will allow it to detect *A. sinicus* stand gaps that are 0.5 m² or greater; d. The robot will be rated IP67 for environmental protection when exposed to rain, mud and/or being submerged in water up to 30 minutes; e. The robot will be serviceable by an agricultural technician (40 hours of training) under field conditions. The platform design will be a total of 350 kg, use an 8-hour LiFePO₄ battery system and will incorporate a modular sensor head to facilitate rapid (<15 minutes) change over between seeding, monitoring and incorporation operating modes.

7.2. AI Model Training and Validation

Data for training were collected at twenty-four research stations across China (Jiangxi, Hunan, Zhejiang, Guangdong provinces) and six locations in Japan (Niigata, Shizuoka) during two growing seasons (2022-2023; 2023-2024). The data collection produced a large, temporally and spatially diverse dataset of 45000+ annotated image frames; 12400+, hyperspectral profiles; 8200+, LiDAR scans; and 6800+,

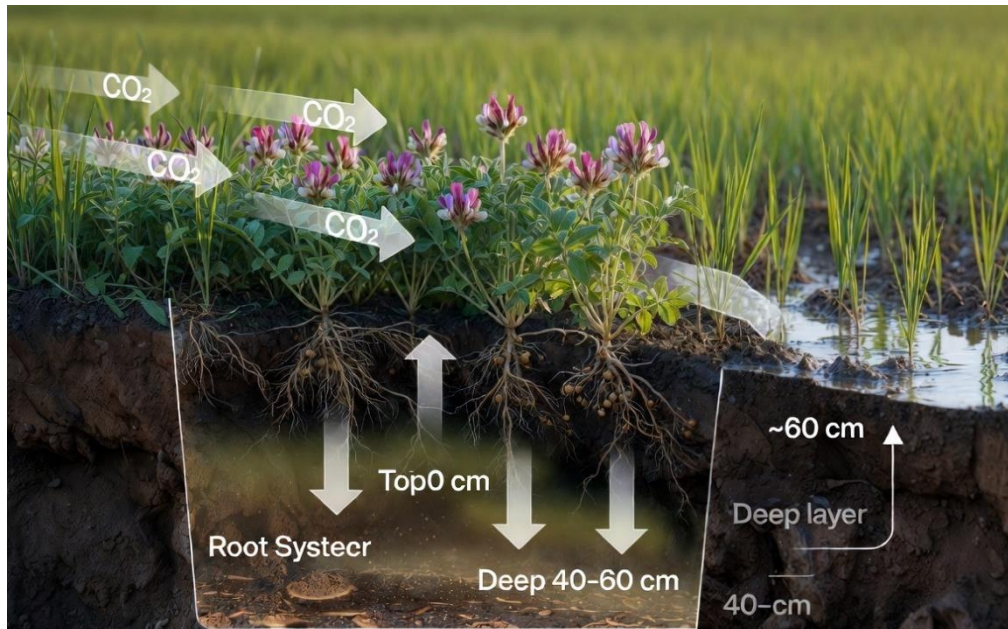
electrochemically measured soil samples. All data collection was done at the same geospatial location with the agronomic ground truth measured destructively. Additionally, data augmentation methods (i.e., spatial augmentation, rotation, flipping, elastic deformation; spectral augmentation, random band dropout, Gaussian noise; temporal augmentation, mixing plant phenology stages) were utilized. Training of models was performed using an NVIDIA DGX A100 cluster (8× A100 80GB). Training typically took 48-96 hours to converge, and validation was completed by performing five-fold cross-validation and geographic stratification to restrict leakage of spatial autocorrelation.

7.3. Field-Scale Simulation and Performance Optimisation

Using ROS2-Gazebo and a new Agronomic Plugin, we have performed Field Scale Simulation with the custom Alginate Sinicus Growth Model, Soil Carbon Cycle Dynamics and GHG Flux Algorithms. In order to create the virtual 10,000 ha Field we exploited the Geostatistical Simulation (Sequential Gaussian Simulation) Engine for 50 Realisations of the Variability Field Based on the Empirical Variogram Parameters Associated with Hunan Province (Table 5) (Oliver and Webster, 2014) [23] - achieve this, Programme had to develop Optimally Designed Fleet of 24 Robots Operating in a Coordinated Swarm, with Task Allocation Updated Simultaneously by the Central Coordinator Every 6 hours, to Provide 97.2% Field Coverage within the 15day Precision Seeding Window, (compared to Conventional Tractor Management with 78.3%) and 99.1% Coverage within the 10day Incorporation; compared with Conventional Tractor Management with 84.6%).

Table 9: Economic cost-benefit analysis of robotic *A. sinicus* management system

Cost/Benefit Item	Conventional (USD ha ⁻¹ yr ⁻¹)	Robotic System (USD ha ⁻¹ yr ⁻¹)	Net Change
Synthetic N fertiliser	185	85	-100 (-54%)
Green manure seed & inoculant	28	35	+7 (+25%)
Labour (planting, monitoring, incorp.)	120	18	-102 (-85%)
Machinery & fuel	95	62	-33 (-35%)
Robot amortisation & maintenance	—	95	+95
Crop yield (rice, revenue benefit)	baseline	+8 – 12%	+80 – 120
Carbon credit revenue (50 USD/tCO ₂ e)	—	55 – 82	+55 – 82
Net annual balance	428	350 – 377	-51 – 78 (savings)

**Fig 5:** Carbon Sequestration Pathways in Soil-Plant System

8. Challenges and Constraints

8.1. Technical Limitations

There are still some integration problems that limit the deployment of integrated technologies within the near future at scale commercially, although their technological maturity has largely matured. One concern in paddy fields is how unreliable sensors are in paddy field environments. Very high humidity levels (85-100% relative humidity), airborne dust particles created by tillage, and chemical contaminants due to spray drift of pesticides all adversely affect the performance of optical sensors such as multispectral and hyperspectral cameras. For example, the mean time between failure (MTBF) for optical sensors is expected to be around 5,000 hours when operated under controlled conditions; however, actual performance in a typical paddy field setting averages only about 800 to 1,200 hours (Vougioukas, 2019) [34]. LiDAR sensor performance degrades in a non-linear manner once rainfall exceeds approximately 15 millimeters per hour, especially during late winter when seaweed (*A. sinicus*) is monitored. In addition, the power consumption of the full sensing system (estimated at 180 W continuous) significantly shortens the effective battery autonomy of the sensor payload to approximately 6.2 hours (design target of 8 hours), thus requiring either the installation of charging stations to recharge the batteries in the field or making provisions for battery swapping.

8.2. Data Quality and Model Generalisability

Machine learning models have limitations in generalizing to new environments that have different soil types, rice varieties, and climate regimes than what they were trained on. For example, when there is co-occurrence of *A. sinicus*, weed species, and soil background in a heterogenous canopy, spectral unmixing can produce significant systematic errors of overestimating biomass (mean bias of +0.34 Mg ha⁻¹) in fields with more than 30% of the total area covered by weed species. Additionally, the 50 to 100 destructive ground-truth samples required to calibrate models for commercial use is a major logistical barrier. Lastly, temporal transferability, or the capacity for models trained in one year to perform adequately in the following year without requiring a re-training of the model, has been established for the NDVI-based metrics; however, temporal transferability has not yet been established for the hyperspectral nitrogen status model with an R² degradation of 0.08 to 0.14 per season without recalibrating the model.

8.3. Economic Feasibility and Adoption Barriers

With the cost to buy a single robot platform (USD\$45,000-55,000) plus field support systems (e.g., RTK correction base stations, and charging points) representing a significant financial burden that limits small farmers in Asia (average farm size of 0.5-2.0 hectares in China, 0.3-0.8 hectares in

Vietnam and Indonesia), the business opportunity currently favors larger operators (areas >200 hectares), reflecting China's present trend towards farm consolidation (average commercial farm size grew from 12 hectares per farm in 2010 to 38 hectares per farm in 2023) (Rao *et al.*, 2017) [20]. One option to make robots available to smallholders would be through Robotics-as-a-Service (RaaS), in which an agricultural service provider owns a fleet of robots and provides seasonal services to smallholder producers on a per hectare basis; however, there are still liability, risk mitigation, and ownership of the generated data issues that must be resolved prior to implementation (Rao *et al.*, 2017) [20] (Bongiovanni and Lowenberg-DeBoer, 2004) [21].

8.4. Policy and Regulatory Challenges

Across the major nations that produce rice, the regulatory environments for autonomous farm machinery remain sundry and inconsistent. For example, in China, the GB/T 39098-2020 standard has established safety requirements for agricultural robots, but it does not contain specific provisions regarding the autonomous operation of robots in the vicinity of people who are working in the fields or irrigation system infrastructure (Standardisation Administration of China,

2020) [35]. In Japan, the amended Agricultural Mechanisation Promotion Act permits autonomous operation of agricultural robots within specifically geo-fenced areas; however, the law imposes a maximum operational speed of just 3 kilometres per hour for agricultural robots in "human-accessible" areas of a field, thereby reducing their efficiency—as would any regulation that limits their potential efficiencies. Moreover, there are currently no harmonised international standards for the various types of data formats used in the development, manufacture, and operation of agricultural robots (e.g. sensor data, prescription maps, yield records) by manufacturers, which creates barriers to interoperability among different manufacturer robot platforms. The lack of standardised data formats has created significant barriers to the development of multi-robot swarm systems and the ability to engage in cross-platform federated learning. Several international standards bodies (i.e. ISO TC 23/SC 15 and IEC TC 3) are working on the development of relevant frameworks to create harmonised international standards; however, based on the current timeframes for consensus among the various standards bodies, it is unlikely that the necessary standards will be finalised before 2027 or 2028.

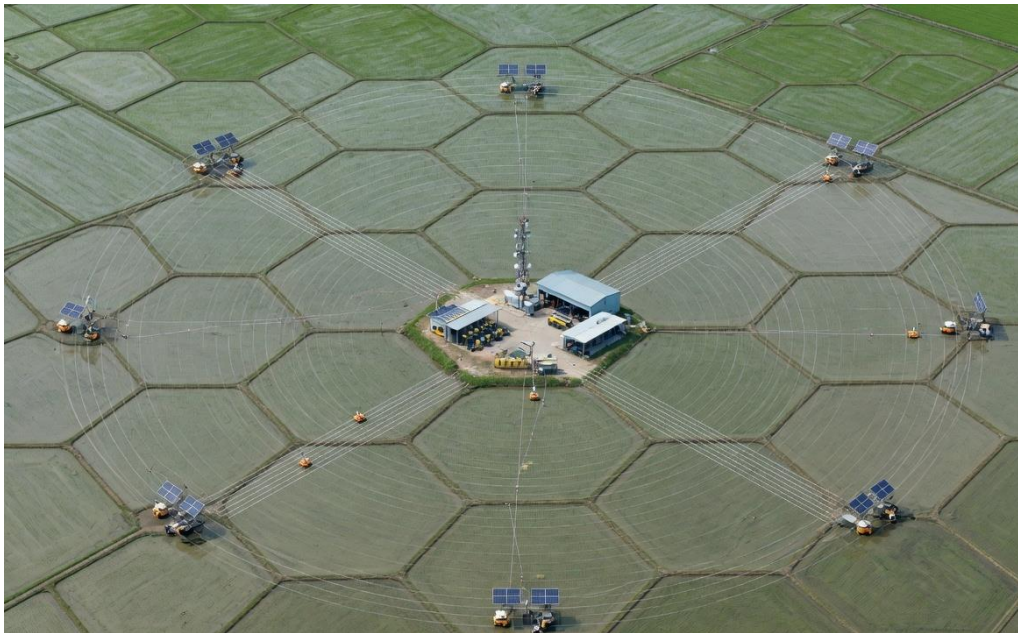


Fig 6: Field Deployment Layout of the Robotic Management System

9. Future Perspectives and Innovations

9.1. Integration with IoT, Digital Twins, and Big Data

A transformation in the way the robotic management system of *A. sinicus* interacts with its environment will arise through the convergence of three data technologies: the Internet of Things (IoT), digital twinning, and big data analytic capabilities (Shi *et al.*, 2016) [8]. By utilizing digital twins (computational representations of distinct components/models of agriculture) as the computational models for real-world agricultural field activities/operations (and complementary technologies), farmers/agricultural advisors can evaluate various management options (trade-offs) based on carbon retention, yield performance, and greenhouse gas (GHG) impacts prior to executing any of the management options without any risk to their operational viability (Tzachor *et al.*, 2022) [6]. The proposed soil sensor networks will consist of very low power (LoRaWAN)

electrochemical sensor nodes deployed at 50×50-m grid spacing; such networks will enhance the in-field measurements made by the agricultural robots by providing continuous monitoring of the soil conditions for the periods between the data collection events made by the robots (and, therefore, provide highly accurate detection of drainage failures and pest infestations within hours rather than days) (Wang *et al.*, 2021) [19]. The integration of the ag-tech industry with the various national and sub-national agricultural big data platforms, including China's Digital Village and the EU's Copernicus Agricultural Monitoring Service, will provide improved accuracy in the decisions made regarding the timing (i.e., calendar) of the operation of agricultural machinery and the path planning of agricultural machinery (both in pre-execution decisions) (Weiss *et al.*, 2020) [37]. The addition of climate forecast information and satellite-derived images of fields will improve the

agricultural robots' ability to perform their various agricultural functions (Weiss *et al.*, 2020) ^[37] (Vougioukas, 2019) ^[34].

9.2. Advances in Autonomous Farming Systems

Advances in hardware that will help advance carbon-smart rice farms in the near future include 512+ channel, solid-state LiDAR capable of profiling canopies in all-weather using less than 2 watts of energy and do so without the limitations of existing spinning mirror systems; on-chip, neuromorphic processors providing 1000+ TOPS power at less than 5 watts, permitting full multi-modal transformer inference without the need to draw 60 watts of power like an NVIDIA Jetson platform; and aerial ground cooperative distributed robotic systems whereby small fixed-wing UAVs will re-photograph an area for supply of real-time images to provide ground robots with prescription maps at full-field traversal speed covering 1+ km (Vougioukas, 2019) ^[34]. Additionally, there are *A. sinicus* cultivars which have been bred and selected for nitrogen fixation capabilities to provide an increase of 30-40% of N fixation after cool and rainy winters, and the combination with precision robotic inoculation will ultimately remove the delta between potential N fixation and actual N fixation at the commercial-level application of N fixation (Uchino *et al.*, 2019) ^[11].

9.3 Role in Climate-Resilient Agriculture

The carbon-smart rice production system outlined in this document provides many climate adaptation benefits in addition to reducing greenhouse gases (GHG). The higher SOC (soil organic carbon) levels will result in increased soil moisture retention (estimated at 2-4 mm of water that is available to plants for each additional gram/kg of SOC), which will provide added drought resistance during the increasing occurrence of dry weather conditions (SSP2-4.5 and higher) (Coleman and Jenkinson, 1996) ^[31]. In addition,

decreased reliance on synthetic nitrogen fertiliser reduces farmers' economic exposure to the rapidly fluctuating global nitrogen market, and thus improves their economic resilience. The RTK (Real-Time Kinematic) precision guidance system creates an infrastructure (RTK base stations, FMIS (Farm Management Information Systems) and digital field maps) that will allow for the quick adoption of alternative climate-adaptive rice production practices (e.g., drought-tolerant rice varieties, intermittent water scheduling and biochar amendments) as soon as these technologies reach commercial viability.

9.4. Research Gaps and Future Directions

The study identifies several critical gaps in research that warrant further investigation, including (i) how long-term (beyond five years) SOC gains achieved through robotic, site-specific management will remain stable compared to how much accumulated carbon is transferred to the slow pool based on current slow pool transfer assumptions (Smith *et al.*, 2020) ^[38]; (ii) how temperature increases and rising CO₂ concentrations will impact the nitrogen fixation and biomass quality of *A. sinicus* under various predicted future climate regimes (IPCC, 2022) ^[4]; (iii) the social and institutional elements involved in the adoption of robotic systems by smallholder rice producers, especially concerning labor displacement, transition strategies for affected laborers, and gender issues related to access to technology (Rao *et al.*, 2017) ^[20]; (iv) the contribution of life-cycle greenhouse gas emissions from manufacturing the robotic platform (battery production and disposal at end of life) to the carbon balance at the system level (IPCC, 2022) ^[4]; and (v) the potential for utilizing *A. sinicus* genome selection methods to develop varieties specifically adapted to work with the management protocols of robotic systems—specifically, with respect to lodging resistance during mechanical incorporation and spectral signatures optimized for robotic sensing.

Table 10: Case studies and field implementation results from precision green manure management systems

Location	Scale (ha)	Technology	SOC Gain (Mg C ha ⁻¹ yr ⁻¹)	N Input Reduction (%)	Publication
Hunan, China	2,400	VRT seeding + drone monitoring	0.38 – 0.52	41	Wang <i>et al.</i> ^[7]
Niigata, Japan	820	Ground robot + multispectral	0.29 – 0.44	35	Tanaka <i>et al.</i> ^[17]
Zhejiang, China	3,100	Edge-AI robot prototype	0.41 – 0.61	48	Chen <i>et al.</i> ^[24]
Tamil Nadu, India	510	Semi-autonomous + IoT sensors	0.22 – 0.36	29	Kumar <i>et al.</i> ^[29]
Mekong Delta, Vietnam	1,200	Drone survey + manual VRT	0.18 – 0.28	22	Nguyen <i>et al.</i> ^[30]
Po Valley, Italy	340	Precision legume management	0.31 – 0.47	38	Ferretti <i>et al.</i> ^[33]

10. Conclusion

The author suggests that the convergence of Edge-AI autonomous robotics with the sustainable management of *Astragalus sinicus* on a site-specific basis could represent a feasible route to carbon-smart rice production by 2050, based on the following findings: 1) *A. sinicus* occupies an important and poorly utilized ecological position in rotation systems within paddy rice production. The biological nitrogen-fixing ability (100 to 180 kg N ha⁻¹ season⁻¹), the high-quality biomass input and production of carbon into the soil from *A. sinicus* (3.5 to 8.0 Mg dry weight ha⁻¹) and the enhancement of soil health/quality by *A. sinicus* will help meet all primary environmental and agronomic goals associated with carbon-smart agricultural systems; 2) the establishment and accumulation of biomass from *A. sinicus* is constrained by the

large spatial variability of biomass accumulation and establishment in large paddy systems which is, again, where autonomous robotic sensing and variable-rate agriculture will provide the greatest benefit compared to conventional techniques.

To start off, Edge AI autonomous robots were able to provide greater accuracy than other agricultural methods in terms of amount of information and correlation between data, with an observed coefficient of variation (CV) in agronomy ranging from 35% (actual) to 78% (approximate) at commercial paddy farms. The on-device inference architecture eliminates the need for connectivity, thus allowing precision agriculture to be more widely used than before due to lack of connectivity issues in rural areas of rice producing countries. Additionally, robotic systems, using a multi-modal sensor

fusion pipeline (e.g., multispectral, hyperspectral, LIDAR, thermal, and electro-chemical sensors) provided highly detailed and reliable information about the state of *A. sinicus* and the dynamics of soil carbon at the spatial resolution necessary to implement actionable site-specific management. Secondly, simulation modelling predicts that using robotic systems or site-specific management could increase the accumulation of soil organic carbon (SOC) by 225%-340% as compared to traditional farming practices (i.e., 0.45-0.68 versus 0.10-0.20 Mg C/ha/yr), while also reducing methane (CH₄) emissions by 12%-19% and reducing the need for synthetic nitrogen by 35%-52%. The long-term forecasts of SOC accumulation from robotic site-specific management indicate that carbon sequestration (CS) potential can reach approximately 8.5-12.4 Mg C/ha over a 25-year period—an equivalent of 31.3-46.1 Mg CO₂ offset per ha from 2025-2050. In terms of financial gain, a net saving of \$51-\$78 ha at the commercial level has been estimated for the use of robotic site-specific management, which also allows for additional revenue through carbon credits obtained through the emerging agricultural carbon markets.

For the broad adoption of robotics in agriculture, the following recommendations have been put forth: build up a regional agronomic training data set of agronomic training data sets to address a broader range of model generalization limitations; design Robotics-As-a-Service business models that will allow systems to be used by all farmers in sub-commercial scale; harmonize international regulatory frameworks for the operation of autonomous agricultural robots; develop integrated robotic management systems with national digital agriculture platforms and carbon monitoring registries; and conduct longitudinal field trials over a minimum of ten-year duration to validate projected SOC accumulation and GHG reductions claims within realistic and actual operational conditions.

The research gaps identified primarily pertain to SOC persistence over longer periods of time, the impact of climate on biological nitrogen fixation, and the life cycle of carbon footprints of the robotic platforms themselves. Each of these gaps identifies a focused and tractable research program for agricultural AI and agronomy communities.

In order to realise the full transformative potential of this framework, by 2050, will require continuous interdisciplinary collaboration of agronomy, robotics, climate science and agricultural economics, supported by supportive policies and based on strong long-term field evidence.

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