



## The challenges posed by global broadacre crops in delivering smart agri-robotic solutions: A fundamental rethink is required



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### ABSTRACT

Threats to global food security from multiple sources, such as population growth, ageing farming populations, meat consumption trends, climate-change effects on abiotic and biotic stresses, the environmental impacts of agriculture are well publicised. In addition, with ever increasing tolerance of pest, diseases and weeds there is growing pressure on traditional crop genetic and protective chemistry technologies of the 'Green Revolution'. To ease the burden of these challenges, there has been a move to automate and robotise aspects of the farming process. This drive has focussed typically on higher value sectors, such as horticulture and viticulture, that have relied on seasonal manual labour to maintain produce supply. In developed economies, and increasingly developing nations, pressure on labour supply has become unsustainable and forced the need for greater mechanisation and higher labour productivity. This paper creates the case that **for broadacre crops**, such as cereals, a wholly new approach is necessary, requiring the establishment of an **integrated biology & physical engineering infrastructure**, which can work in harmony with current breeding, chemistry and agronomic solutions. For broadacre crops the driving pressure is to sustainably intensify production; increase yields and/or productivity whilst reducing environmental impact. Additionally, our limited understanding of the complex interactions between the variations in pests, weeds, pathogens, soils, water, environment and crops is inhibiting growth in resource productivity and creating yield gaps. We argue that for agriculture to deliver knowledge based sustainable intensification requires a new generation of **Smart Technologies, which combine sensors and robotics with localised and/or cloud-based Artificial Intelligence (AI)**.

### 1. Introduction

There is a clear threat to global food supplies from the 'Perfect Storm' that is hitting international agriculture (Godfray et al., 2010). This includes:

- The forecast increase in worldwide populations from 7B in 2011 to an estimated 11B by 2055 (United Nations, Projected population growth 2017).
- The greater severity of extreme weather events due to climate change (Turrall et al., 2011).
- The trends in population demographics from political pressures affecting cross-border migration, economic relocation from rural to urban areas and the resulting average increase in the age of the farming communities.
- The increase in the numbers and wealth of the middle-classes,

particularly in the emergent economies which are also seeing the greatest population growth.

- The related transition of these communities from vegetarian diets to the comparative luxury of more resource intensive meat based ones (Sans and Combris, 2015) with the secondary effects on agricultural land requirements, i.e. poultry and cattle based diets being just 40% and 3% as efficient, respectively, on land usage as the equivalent vegetarian diet (Flachowsky et al., 2017).
- The increased tolerance of pests, pathogens and weeds to crop protection products (Brent and Hollomon, 1995) alongside the lack of new active ingredients coming from the agri-industry pipeline; the last significant globally registered synthetic products being arguably QoI (Strobilurin) (Bartlett et al., 2002), Succinate Dehydrogenase Inhibitor (SDHI) fungicides (Sierotzki and Scalliet, 2013) or Neonicotinoid insecticides (Mcgrath, 2014) in the 1990's, which has left the sector reliant on the design of new formulations and

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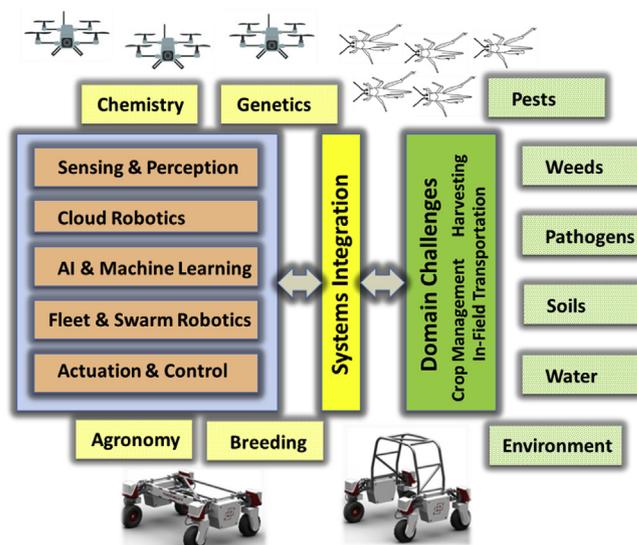
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blends to address developing biotic threats to crop supply.

In addition there are strong political drivers to minimise chemical usage and environmental impact, matched to policy instruments. For example, as of January 2014, the EU ‘Sustainable Use of Pesticides’ directive (Directive, 2009) requires priority to be given to non-chemical methods of plant protection wherever possible. These drivers point towards the needs for a fundamental change to global farming systems. Weaknesses in the selective breeding and crop protection chemistry solutions, that underpinned the first ‘Green Revolution’ of the late 20th Century (Evenson and Gollin, 2003), have been alleviated in recent decades by Integrated Pest Management (IPM) strategies, such as intercropping and beneficial insects (Barzman et al., 2015). The rapid fall in cost combined with the dramatic increase in efficiency and computational power, offered by electronic systems incorporating embedded microprocessors and parallel GPUs (Graphic Processing Units), offers opportunities to revolutionise agriculture, in a similar manner to the way these e-technologies have changed the face of retail, finance and broadcast media once access to internet enabled devices became commonplace. Within the agricultural context the latter may be characterised by electronic systems that include: Active sensors, that can both manipulate and then sense the subsequent effects on their environment; Singular or networked (swarm) autonomous robotic systems (Bayindir, 2016); Wireless networked Internet-of-Things (IoT) devices (Gubbi et al., 2013); Responsive effector systems & novel materials and, of particular note; the rapid advances in Artificial Intelligence (AI) and machine learning, at appropriate speeds and cost to be applied at large scale in a commercial context. The diagram below depicts these subsystems within the context of a Smart Technology for broadacre agriculture (see Fig. 1).

For arable agriculture, the adoption of these Smart Technologies is starting to gather apace in those higher value, but comparatively lower volume, sectors where labour costs are dominant. These are principally where crops have been traditionally been tended on an individual level, such as horticulture or soft fruit production. These sectors are acting as early adopters of smart systems driven, in many cases, by the sheer lack of available people resources to selectively tend and harvest the crops. The in-field implementation, even in these duties, is currently patchy and reliant on the retrofitting of systems as attachments to established machinery (Duckett T., 2018). At the opposite extreme is the production of crops within sealed protected environments (Kozai et al., 2015), typically using enhanced or totally artificially derived photosynthetic illumination sources. It can be argued that this rapidly growing sector has been catalysed by the introduction of smart LED technologies and autonomous intelligent systems, but again the costs dictate that they are targeted currently only at the higher value fruits, vegetables and medicinal crops.

While the potential and general principles of robotics technologies for agri-food production, especially for UK high-value crops, have previously been reported by the authors (Duckett T., 2018) this article provides a new analysis specifically addressing the needs of broadacre agriculture. This is then illustrated with three case studies and recommendation given that are relevant across all sectors of global agriculture, to gain mass adoption of these Smart Technologies. Enabling their transition across from specialty crops to bulk crop production, such as for cereals, maize or canola (oil seed rape) will require a paradigm shift in their capabilities. Traditionally to achieve the necessary economies of scale in a sector with low value products and large crop areas, farm management has focused on decisions made at the field level. In recent years this has begun to move to decisions made for areas within a field, which current precision agricultural mapping and operational systems can facilitate. Even at the level of a few square metres resolution, which is typical for current yield mapping, variability in productivity can often be twice as much, or more, between the highest yielding areas within a field compared to the poorest. A UK study indicated that when analysing wheat yield maps over multiple



**Fig. 1.** Broadacre Agricultural Smart Technology Subsystems. Sensing & Perception technologies will provide vast data streams from both existing platforms, e.g. satellite data, UAV cameras, ground sensors, IoT sensor networks, and emerging robotic platforms to measure: single plants; phenotype crops or detect individual pests (Wolfert et al., 2017). Cloud Robotics technologies will enable storage, processing and sharing of information from diverse sources across a multitude of systems and farming environments (Waibel et al., 2011). AI & Machine Learning technologies will leverage this abundance of information to extract useful knowledge, recommend treatments and predict future outcomes based on past experience. Fleet & Swarm Robotics technologies are key enablers to actively collect sensory information and distribute treatments, by integrating ground and airborne platforms into heterogeneous fleets, coordinated centrally or in distributed fashion (Sørensen and Bochtis, 2010). Actuation & Control technologies will in turn enable the deployment of selected treatments in the field. Systems Integration activities require further research and longitudinal studies to coalesce, scale and bring the benefits of these new technologies to bear on a range of Domain Challenges including applications in crop management, harvesting and in-field transportation.

seasons, from the same cohort of fields, intra-field spatial variability was similar to the inter-year mean yield variability (Blackmore et al., 2003). However, the temporal stability of the spatial variation was low and this tended to cancel over time. Similarly, a second study showed that across 82 fields analysed the coefficient of variations in intra-field yield ranged between 0.05 and 0.22 depending on crop and prior rotation (Joernsgaard and Halmoe, 2003). The conclusion being that yield can be driven significantly by reducing intra-field spatial variability, however, the drivers of this variability are complex and brought about for different reasons within each year. This level of complexity is a function of the high degree of interactions between multiple biotic, abiotic, soil and environmental factors impacting plant growth and ultimately yield.

Moving to management decisions at individual plant level could help to target resources more effectively, and, in theory, improve crop economics. However, most farmers using yield mapping, and similar technologies, have yet to fully exploit the potential of these systems. The ideal scenario would be to manage crops at the plant-level but the complexity of both the volumes of data analysis, that this implies, and the lack of ability to then implement timely treatments, at that finesse, means this is as yet to be realised for broadacre agriculture. In UK wheat crop, it is recommended that the target plant population is 90 plants per square metre, or 900,000 plants per hectare (HGCA, 2000). Each hectare of wheat is typically worth UK£1,290, meaning, that the output value per wheat plant is UK£0.0014 (Redman, 2016). Clearly, to manage the wheat crop at the individual plant-level, with the current engineered systems, is not economically feasible. Furthermore, with the UK growing 1.792 million hectares of wheat in 2017 (DEFRA, 2018a,

b), this suggests in excess of 1.6 trillion wheat plants per annum are grown across the country. Therefore, as well as the poor cost effectiveness of this level of management, the scale of datasets would be beyond the scope of current precision agricultural management and control systems. Currently there are few detailed studies to analyse the economics of more targeted crop management and those that exist compare the introduction of robotic systems, that can operate continuously, versus manual or semi-autonomous tractor units, operated by day-working labour (Pedersen et al., 2006, 2008; Goense, 2003). These indicate that small, agile, robotic systems are a viable alternative to mitigate the lack of availability of appropriate farm labour for conventional duties, such as soil tillage and crop establishment. However their current capital and operational costs would require such machines to operate around 23 h a day. Though value-engineering of such systems may reduce these restraints to an extent it is reasonable to assume that, outside of specialty crop production (Pedersen et al., 2007), the machinery alone would not be capable of maximising biomass by treating individual plants due to the high plant populations involved and very low value per plant.

Addressing these sources of variability would require smart agri-systems that self-evolve, as nature's pests, pathogens and weeds do in the face of climate change, but more rapidly. That is, machine learning systems that can autonomously identify any emergent tolerance to current preventative treatments and then both flags those to operators whilst also attempting to alleviate the impacts by predicting the trend in those tolerance changes and spontaneously adjusting the timing, location or concentration the existing interventions to mitigate the impacts. Effectively using AI to constantly learn and reliably predict the evolutionary processes of pests, pathogens and weeds. However, delivering the required, plant-by-plant interventions is not going to happen through brute-force engineering alone. Putting the cost arguments to one side, at the speeds required to individually process cereal plants the application systems would soon hit barriers from the inertia associated with moving any mechanical components, e.g. from injector mass, manipulator mass, coil self-induction, air resistance, speed-of-sound, etc. As a consequence, to introduce the benefits of Smart Technologies to broadacre crop production is likely to require a subtle integration of machine learning (AI) technologies, networked electronics, sensing, materials-engineering and mechatronic approaches with the design of plant genetics, crop protection chemistries, soil management (structure, composition and mycorrhizal community) as well as traditional IPM techniques.

However, this will also be reliant on a new generation of AI and Big-Data analytics that is equipped with the necessary knowledge of the crop dynamics alongside sensing capabilities to gather, understand and measure any changes in the agri-environment, directly adjusting inputs or making suggestions for new interventions, such as chemistries, genetics, soil structures, insect communities, etc. AI may build a complete knowledge base, through continual sampling, on the complex behaviours of crops as they respond to diseases and other stress factors. That knowledge base may then also enable the identification of specific conditions, so that treatments can be applied with greatest efficacy, both spatially and temporally. To be truly effective these AI derived autonomous interventions will need to address the so-called exploration-exploitation dilemma (Berger-Tal et al., 2014). It is important then to deliver AI systems that manage the trade-off between exploiting their existing knowledge and occasionally 'trying out' new treatments, notably in particularly uncertain cases, to advance their future knowledge. This is akin to the random selection and mutation processes in the natural evolution of crop and pest genetics, but with suitable checks and balances to prevent detrimental impacts.

## 2. Illustrative scenarios for pest, pathogen & weed management

### 2.1. Rust in wheat

The rust fungi (order: *Pucciniales*) are a group of widely distributed fungal plant pathogens which can infect representatives of all vascular plant groups from bulk cereals through to high-value specialty crops, such as Arabica coffee. Rust fungi are obligate biotrophs, requiring a living plant on which to complete their life cycle. The current strategy for dealing with rusts is a combination of strategic deployment of genetic resistance, within defined plant varieties, and growth-stage specific application of chemical fungicides. However, in common with all biotic stresses, this is not a static scenario as rusts are constantly evolving, shifting their severity profiles to overcome resistance and in some cases evolving tolerance to fungicide groups. Three species of rusts are known that infect wheat (*Triticum aestivum*), stem (black) rust (*Puccinia graminis* f. Sp. *tritici*), leaf (brown) rust (*P. triticini*) and stripe (yellow) rust (*P. striiformis* f. Sp. *tritici*). Like most rusts, wheat rust species have a life cycle that requires two very different plant species. While wheat is the host for the asexual stage of the rust life cycle the sexual stage is undertaken on a non-cereal, e.g. barberry and mahonia (Pretorius et al., 2017).

Taking stripe rust of wheat as an exemplar, how could Smart Technologies assist in the future? As stripe rust (Roelfs, 1992) takes two to three weeks from first infecting the host plant through to the appearance of the characteristic stripes of uredinia on leaves, manual observation is not an effective way to control the disease. By the time disease symptoms are clearly visible fungicide applications would be mostly ineffective. The first challenge is therefore to autonomously sense the disease directly in the field at the very outset of a successful infection event, i.e. entry of a spore germ tube through a stomatal opening into the stomatal cavity. It is conceivable to cost effectively detect viable pathogen activity, such as from stripe rust, in the first 12–24 h following germination. At this early phase of the disease, when the infection hyphae have located the leaf stomata and entered the substomatal cavity, the amount of pathogenic fungal DNA present within the leaf is not reliably detectable (Coram et al., 2008). Thus unless many leaves are tested individually, the foreign DNA may not be measurable whether by immunological methods, such as lateral flow devices, in-field DNA-based methods, such as LAMP assays (loop-mediated isothermal amplification), or lab-based PCR (polymerase chain reaction) amplification and analysis (Hubbard et al., 2015). Promising methods using mobile PCR and portable sequencing devices such as the 'MinION' (Jain et al., 2017) are able to detect and genotype the race of the pathogen when the infection is advanced enough to have sporulating pustules present (Hubbard et al., 2015). However, for very early detection, on-going materials engineering research (Grieve et al., 2018) is aiming at combining Computer Aided Design (CAD) with additive manufacturing of biological structures to deliver micro-assays that will specifically respond to single, viable stripe rust pathogens. Though currently speculative, these systems offer the potential to incorporate fungicides within their structures so as to detect whether any new infection is becoming tolerant to selective fungal treatments.

If achievable, infected crops could be precision treated, minimising both chemical inputs and inventory requirements. Of greater significance though, is the ability to accurately time and location stamp that data as part of a network of similar sensing devices. In this way each sensor could act as a node in a network that together creates a real-time map of disease spread, which may then be applied to correct and inform predictive rust disease forecast models. These models, if incorporated within regional, national and international governmental crop disease management programmes have the potential to ensure that the appropriate crop protection chemistries are moved in a timely manner to the threatened areas. Halting of further disease spread could be facilitated by offering cash incentives for, or free issue of, crop protection products to growers in identified 'disease feeder' areas. This

technology infrastructure is readily achievable from the IoT chipsets (DA Xu et al., 2014), which allow network connectivity between a wide variety of devices and services.

From this networked disease sensor data comes two opportunities from AI for gaining further insights into the crop disease development. Firstly, if the micro-assays are formed into arrays, such that each element of the array is comprised of a number of replicate assays that are pathogen and host plant specific, then machine learning could use the temporal and spatial data patterns from the replicate assays to gauge or model the severity of the disease outbreak from that pathogen, as well as correct and minimise for false positives. This would require the AI system to have access to additional, on-node environmental sensor meta-data, such as temperature, humidity, light levels, etc., to learn the complex interactive relationships between the elements of the assay. Secondly AI may operate at the inter-sensor level, using the temporal and spatial relationships between sensor-node locations, alongside meta-data on the surrounding land topology, usage, agronomic practices, meteorological information, etc., to further quantify and refine the quality, spatial-resolution and sensitivity of the rust forecast models. By incorporating harvested yield data and/or seasonal biomass development information gathered from camera platforms, such as on field robots, spray booms, satellites or aerial drones, AI may then also start to detect the breakdown of pathogen defence systems within the standing host crops (Freeman and Beattie, 2008), and so inform future breeding programmes.

These sensing and AI concepts then require complementary, cost-effective and timely disease intervention methods to control an outbreak. Here again Smart Technologies, in the form of small autonomous ground or aerial robotics may assist with the solution. Accurate, real-time mapping of a rust outbreak opens the opportunity to use such systems in isolation or acting in concert (swarm robotics) to contain and manage the spread of disease (West et al., 2003). Early application would minimise the chemical inventory needed on each robot, making them a more agile, economic and viable alternative to a tractor-based spray programme. Using patch application technology (Oerke et al., 2010) also addresses the practicalities of having enough tractor units available at the right time and in the right place. Early application could minimise the chemical inventory that would be needed on each robot so making them a more agile, economic and viable alternative to a tractor-based spray programme. For example, Unmanned Air Vehicles (UAV) are a useful platform for environment monitoring, but with limited payloads and operational durability they are constrained when it comes to delivery of intervention or treatments on a larger scale. However, ground and airborne vehicles may be integrated into heterogeneous fleets and coordinated, either centrally or in a distributed fashion, to deliver a solution (Duckett T., 2018). Currently many pesticides are not registered for aerial application in the EU but this mode of application is starting to be used elsewhere (Kale et al., 2015). Planning, scheduling and coordination are fundamental to the control of multi-robot systems on the farm, and more generally for increasing the level of automation in agriculture and farming. Such coordinated fleets will necessitate in-field communication infrastructures, such as Wi-Fi meshes, WiMAX ad-hoc networks, 5G approaches or other proprietary peer-to-peer communication methods. On a larger scale, the heterogeneous fleets deployed in-field may also include collaborating humans sharing the working environment with their robotic counterparts, giving rise to interaction and communication requirements between the robots and the human operator. Example applications include in-field logistics, where vehicles need to be scheduled for area coverage and routing problems.

Appealing as they might be these engineering solutions alone can only go so far in enabling faster, cheaper and/or more precise variants of existing crop management processes. It is likely that the true potential of AI in broadacre agriculture will only be achieved if the intelligent systems also work in harmony with the natural plant defence systems, to deliver symbiotic solutions. It is well documented how

plants can detect the attack of a pathogen or pest and then elicit a preprogrammed reaction. (Freeman and Beattie, 2008). For biotrophic pathogens, this may be in the form of primary basal resistance (BR) triggered in response to recognition of broadly conserved Microbe-Associated Molecular Patterns (MAMPs), or an isolate-specific secondary line of defence when BR has been breached. This secondary line of defence is often associated with a Hypersensitive Response (HR), where a plant deliberately undergoes cell suicide around an area of infection, so as to save the rest of the plant. Extreme as this may be, a HR response also results in plants entering a heightened state of readiness (Systemic Acquired Resistance-SAR), where plants can become resistant to a broad range of pathogens for an extended period of time. This SAR can also be artificially induced by applying Plant Activator chemicals (Tally et al., 1999).

These self-protective mechanisms all require the plant to divert vital resources away from the generation of primary metabolites, associated with growth and development, and expend energy on the formation of defensive secondary metabolites. Therefore it would be detrimental to crop production and water or nutrient usage to cause plants to enter such a state, unless absolutely essential. However, plants can only respond to localised stimuli from direct attack by a pathogen, or pest, and localised signalling from volatiles released by their immediate neighbours (Dudareva et al., 2006) or possibly sub-soil stimuli via mycorrhizal fungi (Gilbert and Johnson, 2017). Powerful as these natural pre-arming systems may be for crops, Smart Technologies offer the potential to give an additional line of prescient defence, akin to the effects of introducing radar to enable wartime defences to see beyond the human look-out tower. As the sensors could be readily networked into regional, national and international pathogen and pest forecast systems broad-acre crop production may realise a new approach to help crops defend themselves, by triggering plant defences at an appropriate point advance of a forecast attack, thereby maximise crop defences at the most opportune point, whilst minimising the necessary plant energy-expenditure on secondary metabolites. Achieving this could be realised through a comparatively small application of activator chemistries or volatiles. It is not suggested that such approaches would replace fungicides entirely but their prescient usage, especially in areas of extreme pathogen infestation, halt the spread and delay the potential for systemic fungicide tolerance developing within a region.

## 2.2. Cabbage stem flea Beetles in oil seed rape

The Cabbage Stem Flea Beetle (CSFB, *Psylliodes chrysocephala*) is a significant threat to crops, notably in Oil Seed Rape (*Brassica napus*) and other brassicas, driven by the loss of neonicotinoid seed treatment to the industry. This follows their ban in the EU in 2013 (HGCA, 2016) and elsewhere due to concerns over their possible linkage to the decline of insect pollinator colonies (Whitehorn et al., 2012). The remaining control technique, pyrethroid insecticide application, is also under threat due to increasing resistance within CSFB populations (Højland et al., 2015). Therefore precisely targeted and minimised usage is recommended to prevent further development of this resistance.

Adult CSFB cause most damage during crop emergence, eating the growing tip of the seedling, and killing the plant. The adult CSFB lay eggs at the base of the stem with the emerging larvae boring into the leaf petioles and shoots (HGCA, 2016). At this stage an infestation would need to be controlled through some form of chemical inputs. This may be a highly localised application of pyrethroids to contain an attack, without risking broad resistance development, or a non-insecticide approaches through semiochemicals, for example pheromone repellents. Either way, these timely and targeted input mechanisms closely reflect the previous pathogen case in how Smart Technologies can enable plant defence states to be triggered, and enable similar defensive physical changes to plant tissue and generate phenolic insect-toxins, e.g. tannins or furanocoumarins (Constable, 1999).

The enabler for this remedial action is the real-time detection of

CSFB versus other benign insects. The conventional method of water-trap monitoring would be too great a lagging indicator for closed loop control and the mobile nature of insect pests would make detection systems mounted on field robots non-representative, unless the units are held static for a period to prevent them disturbing the colonies. Smart Technologies could achieve this through various non-invasive intra-field sensing approaches. One such approach is the development of active, laser driven, field boundary scanners, operating at the Fraunhofer wavebands where the sun's spectrum has dark spots, to image the presence of insect 'signatures' from the backscatter produced by their wings. Such systems could detect significantly smaller pests, including CSFB, than achievable from radar. AI may then help identify the species of the insect through characterising the movement of the insect trajectories, as well as their wing beat frequency. Non-visual sensors and machine learning systems are also being developed that use multiple acoustic microphones to locate and speciate insects (Bunting et al., 2009), even if hidden from view. These types of Smart Technologies may be readily applied in-field, by virtue of the availability of many of the subsystem components at low-cost from the consumer electronics industry.

### 2.3. Black grass in cereals

The presence of grass weeds, such as black grass (*Alopecurus myosuroides*) within grass crops, such as wheat, barley and oats, is a major issue in Northern Europe and has grown in prominence recently due to a combination of its increasing resistance to the commercially available selective herbicides (Hicks et al., 2018) alongside the fact that black grass now predominantly emerges within crops rather than before drilling, when they could have been eradicated more easily (HGCA, 2014).

Unlike pathogens or pests, weeds do not typically elicit a defence response from a crop unless they are parasitic. As a consequence, the intermingled nature of weeds within a crop renders the usage of spot application of non-selective herbicides untenable. Even if it could be achieved with the degree of coverage and cost that would make it viable for broadacre crops the ability to hit the weeds alone, without significant damage to the crop from chemical splash-over, or identify them under the crop canopy makes it unviable even for systemic herbicides, such as Glyphosate. Thus for broadacre crops the robotically targeted usage of selective herbicides, under AI control, may enable the rate of resistance build up within weed colonies to be reduced but not eradicated.

Smart Technologies can help deliver a step change if integrated with an IPM strategy which includes minimal or no-till soil management. Though visually very similar to wheat, black grasses do have unique characteristics that may be detected morphologically at later growth-stages, such as a characteristic twist in the flag leaves, as well as minor spectral changes that do occur much earlier, notably in their specular reflectance and tonal qualities. Even with very high spatial resolution Multispectral Imaging (MSI), these features are too subtle for remote sensing, from satellites or wide-area drone technologies, to detect at anything more than a few metres above the ground (Lambert et al., 2018). However, such factors may be readily detected if the imaging sensors are both located close to the crop canopy and the illumination conditions are controlled. The latter is key when considering extremely subtle measures, such as detecting the causes of abiotic or biotic stress symptoms (Mahlein et al., 2010), identifying insect pests (Fennell et al., 2018) or identifying plant varieties (Alsuwaidi et al., 2018). This is because the variations in the spectral composition and polarization of sunlight, as well as its incident angle on a leaf, are extremely variable diurnally as well as seasonally.

A significant body of work exists in the use of multivariate and machine learning technologies alongside passive machine vision systems, notably in broadleaf weed control. For drilled crops, precedents exist such as vision processing to guide a robot along the crop rows

whilst removing inter-row weeds with a mechanical hoe (Tillett et al., 2002; Cordill and Grift, 2011). However these exemplars have tended to struggle to control intra-row weeds and so provide total management of the crop bed. It has been suggested (Cordill and Grift, 2011) that smart systems, such as this, are unable to offer any advantage over non-intelligent versions unless they can also deliver intra-row weed control. Crop identification using machine vision is currently at the forefront of precision agriculture (Mahlein et al., 2012; Thenkabail et al., 2016; Cordill and Grift, 2011), and the underpinning research has a long history (Shearer and Holmes, 1990). Leading methods today, for row crops, primarily revolve around the speed of detection, and recognition mechanisms which can ascertain more detail than just the crop type, but also crop health (Tillett et al., 2008; Chen et al., 2002).

This indicates that for non-individually drilled broadacre crops, to deliver the level of subtlety required to repeatedly identify the most early symptoms of crop stress or emergence of embedded grass weeds requires significantly greater sensitivity and selectivity to detect the minor spectral and morphological changes than is currently possible to extract at field application speeds. Machine learning and passive MSI sensing has been proven to yield this level of specific weed, pest and disease discrimination within static systems, when leaves are held at a defined orientation (Mahlein et al., 2010). To take this level of discrimination into the field environment and rapidly process the 3-dimensional topology of crop canopies, next generation AI combined with active MSI is now making such approaches viable (Veys et al., 2019). To achieve this, a ground-based robot or low down-draught rotor UAV are potentially useful platforms, especially if the latter is integrated with the ground unit such that it can be constantly powered and provide the capacity to inspect areas of the field that the terrestrial rover cannot reach in a timely or cost-effective manner.

As a consequence, the weed bank within a field may be mapped to millimetre accuracy at early stage growth of the crop and then verified again later in the season through robotic units. From that data, if minimum till farming is used so as not to significantly disturb and redistribute the weed seed bank, then a post-harvest programme of targeted weed control may be expedited prior to drilling for the next season. Here again, robotic systems offer the potential to undertake that programme, either as an attachment to a conventional tractor toolbar or as an independent unit. The weed seed map being linked to precise spot application of soil based non-selective herbicides or alternate non-chemical approaches, such as localised and targeted injection of microwaves (Brodie et al., 2017) at appropriate power levels for inclusion within transportable systems. The latter approaches have their drawbacks, notably with respect to the potential adverse effects on the soil microbiota being sterilised, but terrestrial robots offer the opportunity to deliver a 'surgical' solution by removing the weed seed with minimised collateral damage to the soil health.

Behind these sensing and effector systems lies AI and machine learning. Firstly in terms of the mechanisms to identify the weeds, pests and pathogens from within the multiple plant characteristics that are reflected within the data-rich output of multivariate sensors, such as MSI. This then leads on to the possibility of AI incorporating the temporal aspects of that data, alongside meta-data on the crop rotation, weather, soil composition, chemical and fertiliser inputs, neighbouring field information and other factors, to forecast the development of systemic changes in the biological potential of a field, farm or region as well as the development of resistance to crop protection chemistries or the variations in the critical factors that may affect an IPM strategy going into the future.

### 3. Discussion

The use of Smart Technologies, that incorporate AI, are still in their infancy in agriculture and therefore the full scope of their impact and potential is yet to be determined. Where reports do exist they tend to conflate AI with automation, robotics and the role of Big-Data in

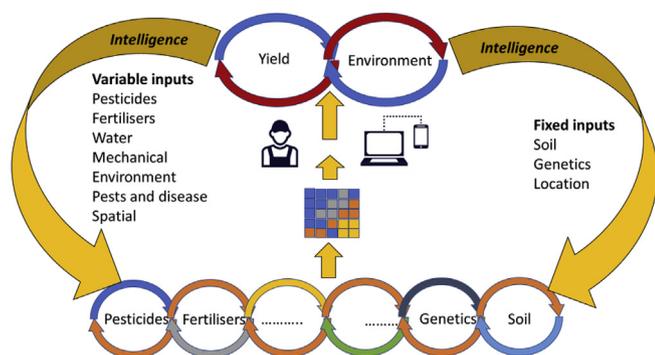


Fig. 2. Agri artificial intelligence innovation dependencies.

agriculture more generally. The specific contribution of Smart Technologies in most of these reports is therefore unclear. McKinsey (Chui et al., 2018) have estimated that AI in agriculture is potentially worth circa US\$120B per annum (p.a.), broadly similar to the potential impact in media and entertainment (Annoni, 2018), but much lower than the US\$600B p.a. projected in retail.

However within agriculture the data interpretation challenges are arguably significantly greater due to the diverse nature, number and differing time and spatial dimensions of the biological, climactic, economic and sociological factors that affect the system. With reference to Fig. 2, in essence the argument is that there are two classes of inputs into a field crops. The first being those which are comparatively fixed on an annual basis, such as soils, microbiomes, field locations, plant genetics, etc. The second are those seasonally variable inputs, e.g. crop rotations, weather, fertilisers, crop protection chemistries, machinery operations, etc. This meta-data is then intimately interlinked in a complex and hitherto poorly understand manner. This is depicted in the figure as the chain links, with the outputs being the variations in spatial yield. The multifaceted nature of AI data processing may then be exploited to deliver an 'intelligence layer' enabling feedback, and potentially feedforward, processing and control of the inputs to optimise output yields and minimise the environmental impacts of crop production. The latter are themselves two outputs that are linked within the chain. Given the unpredictable effects from short-term weather variations, this will never be an exact science but AI offers the potential to identify and mitigate the effects using an integrated package of interventions that take into account learning from prior related agricultural scenarios.

With respect to technology adoption, in the UK the Department for Environment, Food & Rural Affairs (DEFRA) reported that the highest performing quartile of farms were 2.5 times more likely to have detailed farm business plans or to attend discussion groups than the lowest performing quartile (DEFRA, 2018a,b). Furthermore, a review of the characteristics of top performing farms by the UK Agriculture and Horticulture Development Board (AHDB) identified the attributes of highest performing farms in three major areas (AHDB, 2018):

- **Operational efficiency:** the ability to control costs; paying attention to farm operational efficiency to capitalise on marginal gains; adopting specialisation so repeated tasks can be standardised.
- **Strategy and leadership:** using management techniques to set strategy, benchmark and manage accounts; assessing and managing risks; understanding the market; developing a mind-set for change and innovation.
- **People:** focus on people management.

The use of Smart Technologies potentially supports all three of these areas, in particular in its ability to support operational efficiency and strategic decision making.

The use of AI for agriculture in the Developing World has also been

a focus for many government agencies, given major concerns about the lack of access to data to help farmers in these nations to improve productivity and sustainability. Accenture estimates that AI tools can impact 70 million farmers by 2020 in India and add US\$9B to farmer incomes (Purdy and Daugherty, 2017). This potential in the Developing World has also been recognised by the CGIAR (King and Wong, 2017), although their work lacks robust and in depth analysis of where the greatest benefits lie. Accenture more broadly estimates that AI has the potential to increase agricultural growth by 2035 from a baseline of 1.3%–3.4%, one of the largest percentage increases of the 16 industries they studied. This is within a global industry of magnitude US\$3,720B in 2016, comprised of US\$2,450B crops and US\$1,270B livestock products (FAO, 2019). The potential to increase this growth rate, as projected by Accenture, suggests McKinsey's estimate of the global value of AI to agriculture could be conservative.

Further work by McKinsey (Laczowski Kevin, 2018) also suggests that in America both agriculture and construction are lagging in their adoption of technology. Specifically in relation to data and its analysis, they reported that privacy was a major concern for farmers with connected machines and components having the potential to collect significant quantities of proprietary data about yield, processes, schedules etc. 73% of farm contractors and 77% of farmers reported that they expect to know why OEM (Original Equipment Manufacturer) provided items are collecting their equipment data, and about half of respondents feel that being personally identified would adversely affect their relationships with an OEM. Similar concerns in Europe have led to a Code of Conduct on Agricultural Data Sharing by Contractual Arrangement (COPA, 2018). The code aims to set transparent principles, clarifying responsibilities for data use and creating trust among partners.

Most reports estimate the value to the technology sector of AI and Smart Technologies in agriculture, but fail to focus on the value to the farmers and the work which has been carried out specifically on the benefits of AI in agriculture is limited in the UK and globally. The potential impact of AI on agriculture is complex and multi-faceted with large variations in the potential between farms, enterprises and countries. In addition to the economic and technological barriers for AI introduction into broadacre agriculture there are also the sociological influences. These factors can be observed across global supply chains but are particularly manifest among groups of food system stakeholders. Agricultural technologies epitomise how demographics, infrastructures and established institutions can coincide to stifle resilient practices. Conventional approaches rely on linear models of technology transfer to farmers, in which innovations stem from the needs for productivity gains to compete in global markets that are remote from, yet fundamental in shaping, the practices of the natural resource management undertaken by farmers. These technological innovations have had successes in raising yields, but in many cases have undermined previously resilient food production (Tilman et al., 2002) and seen sporadic adoption within farming communities. To overcome this, it is increasingly recognised that there is a need to ensure that the motivations, sensibilities, priorities and knowledge of farmers is appropriately integrated with any new AI, or related, agri-products (Klerkx et al., 2012, Macmillan and Benton, 2014). More research is needed to model the impact on agriculture specifically to review where, how quickly and how practically AI will impact the industry.

This can only happen if in the future agriculture is aligned closely to the 'Industry 4.0' initiative, as widely being adopted in manufacturing, homes, health, transportation, distribution, etc. (Lasi et al., 2014). Given that agriculture also has substantial externalities associated policy is increasingly focusing on the sector's impact on the environment and health, through diet, so any review of the potential of AI on agriculture should review the impact on these externalities, as well as productivity and profitability.

#### 4. Conclusions and recommendations

For these AI enabled Smart Technologies to impact across all sectors of global agriculture the agri-food sector needs to realise major changes in the infrastructure and mind-set of the community. First and foremost is the need to create a cohort of physical engineering graduates who are also have adequate familiarity with biological concepts and agronomy, and vice-versa for a complementary cohort of biology graduates to be trained to have an appreciation of the possibilities offered by relevant elements of engineering and AI. Therefore enabling that community to work together to make the bidirectional linkages between how next-generation engineering may enable the emerging biological sciences, plant breeding, IPM and soil health. Resolving this in such a manner that a physical engineering student is as comfortable with the concept of a pathogenic fungi interacting with a plant host is a non-trivial issue. Not least, as most university engineering courses are already stretched to give the breadth of technical and commercial skills at an appropriate depth to equip engineering graduates to enter the work environment within a 3–5 year undergraduate programme. Adding additional agriscience would thus extend the degree programme or require elements of the current syllabus to be dropped. For the Agri-Tech sector this situation is further exacerbated as, with very limited exceptions, there are few companies and even fewer identified career paths that a young engineer may be able to consider as precedents for undertaking cross-functional study in this area. This is a dilemma that will need to be addressed, as the lack of the entrepreneurial hybrid bio & engineering students to form new companies in this sector then prevents the next generation having precedents to follow. The challenge to global broadacre farming and plant science community is to come together as cohort, alongside the large engineering and software businesses (Vasisht et al., 2017) who have not traditionally been within this agri-food domain, to deliver a number of flagship exemplar products where AI, robotics and sensing mutually assist nature's crop defences. In achieving these, the SME, research and funding infrastructure to develop and grow the sector may be catalysed.

This paper has introduced and endeavoured to illustrate, with case studies, a number of scenarios in which AI enabled Smart Technologies working in harmony with plant and soil sciences may deliver new mechanisms to manage pathogens, pests and weeds in broadacre crops. However, To deliver this there are a number of major and interlinked challenges that need to be addressed, namely enabling investment, professional education and regulatory or policy constraints. These three aspects have been cited as they represent the people and technology infrastructure aspects, the catalysts to deliver change and the potential blockers to delivery. As they are interlinked a prioritised list of proposals to achieve those changes would not be appropriate, instead the suggestions below have been structured in terms of timelines to initiate the first iterations of the suggested activities, the shortest being first:

- Existing governmental investment tends to be targeted at close-to-market applied research, this is certainly apparent in the UK. However, the necessary developments in integrated sensing, robotics and AI that are essential for, the speeds and volumes of data processing in, broadacre crops requires complementary fundamental research to be taken, at low 'Technology Readiness Level' (TRL), on the discrete building-block technologies. This must then also be linked to a joined-up programme of investments, which does not leave those successfully delivered embryonic AI and agri-technologies orphaned but instead nurtures them along from fundamental research through to a series of applied field demonstrators.
- Current, but fragmented, research into the sociological and psychological factors influencing the uptake of any new Smart Technology concepts by the agricultural sector needs to be both extended and factored into the early phases of AI projects. Ideally incorporating farming stakeholders and users of ecosystem services in the initial theoretical designs of such products and interactively

as they progress along the TRL process, so as to maximise the potential impact.

- To start the process of creating a new generation of professionals capable of delivering on these technological and commercial opportunities, the most rapid mechanism maybe through Continuing Professional Development (CPD) modules and courses, both residential and remotely delivered, designed such that they are specifically focused at existing computer, IT and engineering scientists to make them aware of the fundamental Agri-Bio concepts around plants, soils their interactions with pests, pathogens and weeds.
  - o Alongside the support for low TRL underpinning technologies, there is also a need for industry and governments to come together to identify and provide leveraged funding for visionary lower TRL programmes of smart Agri Technology development, such as zero-carbon footprint meals that address daily personalised dietary requirements or climate-resilient, guaranteed, just-in-time production of foodstuffs to meet accurately predicted global demands. This would go beyond the capabilities of any one business, not just in terms of funds available but also with respect to access to the necessary competencies and assets in-house to deliver. Potentially requiring vertical integration, from primary agricultural input providers through to tertiary food retailers and consumers, as well as horizontal integration, equally well incorporating the capabilities of the electronics and creative gaming industries as the agri-machinery and crop protection providers.
  - o A universally agreed protocol for physical and data connections and communication protocols is required, ideally enabling open-access for entrepreneurs and large businesses alike to design and get approval for Smart Technologies to be used across global agriculture. Setting these standards would facilitate a pipeline of highly innovative, but safe, products to be delivered that can be seamlessly interconnected into farming infrastructures and so help drive down costs through enabling commercial competition.
  - o Inclusion of Agri-Bio concepts as elected modules within physical engineering and computer science undergraduate and masters courses across the board, to enable a broad appreciation of the opportunities and challenges. To reflect this, within the plant and biological sciences a complementary series of elected sensing, robotic and AI modules should be made available, such that undergraduates from both domains have adequate awareness, but not necessarily expertise, of the possibilities from their counterparts.
  - o Introduction of a new generation of specialist applied electronic, mechanical, automation and computer science courses to undergraduates to provide a foundation in these mainstream engineering capabilities but with an agri-biological angle, e.g. "Agri-Bio Mechatronics and AI".
- Across the globe the broadacre crop sector has heavily invested in capital for machinery. To avoid this infrastructure becoming legacy, within its working lifetime, the timely transition of the developed smart sensing, AI and robotics technologies into this mainstream sector may require governmental subsidies so that the commercial and environmental benefits can be realised quickly, beyond the early-adopter farmers. Additionally, given the rate at which smart systems develop, there is also a need for a financial strategy that ensure maintenance and upgrading of the novel systems
  - o A pragmatic evolutionary step, to enable early adoption of Smart Technologies, would be their retrofitting as semi-autonomous robotic effector, sensing and machine learning systems on to implements, compatible with existing tractor units.
  - o If this were to be the case, then manufacturers would ideally need to be mindful in those designs so that they are modular, AI-ready and forward compatible with downstream fully autonomous field robots. The agri-sector needs be aligned with the Industry 4.0 programme.
  - o Alongside the investment policy changes, within governments

there may be potential to adapt the regulatory environment to reflect the capabilities of the new technologies. For the broadacre crop industry this comes from two perspectives. Firstly chemical regulation. Smart Technologies and robotics may enable selective crop protection chemistries to be formulated to a significantly higher potency and applied earlier in a disease or infestation cycle than could be applied by wide area spray programmes, even those applied on a patch-spray basis, so rapidly containing the problem whilst minimising average chemical usage per unit area and the potential for systemic resistance to be developed to the products. Such approaches could enable a change in the regulatory approval process, possibly linked to technology-derived machinery interlocks that allow field-usage of formulated chemistries with higher active ingredient concentrations but only from approved smart robotic units.

- o The second area for regulatory change is the need for national and international standards on the format of intelligent autonomous agri sensing and robotic systems, such that they can operate safely 24/7 in an unimpeded manner without the need for local human supervision. The current standards are specific to individual agri-machinery manufacturers which results in a lack of interoperability and variable methods of operator protection being incorporated. For large area automation to come into force in broadacre crops there is an imperative to define a prescient set of standards that will meet future requirements. This may include a redefinition of the farm-field, in a similar manner to the robotic production environment in other sectors (Matthias et al., 2011), such that when autonomous machinery are in attendance the area is restricted to prevent human interference.

The Agri-Food sector faces significant challenges that cannot be addressed through conventional approaches to agri-product development. These threats will continue to grow unless action is taken in the near future to investigate the infrastructure necessary to mitigate the effects. The emergent fields of bespoke agricultural sensing, AI and robotic manipulation may offer part of the solution but for broadacre crops this will only be achieved through seamless integration with more traditional biological and chemical approaches.

## Declarations of interest

None

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.gfs.2019.04.011>.

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