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Robotics and Autonomous Systems for Net Zero Agriculture

Simon Pearson[1] · Tania Carolina Camacho-Villa[1] · Ravi Valluru[1] · Oorbessy Gaju[1] · Mini C. Rai[2] · Iain Gould[1] · Steve Brewer[1] · Elizabeth Sklar[1]

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Abstract

Purpose of Review The paper discusses how robotics and autonomous systems (RAS) are being deployed to decarbonise agricultural production. The climate emergency cannot be ameliorated without dramatic reductions in greenhouse gas emissions across the agri-food sector. This review outlines the transformational role for robotics in the agri-food system and considers where research and focus might be prioritised.

Recent Findings Agri-robotic systems provide multiple emerging opportunities that facilitate the transition towards net zero agriculture. Five focus themes were identified where robotics could impact sustainable food production systems to (1) increase nitrogen use efficiency, (2) accelerate plant breeding, (3) deliver regenerative agriculture, (4) electrify robotic vehicles, (5) reduce food waste.

Summary RAS technologies create opportunities to (i) optimise the use of inputs such as fertiliser, seeds, and fuel/energy; (ii) reduce the environmental impact on soil and other natural resources; (iii) improve the efficiency and precision of agricultural processes and equipment; (iv) enhance farmers' decisions to improve crop care and reduce farm waste. Further and scaled research and technology development are needed to exploit these opportunities.

Keywords Net zero agriculture · Nitrogen-use-efficiency · Robotic plant breeding · Electric farm vehicles · Artificial intelligence for farm waste · Socio-eco-technical approach

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✉ Simon Pearson
SPearson@lincoln.ac.uk

Tania Carolina Camacho-Villa
Ccamachovilla@lincoln.ac.uk

Ravi Valluru
rvalluru@lincoln.ac.uk

Oorbessy Gaju
OGaju@lincoln.ac.uk

Mini C. Rai
mrai@lincoln.ac.uk

Iain Gould
IGould@lincoln.ac.uk

Steve Brewer
SBrewer@lincoln.ac.uk

Elizabeth Sklar
Esklar@lincoln.ac.uk

[1] Lincoln Institute of Agri-Food Technology, Riseholme Campus, University of Lincoln, Lincoln LN2 2LG, UK

[2] School of Engineering, University of Lincoln, Lincoln LN6 7TS, UK

Introduction

There is an urgent need to decarbonise the agri-food system which, from farm to fork, accounts for 21 to 37% of global greenhouse gas (GHG) emissions [1•, 2••]. The total global food system emissions are c.18Gt carbon dioxide (CO_2) equivalent with 72% of that derived from agricultural production (40%) and land use/change activity (32%). Of the total food system emissions 52%, 35%, 10%, and 2% are derived from Carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and F gases, respectively. Land use change emissions are primarily CO_2, brought on by the oxidation of soil carbon following conversion of land into agriculture, for example from the intensive cultivation of soil and drainage of peatlands soils. Enteric fermentation within animals, rice cultivation, and manure management contribute to 62% CH_4 emissions, whilst N_2O emissions are primarily derived from nitrogen fertilisers. In addition to N_2O soil emission, energy used in the Haber–Bosch process to produce ammonia accounts for 1.2% of global CO_2 emissions [3].

Decarbonising the food system is a primary challenge for all humanity. The Paris Agreement goal of limiting global temperature increases to 2 °C (preferably 1.5 °C) cannot be met without significant reductions in CO_2 equivalent emissions from across the food system [4]. However, these emission reductions cannot impact the availability and cost of healthy foods demanded by an ever-increasing global population [5]. There is no single panacea to the resolution of this paradox (produce low emission, low cost, and healthy food); it will require a layer of interventions and a complete socio-eco-technical reappraisal of the technology used to produce food. This article considers the opportunities for robotic and artificial intelligence technologies to transform and help decarbonise food production. Our focus is on the production of agricultural crops but recognises that robotics will also play a key role in the decarbonisation of animal production systems.

Agri-robotic technology development is now the focus of considerable global research and innovation [6–8]. Application development is diverse with emerging focus on robotic systems that can selectively harvest crops [9, 10]; control pest, diseases, and weeds [11, 12]; monitor the agricultural environment [13] and crops [14, 15]; autonomously support farm logistic operations [16]; and accelerate the breeding or phenotyping of crops [17•]. Robotic technologies are providing viable opportunities for the repurposing of agricultural systems, for example by supporting a transition from large high-mass machines (typical tractor mass is > 5 Mg, harvesters > 30 Mg) towards autonomous fleets of medium capacity [18] or small machines (mass < 0.5 Mg) [6, 19]. The key question now is how these robotic technologies can be deployed to decarbonise agricultural production and what are the key challenges to realise their potential. Given the known extent of CO_2 equivalent emissions in agriculture, we prioritised our discussion around five key agri-robotic opportunities, whilst recognising multiple approaches will be required:

1. Robotic systems to optimise crop nitrogen use and reduce N_2O emission
2. Accelerated breeding of low carbon crops
3. Lighweight robotic machines to regenerate soils and reduce compaction
4. Electrified robotic vehicles
5. Artificial intelligence (AI) and machine learning to reduce farm waste, including losses from pests and disease

Nitrogen

Nitrogen (N) is one of the most essential macronutrients required by crops for growth and development. Nitrogen fertiliser represents a significant cost for the grower with global nitrogen price at least doubling in 2021 [20]. Crops in the UK receive N fertiliser in the range of 60–200 kg ha^{-1} [21]. At a global level, average N use-efficiency (NUE: amount of dry matter produced per unit of N available in the soil) has only increased slowly during the past 20 years [22]. It sits in the range of 40–50% when using input–output budgeting approaches [23]. The remainder can be released as N_2O or might enter the aquatic environment as a pollutant. This suggests that there is considerable potential for precision agriculture and robotic technologies to improve NUE by improved spatial and temporal deployment of N. Spatial variable rate application approaches typically use optical and possibly soil sensors to assess N requirement.

Optical approaches are typically based on leaf and canopy colour normalised difference vegetation index (NDVI) or greenness. Aula et al. [24] showed variable rate application using optical sensors can substantially increase NUE by 10.4%, saving as much as 53 kg N ha^{-1}. However, the benefits from spatial applications are not consistent, with N input reductions of 10 to 80% reported depending upon the crop, sensors used, and geographic location [25]. Inconsistency in response is not surprising since use of optical sensors assumes a direct correlation between crop N requirement and canopy colour. This assumption is not likely to hold in all instances since canopy "greenness" can be a function of many factors (crop variety, shade, soil compaction, water availability, etc.), not just N requirement. The existing N status of crop or even the soil does not infer future fertiliser requirements. These will be a function of initial canopy status, future crop growth, and N demand plus likely forward environmental and soil conditions. Given the complexity of N requirements, next-generation precision agriculture and robotic systems are likely to deploy machine learning tool to optimise NUE [26]. These tools need to be developed but will use robotic technologies that analyse baseline N status, predict crop needs, and apply precise fertilisation at high spatial resolutions.

Autonomous robotic platforms, agnostic of any specific sensor, show considerable potential to provide decision support by optimising the exploration of variable soil and field environments [27]. This could include sensing of soil fertility (e.g. nitrogen, phosphorous, and potassium (NPK)), health (microbial activity), moisture, or physical properties (compaction, etc.). In addition to agricultural environments, research focus has been directed and stimulated by extraterrestrial robotic platforms that explore soils on planets such as Mars [28]. Robotically mapped terrestrial agricultural environment parameters that impact net zero include soil nutrition (including N) using advanced laser-induced breakdown spectroscopy (LIBS) sensors [29], moisture using cosmic neutron detectors [30], compaction using penetrometers [27], and more recently spatial carbon dioxide emissions across fields using robot actuated infra-red gas analysers (see Fig. 1A). Autonomous robotic soil sampling and measurement systems reduce the cost and increase the scale of sampling. They have the potential to step change precision and farmer decision support.

Robotic Plant Breeding

Robotic phenotyping can accelerate breeding for new varieties in crops through precise phenotyping of traits [31]. On-farm studies have estimated that if yields rise by 1.75%, energy inputs would drop by $7–13 per acre while irrigation could be reduced by 8% [32]. Hence, robotic phenotyping opens a plethora of possibilities that could enable net zero agriculture.

Most breeding programs require thousands of field plots but are sampled at great cost by human technicians. Yet diverse robotic phenotyping platforms (both ground- and aerial-based) have been designed and deployed in both controlled environments [33, 34] or field conditions [35, 36]. The efficacy of such robotic systems varies substantially [37]. However, they have shown considerable potential to capture the environmental responses of key traits, particularly under controlled environments [17•, 38]. Robotic deployment of novel sensors, both 2D and 3D imaging (RGB, hyper/multispectral, thermal or fluorescence; Fig. 1B–E), capturing morphological and structural traits [38] and tomography techniques [39] show great promise to study internal structures of plant organs, roots, and soils. However, plant deep architectural trait characterisation remains challenging largely due to the complex and deformable nature of plants [40], where highly specialist robotic systems are required.

Robotic phenotyping for physiological and biochemical traits contributing to net zero agriculture deserves further attention. Most physiological and vegetative indices are purely spectral-based derivations while robotic platforms for measuring cellular traits under field conditions are currently unavailable. Such robotic systems need viable designs such as specialised and sensible robotic arms to attach sensors and to hold plant organs [41] and need precise deployment of vision-guided segmentation of specific plant organs [42]. Field-viable mobile robotic platforms for large-scale phenotyping are scarce and any such existing robotic phenotyping platforms have temporal limitations due to energy demands [6], sensor usage restrictions [43], or unable to cope with unstructured and harsh field environments. Novel swarm robotic platforms that could achieve distributed sensing [44] offer the next step change, accurate phenotyping of large number of replicated field-plots at sensible economic costs.

Robotics and Regenerative Agriculture

Robotic technologies offer opportunities as next-generation farm machinery; key intrinsic properties required are of low mass and high geospatial precision. These functional properties are critical for the adoption of regenerative agriculture systems [45]. These systems are aimed at restoration and sustainable management of soil health through sequestration of soil organic carbon (SOC). They include a diverse range of techniques integrated within a systems approach to farming that include no-till farming (ploughing eliminated), complex rotations, and novel technologies, including controlled traffic farming (CTF). CTF systems in arable cropping use real-time kinematics from the global positioning system (RTK-GPS) to precisely guide field vehicles along permanent traffic lanes within a field [46]. This reduces soil compaction to only the traffic lanes and not in the cultivated soil. As N_2O emissions are a function of the degree of water saturation within a soil [47], any farming system that reduces compaction might be beneficial. Review [48] suggested CTF could reduce N_2O emissions by 20 to 50% compared to non-CTF. In addition, regenerative agriculture, specifically no-till, focusses on building SOC; gains of c.350 kg C ha^{-1} $year^{-1}$ have been reported [49]. This may

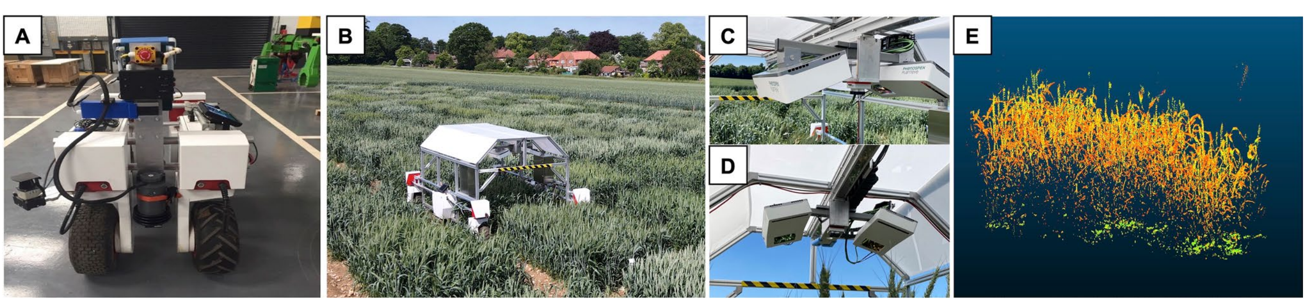

Fig. 1 Infrared gas analyser fitted to a mobile robotic platform to collect soil carbon fluxes in the field (**A**). A mobile robotic phenotyping system (LIPS, Lincoln Phenomic System) developed at the University of Lincoln, UK. The LIPS has been deployed for phenotyping wheat plots in the field (**B**), which is equipped with a dual set-up of three-dimensional (3D) multispectral laser scanners (PlantEye, Phenospex, **C**), and fitted to, and operated through, linear actuator inside the platform (**D**) to obtain a high-resolution wheat canopy 3D data (**E**)

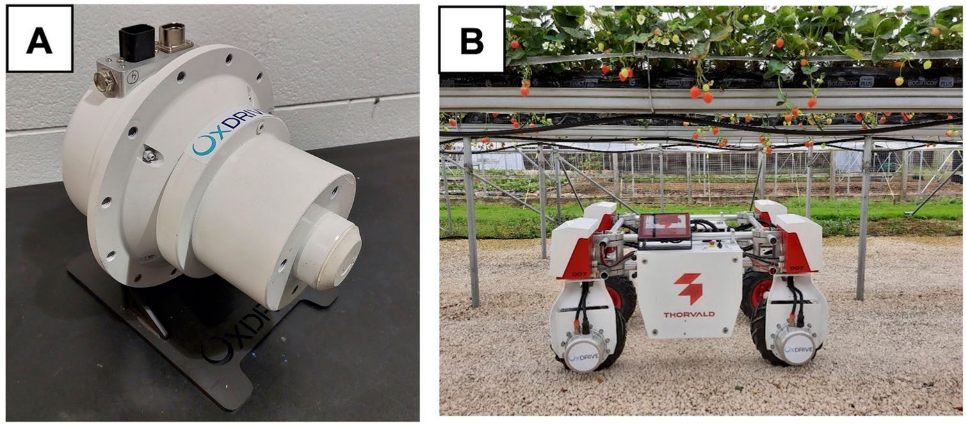

Fig. 2 The new generation of e-hub-powered agri-robots developed by the University of Lincoln, UK, in partnership with OxDrive and Saga Robotics (**A**). 0.8-KW e-hub-powered Thorvald robot from Saga (**B**)

have great significance for net zero agriculture since soil is a globally significant carbon sink, holding c.1550Pg of carbon compared to 560Pg in vegetation and 760Pg in the atmosphere [50]. High SOC might also increase yields; Lal [51] estimates that global food production could increase by between 24 and 40 m Mg year^{-1} if SOC sequesters at a rate of 1 Mg ha^{-1} each year.

Robotic platforms might enable a new paradigm for agricultural equipment. This could include large fleets of ultra-light weight or medium mass (> 5 Mg) machines [16]. Given concerns with the availability and cost of labour on farms [52], future robotic systems will require both a high degree of autonomy and potential to operate as a fleet [6]. Fleet operations might require the operation of large numbers of either homogenous or even heterogenous machines [6]. An example of a heterogenous robotic fleet might be a human-driven combine harvester with logistics support for grain carrying by multiple autonomous tractors. Fleet operations require systems to optimise machine planning [53] and operational precision with minimal risk to operators, machines, the environment, and the public. The physics of agriculture rather constrains the potential for machinery down scaling, for example typical agricultural machines generally require significant power and torque to traverse soils regardless of additional operational tasks (ploughing, cultivating, crop care, etc.) [54]. In addition, robotic sensors and processing including Light Detection and Ranging (LIDAR) can create significant fixed costs for small platforms that, without further innovation on platform hardware and software design, might create barriers to scaling [55].

Electric Vehicles

Conventional fossil fuel tractors substituted by lighter electric machines offer new possibilities for precision robotic technologies and automation [56]. In the UK, an average cereal farm uses 115.6 l of diesel ha^{-1} year^{-1} (4,393MJha^{-1}, or 931Gg CO_2 equivalent for UK's 3.1Mha cereals); moving to a no-till system might reduce the input energy by 50% [57]. These energy inputs are significant and might limit the application of electric vehicles, scalability, and operational performance. The energy density of lithium-ion batteries (*c.* 200Whkg^{-1}) [36] is significantly lower than diesel (11.6kWhkg^{-1}). However, not all agricultural operations require high-energy input machines. In addition to reducing the issues with soil compaction, small robotic platforms with low to medium power ratings will be suitable for selective harvesting, weeding, logistics support, or crop care only mandate in the order of 1 to 5KW power [58–60]. For instance, 0.8 to 8 KW e-hub powered agri-robots shown in Fig. 2 (A–B) exemplify how electrification of farming vehicles and downsizing could revolutionise the art of farming. These smaller robotic systems can provide critical agricultural functionality with reasonable duty cycles whilst reducing the carbon footprint. Smaller electric farm vehicles can have low costs if batteries can be recharged using renewable energy sources such as solar electricity. Such innovations in farming vehicle technology will enable sustainable development, not least the provision of low cost and durable platforms to support small holder farmers across the globe, for example to transport harvested produce or move water to fields.

Robotics, Artificial Intelligence (AI), Crop Care, and Waste

Any robotic system or associated AI analytics that reduces food loss and waste, up to one-third of all food produced, contributes directly to net zero [61]. Waste specifically represents 13% of all the Organisation for Economic Co-operation and Development (OECD) Europe food system GHG emissions [2••]. Robotic systems are being deployed that directly or indirectly reduce waste. Direct robotic solutions include the use of autonomous systems that eradicate diseases such as

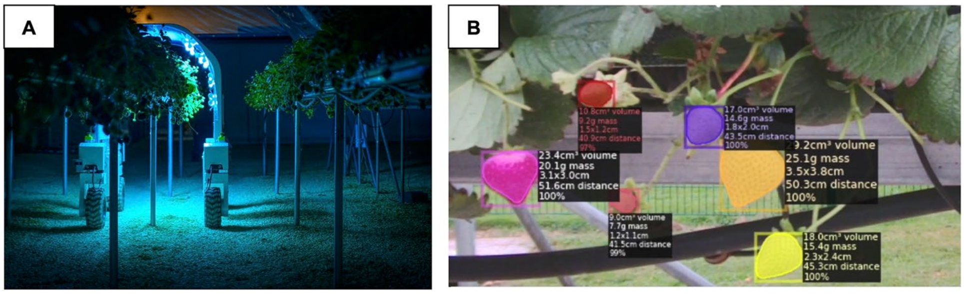

Fig. 3 A mobile robotic system equipped with an UVC light used for treating powdery mildew in strawberry developed by the partnership between Saga Robotics and University of Lincoln (photo by Kristoffer Skarsgård) (**A**). Machine learning model used to recognize, count, and measure strawberry fruits developed by Kirk et al. (2021a, 2021b) (**B**)

powdery mildew by applications of ultraviolet C (UVC) light [62, 63] (Fig. 3A). This approach fully exploits the gain from autonomous systems as UVC can be applied with minimal hazard to human operators. Robotic systems for crop weeding are now well established, using cameras to detect weeds, controlled with a range of tools including hoes [12] and lasers [64]. Direct robotic waste reduction and crop care systems are likely to evolve rapidly, but key barriers will be computational speed, access to labelled data sets, and transfer learning [65] for generic application remain.

Indirect robotic waste reduction technologies include the use of machine learning and robotic sensors to improve farmer decision support. This might include tools that improve crop forecasting by recognition, counting, and measurement of fruit [15, 66–68] (Fig. 3B) or use of machine learning to fuse data from multiple sources (e.g., unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV's) to inform agronomic decisions [69, 70]. Crop forecasting gains alone are significant since they not only enable farmers to increase the proportion of crop sold but also inform price negotiation.

Deployment of Robotic Technologies to Decarbonise Agricultural Production

The deployment of these five agri-robotic opportunities requires a systemic transformation in agricultural production. This transformation involves enabling environments in which robotic technologies become innovations that reduce GHG emissions. A social-ecological-technological systems (SETS) approach that also considered the responsible adoption of robotic innovation [71] is needed to create environments that promote the interaction amongst technical innovation, social systems, and ecosystem functions [72]. Recent literature on net zero recognises that effective mitigation of climate change will require a just transition that involves a societal transformation at different scales to create new rules and institutions that facilitate the adoption and scaling of technological innovations developed around ecological principles [73]. In a growing literature for climate action, SETS appear as an approach to deliver more just, equitable, sustainable, and resilient futures [74]. The emphasis is on enhancing the integration of technical systems with social and ecological systems during the design, manufacture, and use [75] of robotic technology.

Conclusion

Agriculture, one of the planet's oldest industries, is now at a technological crossroads, fighting climate change while feeding the world. Robotics and autonomous systems now emerge as next horizon technologies with considerable potential to transform diverse agricultural activities including minimising on-farm emissions, food and farm waste, and decision support. A context-specific design of RAS innovation and deployment is warranted to reap maximum agricultural benefits. Global coordination of multidisciplinary researchers, investors, consumers, farmers, and policy regulators will be vital for driving a paradigm shift in net zero agriculture.

Declarations

Conflict of Interest The authors declare no competing interests.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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