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Manuscript Details

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Title	The Challenges Posed by Global Broadacre Crops in Delivering Smart Agri-Robotic Solutions: A Fundamental Rethink is Required
Article type	Review Article

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).

Keywords	Artificial Intelligence; Plant Defence; Sensors; Robotics; IoT; Agriculture

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Order of Authors	Bruce Grieve, Tom Duckett, Martin Collison, Lesley Boyd, Jon West, Farshad Arvin, Hujun Yin, Simon Pearson

Suggested reviewers	Tim Benton, Tony Pridmore

Submission Files Included in this PDF

File Name [File Type]

Response-to-reviewers_Rev1.pdf [Response to Reviewers (without Author Details)]

GFS_Paper_Big_Ag_Agri-Tech._Highlights_Rev1.docx [Highlights]

GFS_Paper_Big_Ag_Agri-Tech._Graphic_Rev1.tif [Graphical Abstract]

GFS_Paper_Big_Ag_Agri-Tech._TitlePage_Rev1.docx [Title Page (with Author Details)]

GFS_Paper_Big_Ag_Agri-Tech._Rev1.docx [Manuscript (without Author Details)]

GFS_Paper_Big_Ag_Agri-Tech._ConflictOfInterestLetter_Rev1.pdf [Conflict of Interest]

Submission Files Not Included in this PDF

File Name [File Type]

Fig1_Rev1.png [Figure]

Fig2.png [Figure]

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Research Data Related to this Submission

There are no linked research data sets for this submission. The following reason is given:
No data was used for the research described in the article

The authors would like to thank the reviewers for their detailed and constructive comments. We have addressed each of these, as detailed below, through the combined inputs from an enhanced authoring team, which now includes additional plant, crop protection and pathogen expertise.

———

Ref: GFS_2019_14
Title: The Challenges Posed by Global Broadacre Crops in Delivering Smart Agri-Robotic Solutions: A Fundamental Rethink is Required
Journal: Global Food Security

Response to Reviewer-1's comments

#1. This manuscript seems to be opinion and advocacy, not a contribution to scientific knowledge. If the journal publishes editorials or columns, this manuscript might be published clearly labelled as such.

- Following advice from the Journal Editorial Board the paper has been retained in the original classification as being the most appropriate for the content.

#2. The opinions expressed are not particularly novel or innovative. Most of the ideas and examples in the manuscript are available in Duckett et al and some other cited documents.

- The text has been modified to explain that, 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, this article provides a unique new analysis addressing specifically the needs of broadacre agriculture, illustrating this with three new case studies and recommendations relevant across all sectors of global agriculture, in order to gain mass adoption of these smart technologies.

#3. The manuscript mentions economics, but does not go into any depth. It seems to assume that the economics and social aspects will sort themselves out if the biology and engineering are done right. History suggests that assumption cannot be made for agricultural technology.

- Additional text around the economics and social aspects of introducing AI and 'Smart Technologies', into broadacre agriculture, has now been added into the Introduction section to reflect the Reviewers points

#4. Abstract – Is "multiflorous" the right adjective here? Multiflorous is usually defined as having many flowers. It is a stretch of the imagination to think of an aging population and climate change as flowers.

- The adjective has been corrected, being a grammatical error introduced by a software spell checking software. It now reads "… multiple …".

#5. Bullet #1 – What do you mean by "self-evolving"?

- The term "…self-evolve …" has been clarified within the text, in this context, as: "…machine learning systems that 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 adapting to and adjusting the timing, location or concentration of existing interventions to mitigate the impacts...".

#6. Bullet #2 – Economics mentioned in the highlights, but hardly mentioned in the text.

- The supporting text around the societal and economic aspects have now been enhanced as per #3 above.

#7. Bullet #3 – Who or what is doing the assisting and enabling? Subject needed for this sentence

- The subject has now been clarified as "… Smart sensing and AI …"

#8. Lines 67-82 - Figure 1 – not very informative

- The figure has now been set in context through the addition of greater detail, and additional references, within the caption to the image.

#9. Line 100 – The word "economics" is mentioned, but nothing in this manuscript explains the economic forces or factors which drive the development of robotic agriculture and/or the link between robotics and other scientific or technological developments in farming.

- Additional text and cited references added to the Introduction paragraphs

-**Reviewer 2**

I enjoyed and appreciated your forward looking perspective, especially the level of detail that you provided in the case study examples. My major concern with the paper is that it should propose more structure to the recommendations it makes. There are a number of different recommendations made of different complexity and I struggle to think about which are more or less important, which are more or less accessible on the near term, and which depend on other innovations in order to be rolled out. My major recommendation is:

1) Think about including innovation dependency diagrams. A diagram which may show a sequence of innovations with connections between them indicating which innovations lead to which other innovations. What are the requirements needed to ultimately end up signalling to the plants that they should up-regulate their defensive compounds. I was wondering if it worth drawing all the innovations you highlight in each case study and the linkages between them. Another way is to map the innovations/opportunities on a graph of relative complexity and impact.
2) I miss some form of conceptual model in which to think of the innovations / opportunities covered in the paper - either at the case-study level or some overall classification.

#10. If you were to include figures/tables for points 1 and 2 then it'd make the overall direction of the arguments easier to understand and think about.

- The recommendations have now been structured in a fashion that indicates the timeline priorities to start the process of change. Additional text has then been added to describe why those suggestions have been structured in this manner.
- An innovation dependency diagram has been incorporated as Figure 2 and supporting text added within the adjoining paragraphs. In essence the argument is that there are basically two series of inputs into a field crops, i.e. those fixed annually (soil, field location, plant genetics, etc.) and variable inputs (fertilisers, pesticides, machinery operations, etc.). The data for all of these are then completely interlinked in a very complex and hitherto not understand way, in terms of the interactions, hence the chain links, the outputs being the variations in yield spatially. AI is then the intelligence layer to feedback on inputs to output optimal yield and environmental impact, though these two outputs are also linked in a chain.

Minor comments.

#11. Needs proof reading. I spotted lots of grammatical errors.

- Grammatical errors corrected.

#12. The first paragraph could perhaps do with the "perfect storm" list of points being given as a bullet list. It doesn't read very well.

- Now bulleted and restructured

#13. line 55 "face or retail"

- Corrected

#14. Line 84 "smart technologies are"

- Corrected

#15. Line 272 "brassicas, driven by the loss of coefficient of variation in spatial crop yield neonicotinoid seed treatment to the industry." - I find this sentence almost impossible to understand.

- Restructured and simplified

#16. Line 408 "Europe have led an EU Code of"

- Corrected

-**Reviewer 3**

#17. This review brings a perspective of engineering, computing and in particular artificial intelligence, to problems facing agricultural production. Of course, one of the main factors affecting yields is the weather, which cannot be forecast sufficiently far enough ahead to predict yield responses ahead of expensive decisions on inputs such as fertilizer application. It is therefore a shame that the review devotes so little at the end of section 2.3 to how AI could help with meta-data on crop rotations, weather, soils, microbiomes, crop densities and other factors.

- Section 3, rather than 2.3, has been extended to take into account an analysis of the interdependencies between the various temporal and spatially diverse factors that affect the delivery of crop. Figure 2 and the associated text have then been included to help illustrate how AI is a potential enabler to reduce the variability arising from these factors, in the face of short-term weather variations.

#18. Unfortunately, there are many technical writing issues that will need to be fixed to improve the punctuation, replace incorrect words and also many inaccuracies that need to be addressed to bring the review up to publishable standard. I will attach a file showing what corrections are needed.

- Grammar and typos corrected in the revised version.

#19. The introduction states incorrectly that “the last significant globally registered synthetic product probably being pyrethroids in the early 1980’s” – they were developed in the 1960s and 70s and several other classes of agrochemicals were released after that, including neonicotinoids, EBIs, QoIs and SDHIs.

- The statement on the chronology of pyrethroids introduction versus later products, such as the neonicotinoid insecticide or succinate dehydrogenase inhibitor (SDHI) fungicide classes, has been corrected. The central message remains as these products were released in the 1990’s, indicating around 3 decades since the last introduction of a new Active Ingredient. It is also telling that in these cases there are now legislative and tolerance issues, respectively, with those product types.

#20. I don't agree that the sustainable use directive is a strong political driver to intensify agricultural production sustainably (note there isn't a verb ' to sustainably intensify' so it should be 'to intensify…sustainably') because yields have gone down substantially in countries like Denmark where IPM was widely adopted, so it seems to be driven by the desire to use less chemicals not to intensify production.

- The rationale of the argument given in the paper has now been adapted in line with the review comment. As a consequence the erroneous verb-usage has been removed, as it is no longer relevant.

#21. What is the so-called 'exploration-exploitation dilemma? Can a reference be added to explain this?

- The original text already included a reference to explain the "exploration-exploitation dilemma", i.e. Berger-Tal, O., et al., *The exploration-exploitation dilemma: a multidisciplinary framework.* PloS one, 2014. **9**(4). This reference has been retained in the revised paper but moved to the previous sentence to link it more appropriately to its usage in the text.

#22. In the fifth paragraph of the long introduction, the authors seem to have ignored social science effects that result in very low uptake of technologies by farmers if the technology is unexplained, which is often the case with AI.

- The reviewer makes a very salient point and this is the subject of a number of research activities in various nations, including a current Global Food Security project (ref. BB/N020626/1) that the authors are part of with UK farming groups. Additional text has been included in the Discussion section, alongside selected references, and again in the Conclusions / Recommendations bullet points, to reflect these sociological factors affecting technology adoption.

#23. In the second paragraph of section 2, the authors say that once a leaf has become infected (note it is infecting not infiltrating the host) and that is noticed by manual observation, that it is too late to save the crop. That is not correct. Depending on the time of year, it takes at least a few cycles of sporulation to build a level of inoculum before it spreads widely throughout the field. We get infections throughout the fall and early spring that can be controlled following detection by observation. Early detection of the pathogen or the disease that it has caused, does help with disease control and that is already done with a wide range of methods including monitoring airborne spores and optical sensing of very early stages of disease.

- The reviewers comments have been integrated into the text of the paper and clarification given as to the potential benefits offered by the proposed direct detection of the yellow rust infection process

#24. The infection hyphae don't penetrate the haustorium - they penetrate the leaf surface and form the haustorium in palisade cells.

- The factual errors has been corrected and the infection biology aspects augmented through edits and additions, elsewhere in the text, from the additional authors.

#25. The authors incorrectly state that DNA of the pathogen might not be detected even after lab extraction of DNA. There are lots of in-field diagnostic assays (immunological LFD tests and isothermal DNA-based assays) already developed that work well with minimal processing of samples. In a lab, purification of DNA allows detection of just a couple of ungerminated spores on a leaf so this bit is not accurate.

- The text has been modified to clarify the original statements and additional details of emerging complementary in-field diagnostic approaches added, again by the inclusion of expert comments from the additional authors.

#26. Citation 18 is a grant award notice - it doesn't actually prove that a method has been demonstrated to work - that is currently just speculation, which can be written in the article but needs to be identified as mere speculation. How would those structures also detect fungicide resistance? Why not mention lots of other work on early detection of pathogens that has been reported?

- The ongoing speculative research has been designated as such and additional specific and review papers cited, with supporting context, on alternate approaches for early detection of pathogenic fungi. Additional clarification has also been included on how the structures may help detect fungicide resistance.

#27. Internet of things chipsets - please add a reference to explain what this is.

- Reference added to IEEE paper defining the terms.

#28. Page 4 paragraph 2 - change 'virulence' to 'severity' and change 'infiltrate' to 'infect'

- Changes made to text as per comment.

#29. It isn't clear in this paragraph how new virulences will be detected using AI? At the end of this paragraph, it isn't clear whether the authors are suggesting that AI can help with plant breeding by identifying new resistance mechanisms - so AI will be analysing gene expression and analysing chemical composition of cells?

- Additional text provided to address the comments with respect to AI

#30. The third paragraph of page 4 needs to mention that current fungicides are protectants so detected patches of polycyclic diseases such as yellow rust will need two applications, sprayed beyond the visible patch in order to prevent further spread. Currently in the EU, aerial applications of pesticides are banned under the sustainable use directive so drone application would need new legislation or product relabelling.

- Additional text and reference added to accommodate this comment

#31. Page 5 end of paragraph 1, the SAR effectiveness is very limited in field conditions and many plants are already primed as much as they can be due to minor attempted infection by opportunistic saprophytes and herbivory. That is why the technique hasn't been widely adopted in the 20 years since reference 21 was published.

- Paragraph restructured to explain that it is not ideal to deliberately induce SAR unless done in a smart / timely way i.e. just before a wave of infection

#32. Page 5 paragraph 5 - there are lots of static insect traps that are now 'smart' - some detecting insect movement using electrodes and reporting insect presence using LoraWAN or WiFi. There is a massive number of existing sensors already reported in this area that could be reviewed at this point.

- Acknowledgement has been made in the text to the existing LoraWAN, and similar, enabled pest trapping systems with embedded processing capabilities.

#33. First line of page 6 - this has been done already without AI. A system would need to be trained to ID a new insect pest and that would mean an expert will need to do the training otherwise the device will not know that an insect with a different wingbeat frequency is a new pest.

- Though the above point is true for some early AI systems and is still a valid approach for single modality sensor systems, and thus acknowledged as such in the text, with the inclusion of appropriate in-field meta-data and alternate sensor modalities, e.g. image trajectory tracking alongside acoustic profiles, it is not mandatory to include a human observer to detect and then characterise the presence of ‘foreign’ insect species within an existing training set.

#34. Section 2.3 paragraph 2 - this could cite a wealth of research reported from the University of Leuven on detection and control of weeds using image recognition methods.

- Additional explanatory text has been included on the precedents for machine vision in weed control, as per the suggestion. References to related research arising from RTOs and Universities elsewhere, including that at Leuven, is set into context via the cited review papers.

#35. Paragraph 3 reports a feature in the flag leaf of blackgrass could help with its identification but that is too late a stage for it to be controlled by herbicides within a crop.

- The Reviewer makes a valid point for conventional chemical applications and the text has been adapted as such as internal studies, and those at Sheffield as elsewhere, indicate that spectral variations are apparent prior to morphological changes suggested.

#36. After [31,32] change 'speciating' to 'identifying' because speciating has a different meaning - forming a new species by evolution.

- Corrected

#37. This paragraph suggests that weed identification by image analysis is currently only done in lab conditions but it has been used successfully outdoors for over 15 years.

- As quite rightly stated by the Reviewer, weed management by passive machine vision has regularly been applied in field with varying degrees of success, notably for drilled crops and inter-row weeds. The original paragraph has been has been rephrased to prevent any misconceptions, as the rationale was to explain that the subtlety of discrimination offered by active multispectral systems has not been applied in the field thus far as the requirement to control the modulation of the light, Lambertian effects of the distance from source / object / imaging plane, topology of the leaf surface, angle and wavelength of penetration into the tissue, polarization of the illumination and other modifying effects creates a data set which only emergent AI approaches offer the potential to understand at field speeds. The text has been modified to prevent any misconceptions.

#38. Page 6 5th paragraph - is this suggesting destruction of individual seeds buried in soil? It is too early for plants to have grown so this section doesn't seem possible and the power consumption for microwaves and especially high tension electricity would have a massive carbon footprint - the robot would be constantly needing to be recharged.

- The Reviewers comments are possibly subjective as research into targeted high frequency electromagnetic waves indicates that targeted and appropriately powered transducers would be capable of removing elements of the weed seedbank and, potentially, parasitic elements of the rhizosphere. Text and citations added to this effect.

#39. Page 7 - Not all smart technologies use AI so in the first line of the discussion, 'which' must be replaced by 'that'

- The text has been corrected

#40. Are the figures e.g. US$120B an amount per annum?

- Yes, this figures, and the subsequent US$600B figure are on an annual basis and have now been designated as such.

#41. State what is 'OEM' in full when first used.

- OEM definition now added - Original Equipment Manufacturer

#42. Page 8 briefly explain what is 'Industry4.0'

- A reference and accompanying text has been added to clarify the term

#43. Section 4 seems implausible and better to argue for collaborative science because it isn't possible to train an engineer to know the wide range of biological or chemical issues they would need to know.

- The Reviewers comments are possibly subjective versus the capabilities of engineering professional. The basis of the narrative is to develop adequate hybrid skills in both engineering and biological science graduates and professional, and vice-versa, so that there is an appreciation of the opportunities and threats from across the disciplines, in order to then open a dialogue to address those in a truly multidisciplinary manner. It is not the authors intention to suggest that more than one profession can simply be learnt by single individuals, as such additional wording has been added to Section 4 to clarify this.

#44. Page 9 the section on government investment a lot of the second bullet point hasn't been discussed at all and this is littered with buzzwords and ends with an incomplete sentence

- The grammatical content of the text has been edited accordingly.

#45. The third bullet point calls for subsidies but then argues that most of this could be delivered by adapting existing machinery.

- The bullet point has been reworded to emphasise that the adaptation of machinery is a pragmatic element of an early adoption strategy and may form part of a portfolio, alongside other mechanisms

#46. The first bullet point of the Policy and Standards part is so unlikely that really it should be omitted as it could break a host of pesticide application regulations.

- The text has been adapted and toned-down to take into account the Reviewers comments though within the UK the authors and affiliates are already at the early stages of such discussions.

#47. For the second point - how will fields be restricted?

- The legislative case as to the designation of fields, when under AI controlled automated production, is beyond the scope of this paper, however the authors are involved in early discussion on unified standards, that reflect the bullet point, with the professional engineering institutes. As a consequence the Agri-Tech sector, in the future, is likely to be subject to similar reviews that were undertaken to redefine work areas in the automotive, marine and aerospace production industries when robotic manufacture was adopted to significant scale. Text has been added to that effect.

#48. Reference 41 and 42 really need to be written in full.

- These original reference IDs have now been extended, versus the format that was autonomously added by the ‘EndNotes’ software.

-**Reviewer 4**

#49. This paper overviews the challenges faced by those attempting to improve yield of broad acre crops and proposes a number of key steps needed, particularly 1. the integration of artificial 'smart' automatic systems with natural biological processes and 2 the development of trains materials and courses intended to create a community of 'biologically-conversant engineers' capable of carrying out that integration. The paper is well-structured and written, moving from a broad introduction to example scenarios to specific recommendations.

Overall I think the authors' points are well-made, and I agree with their conclusions. Their emphasis on integration of smart technologies with existing knowledge and practices is novel, and I have not seen anyone argue for the interdisciplinary training programmes discussed here. The paper is intended for a broad readership, but makes a contribution to the ongoing debate around agricultural technologies.

My only concern about the paper is that while statements about agricultural practice, sensors and robotics are well-supported with references to the literature, the material on the potential of AI is more speculative. The paper would be improved if more references were made to existing systems and techniques. The recent Elsevier report https://www.elsevier.com/?a=827872 might be of use here. I don't think any of the scenarios presented are unrealistic, but that the argument for the AI component of them is not so strongly made as the others.

- The paper has been cited and the text augmented, especially around the Innovation Interdependencies that AI can help to address.

I would also make a number of minor comments, and noticed a small number of typographical errors:

#50. on line 53, it might be worth mentioning GPUs alongside embedded microprocessors, as they have a significant role to play in the practical implementation of AI systems

- Text modified as per recommendation

#51. on line 88, 'Shear' should be 'sheer'?

- Corrected

#52. on line 196 'plant genera. Then' should be 'plant genera, then'?

- Corrected

#53. I may be over-interpreting 'engineering' but I was surprised at the emphasis on engineering courses and students, in the first paras of section 4. Given the emphasis on AI I expected a similar recommendation around computer science courses and students.

- Additional text added to reflect the suggestion

#54. on line 467, I agree re. UG courses, but is there a need for MSc provision too? that may be easier to establish.

- MSc course also included in the statement.

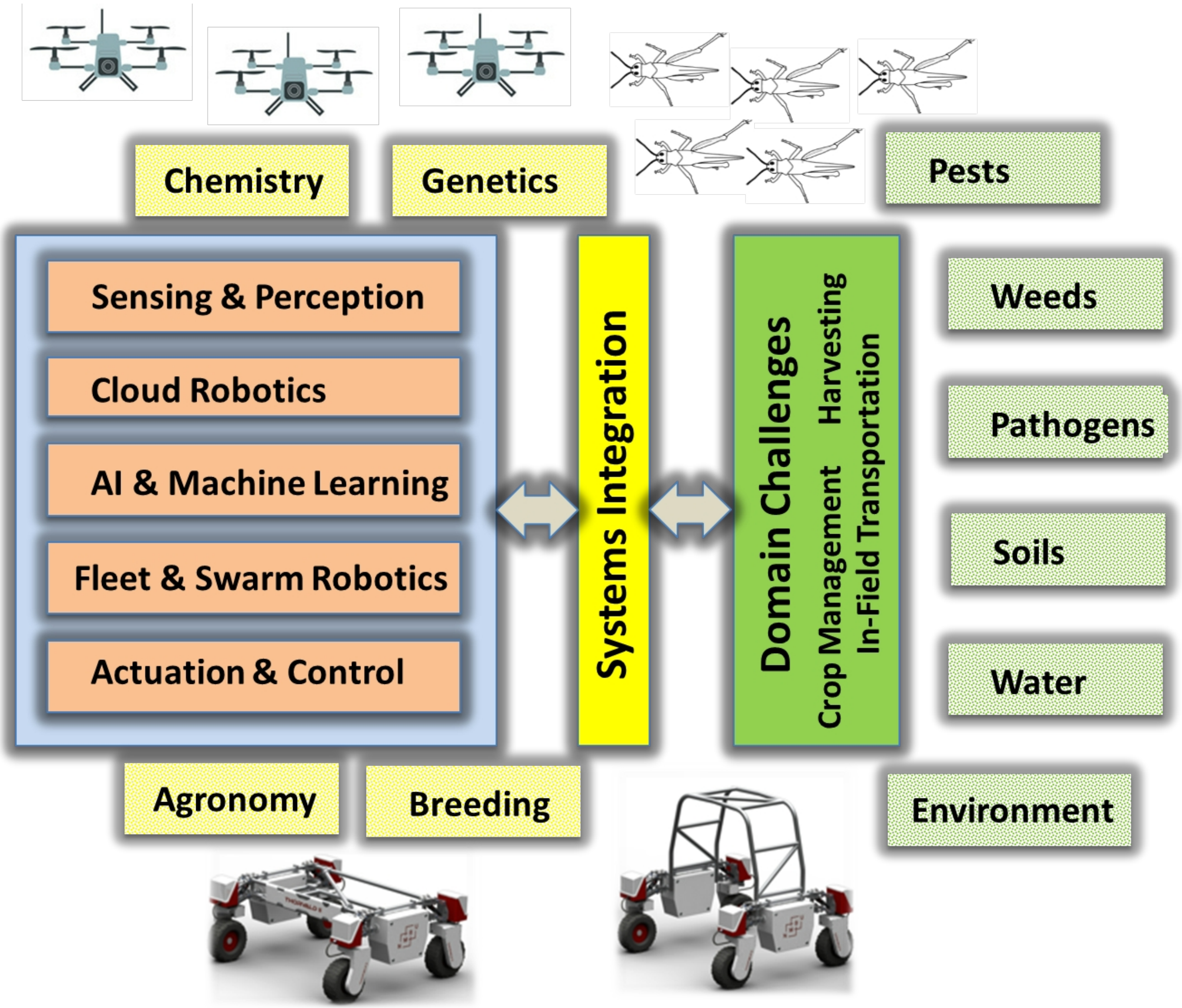
#55. on line 507, I agree re infrastructure funding and the danger of infrastructure becoming legacy. Given the speed with which smart systems develop, is there also a need for a financial strategy that ensure maintenance and upgrading of the systems the authors' envisage?

- Additional text added to reflect this.

The Challenges Posed by Global Broadacre Crops in Delivering Smart Agri-Robotic Solutions: A Fundamental Rethink is Required

Highlights:

- Sustainable intensification can be catalysed by self-evolving Smart Technologies
- Mainstream agri-economics drives the integration of biology & physical engineering
- Assisting & enabling current breeding, chemistry and agronomic solutions.
- Combining agri-sensors and robotics with localised and cloud-based AI.
- Paradigm shift in professional education: Biologically conversant Engineers & Vice Versa



Chemistry
Genetics
Pests
Sensing & Perception
Cloud Robotics
AI & Machine Learning
Fleet & Swarm Robotics
Actuation & Control
Systems Integration
Domain Challenges
Crop Management
Harvesting
In-Field Transportation
Weeds
Pathogens
Soils
Water
Agronomy
Breeding
Environment

The Challenges Posed by Global Broadacre Crops in Delivering Smart Agri-Robotic Solutions: A Fundamental Rethink is Required

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Declarations of interest:

- None

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The Challenges Posed by Global Broadacre Crops in Delivering Smart Agri-Robotic Solutions: A Fundamental Rethink is Required

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 [1]. 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 [2].
- 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 [3] 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 [4].
- The increased tolerance of pests, pathogens and weeds to crop protection products [5] alongside the lack of new active ingredients coming from the agri-industry pipeline; the last significant globally registered synthetic products being arguably QoI (Strobilurin) [6], Succinate Dehydrogenase Inhibitor (SDHI) fungicides [7] or Neonicotinoid insecticides [8] in the 1990's, which has left the sector reliant on the design of new formulations and 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 [9] 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 [10], have been alleviated in recent decades by Integrated Pest Management (IPM) strategies, such as intercropping and beneficial insects [11]. 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 [12]; Wireless networked Internet-of-Things (IoT) devices [13]; 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.

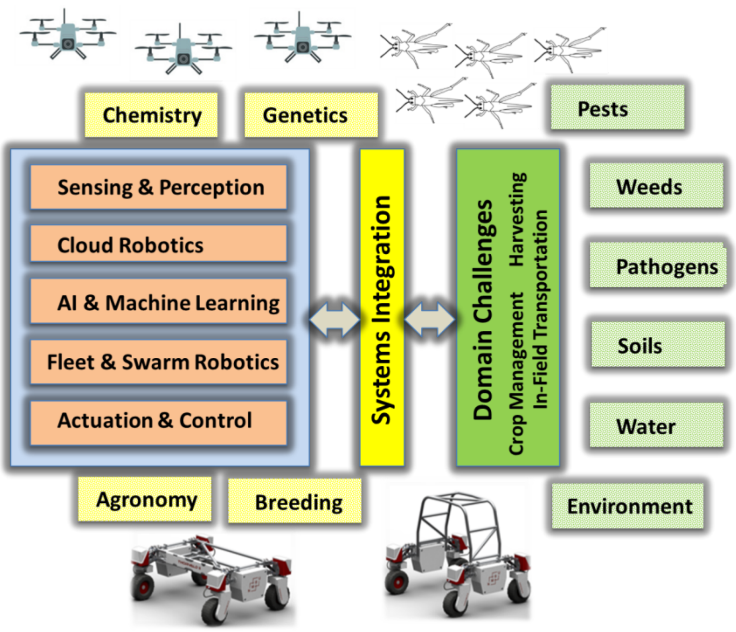

Figure 1: Broadacre Agricultural Smart Technology Subsystems. Sensing & Perception technologies will provide vast data streams from both existing platforms, e.g. satellite data, UAV cameras, ground sensors, IoT sensor networks, and emerging robotic platforms to measure: single plants; phenotype crops or detect individual pests [14]. Cloud Robotics technologies will enable storage, processing and sharing of information from diverse sources across a multitude of systems and farming environments [15]. 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 [16]. 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.

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 [17]. At the opposite extreme is the production of crops within sealed protected environments [18], 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 [17] 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 seasons, from the same cohort of fields, intra-field spatial variability was similar to the inter-year mean yield variability [19]. 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 to 0.22 depending on crop and prior rotation [20]. 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 recommend that the target plant population is 90 plants per square metre, or 900,000 plants per hectare [21]. Each hectare of wheat is typically worth UK£1,290, meaning, that the output value per wheat plant is UK£0.0014 [22]. 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 [23], 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 [24-26]. 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 hours 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 [27], 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 [28]. 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 [29].

Taking stripe rust of wheat as an exemplar, how could Smart Technologies assist in the future? As stripe rust [30] 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 hours following germination. At this early phase of the disease, when the infection hyphae have located the leaf stomata and entered the sub-stomatal cavity, the amount of pathogenic fungal DNA present within the leaf is not reliably detectable [31]. 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 [32]. Promising methods using mobile PCR and portable sequencing devices such as the 'MinION' [33] are able to detect and genotype the race of the pathogen when the infection is advanced enough to have sporulating pustules present [32]. However, for very early detection, on-going materials engineering research [34] 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 [35], 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 [36], 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 [37]. 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 [38] 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 [17]. Currently many pesticides are not registered for aerial application in the EU but this mode of application is starting to be used elsewhere [39]. 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 preprogramed reaction. [36]. 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 [40].

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 [41] or possibly sub-soil stimuli via mycorrhizal fungi [42]. 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 broadacre 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 [43] and elsewhere due to concerns over their possible linkage to the decline of insect pollinator colonies [44]. The remaining control technique, pyrethroid insecticide application, is also under threat due to increasing resistance within CSFB populations [45]. 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 [43]. 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 [46].

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 [47], 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 [48] alongside the fact that black grass now predominantly emerges within crops rather than before drilling, when they could have been eradicated more easily [49].

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 [50]. 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 [51, 52], identifying insect pests [53] or identifying plant varieties [54]. This is because the variations in the spectral composition and polarization of sunlight, as well 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 exists such as vision processing to guide a robot along the crop rows whilst removing inter-row weeds with a mechanical hoe [55, 56]. 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 [56] 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 agricultural [56-58], and the underpinning research has a long history [59]. 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 [60, 61].

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 [51]. 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 [52]. 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 [62] 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 agriculture more generally. The specific contribution of Smart Technologies in most of these reports is therefore unclear. McKinsey [63] 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 [64], 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 Figure 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.

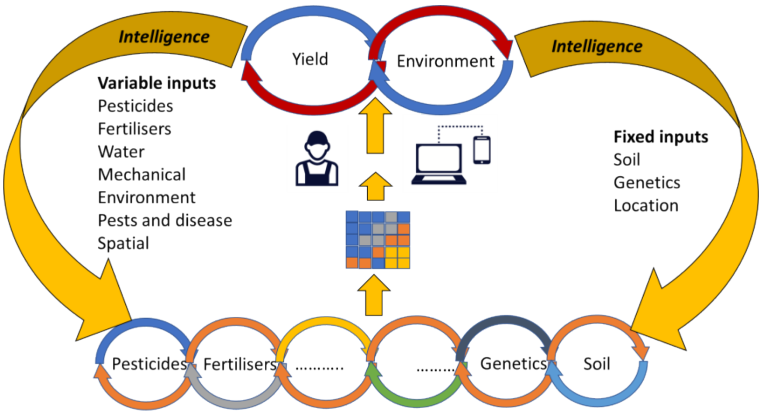

Figure 2: Agri Artificial Intelligence Innovation Dependencies

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 [65]. 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 [66]:

- **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 [67]. This potential in the Developing World has also been recognised by the CGIAR [68], 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% to 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 [69]. 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 [70] 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 [71]. 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 [72] 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 [73, 74]. 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. [75]. 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 agri-science 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 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 [76] 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 natures 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 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.
- 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 the capabilities of the electronics and creative gaming industries as the agri-machinery and crop protection providers.
- 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.
- 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.
- 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 with which smart systems develop, there is also a need for a financial strategy that ensure maintenance and upgrading of the novel systems

- 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.
- 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.
- 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.
- 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 [77], 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 instigate 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.

5. References

1. Godfray, H.C.J., et al., *The future of the global food system*. 2010, The Royal Society.
2. Turral, H., J.J. Burke, and J.-M. Faurès, *Climate change, water and food security*. 2011: Food and Agriculture Organization of the United Nations Rome.
3. Sans, P. and P. Combris, *World meat consumption patterns: An overview of the last fifty years (1961–2011).* Meat science, 2015. **109**: p. 106-111.
4. Flachowsky, G., U. Meyer, and K.-H. Südekum, *Land Use for Edible Protein of Animal Origin-A Review.* Animals : an open access journal from MDPI, 2017. **7**(3): p. 25.
5. Brent, K.J. and D.W. Hollomon, *Fungicide resistance in crop pathogens: how can it be managed?* 1995: GIFAP Brussels.
6. Bartlett, D.W., et al., *The strobilurin fungicides.* Pest Management Science: formerly Pesticide Science, 2002. **58**(7): p. 649-662.
7. Sierotzki, H. and G. Scalliet, *A review of current knowledge of resistance aspects for the next-generation succinate dehydrogenase inhibitor fungicides.* Phytopathology, 2013. **103**(9): p. 880-887.
8. McGrath, P.F., *Politics meets Science: The case of neonicotinoid insecticides in Europe.* SAPI EN. S. Surveys and Perspectives Integrating Environment and Society, 2014(7.1).

9. Directive, E., *128/EC of The European Parliament and of the Council of 21 October 2009 establishing a framework for community action to achieve the sustainable use of pesticides*. EU, Brussels, 2009.
10. Evenson, R.E. and D. Gollin, *Assessing the impact of the Green Revolution, 1960 to 2000*. science, 2003. **300**(5620): p. 758-762.
11. Barzman, M., et al., *Eight principles of integrated pest management*. Agronomy for sustainable development, 2015. **35**(4): p. 1199-1215.
12. Bayındır, L., *A review of swarm robotics tasks*. Neurocomputing, 2016. **172**: p. 292-321.
13. Gubbi, J., et al., *Internet of Things (IoT): A vision, architectural elements, and future directions*. Future generation computer systems, 2013. **29**(7): p. 1645-1660.
14. Wolfert, S., et al., *Big data in smart farming–a review*. Agricultural Systems, 2017. **153**: p. 69-80.
15. Waibel, M., et al., *Roboearth-a world wide web for robots*. IEEE Robotics and Automation Magazine (RAM), Special Issue Towards a WWW for Robots, 2011. **18**(2): p. 69--82.
16. Sørensen, C.G. and D.D. Bochtis, *Conceptual model of fleet management in agriculture*. Biosystems Engineering, 2010. **105**(1): p. 41-50.
17. Duckett T., P.S., Blackmore S., Grieve B.D., et al, *Agricultural Robotics: The Future of Robotic Agriculture*. UK-RAS White Paper, 2018.
18. Kozai, T., G. Niu, and M. Takagaki, *Plant factory: an indoor vertical farming system for efficient quality food production*. 2015: Academic Press.
19. Blackmore, S., R.J. Godwin, and S. Fountas, *The analysis of spatial and temporal trends in yield map data over six years*. Biosystems engineering, 2003. **84**(4): p. 455-466.
20. Joernsgaard, B. and S. Halmoe, *Intra-field yield variation over crops and years*. European Journal of Agronomy, 2003. **19**(1): p. 23-33.
21. HGCA, *Optimum winter wheat plant population*. Agriculture and Horticulture Development Board Information Sheet, 2000. **36**: p. 2.
22. Redman, G., *John Nix farm management pocketbook*. John Nix farm management pocketbook., 2016(Ed. 47).
23. DEFRA., *AGRICULTURE IN THE UNITED KINGDOM 2017*. 2018: DANDY BOOKSELLERS Limited.
24. Pedersen, S.M., S. Fountas, and S. Blackmore, *Agricultural robots—Applications and economic perspectives*, in *Service robot applications*. 2008, InTech.
25. Goense, D., *The economics of autonomous vehicles*. 2003.
26. Pedersen, S.M., et al., *Agricultural robots—system analysis and economic feasibility*. Precision agriculture, 2006. **7**(4): p. 295-308.
27. Pedersen, S.M., S. Fountas, and S. Blackmore, *Economic potential of robots for high value crops and landscape treatment*. Precision Agriculture, 2007. **7**: p. 457-464.
28. Berger-Tal, O., et al., *The exploration-exploitation dilemma: a multidisciplinary framework*. PloS one, 2014. **9**(4): p. e95693.
29. Pretorius, Z., et al., *Advances in control of wheat rusts*. Achieving sustainable cultivation of wheat, 2017. **1**.
30. Roelfs, A.P., *Rust diseases of wheat: concepts and methods of disease management*. 1992: Cimmyt.
31. Coram, T.E., M. Wang, and X. Chen, *Transcriptome analysis of the wheat–Puccinia striiformis f. sp. tritici interaction*. Molecular Plant Pathology, 2008. **9**(2): p. 157-169.
32. Hubbard, A., et al., *Field pathogenomics reveals the emergence of a diverse wheat yellow rust population*. Genome Biology, 2015. **16**(1): p. 23.
33. Jain, M., et al., *MinION analysis and reference consortium: phase 2 data release and analysis of R9. 0 chemistry*. F1000Research, 2017. **6**.

34. Bruce Grieve, C.G., Linda Hanley-Bowdoin, David Hodson, Paulo JDS Bartolo, *Biomimetic In-Field, IoT, "Sentinel" Fungal & Viral Sensor*. 2018, Bill & Melinda Gates Foundation: UK. p. 2.
35. Da Xu, L., W. He, and S. Li, *Internet of things in industries: A survey*. IEEE Transactions on industrial informatics, 2014. **10**(4): p. 2233-2243.
36. Freeman, B.C. and G.A. Beattie, *An overview of plant defenses against pathogens and herbivores*. The Plant Health Instructor, 2008.
37. West, J.S., et al., *The potential of optical canopy measurement for targeted control of field crop diseases*. Annual review of Phytopathology, 2003. **41**(1): p. 593-614.
38. Oerke, E.-C., et al., *Precision Crop Protection-The challenge and use of heterogeneity*. Vol. 5. 2010: Springer.
39. Kale, S.D., et al., *Agriculture drone for spraying fertilizer and pesticides*. published in iijarsse, 2015. **5**(12).
40. Tally, A., et al., *Commercial development of elicitors of induced resistance to pathogens*. Induced plant defenses against pathogens and herbivores, 1999: p. 357-369.
41. Dudareva, N., et al., *Plant volatiles: recent advances and future perspectives*. Critical reviews in plant sciences, 2006. **25**(5): p. 417-440.
42. Gilbert, L. and D. Johnson, *Plant–Plant Communication Through Common Mycorrhizal Networks*, in *Advances in Botanical Research*. 2017, Elsevier. p. 83-97.
43. HGCA, *Cabbage stem flea beetle*. Agriculture and Horticulture Development Board Information Sheet, 2016. **55**: p. 2.
44. Whitehorn, P.R., et al., *Neonicotinoid pesticide reduces bumble bee colony growth and queen production*. Science, 2012: p. 1215025.
45. Højland, D.H., et al., *Incidence, spread and mechanisms of pyrethroid resistance in european populations of the cabbage stem flea beetle, Psylliodes chrysocephala L.(Coleoptera: Chrysomelidae)*. PloS one, 2015. **10**(12): p. e0146045.
46. Constable, C., *A survey of herbivore-inducible defensive proteins and phytochemicals*. Induced plant defenses against pathogens and herbivores, 1999: p. 137-166.
47. Bunting, O., et al., *Instrument for soundscape recognition, identification and evaluation (ISRIE): technology and practical uses*. 2009.
48. Hicks, H.L., et al., *The factors driving evolved herbicide resistance at a national scale*. Nature ecology & evolution, 2018. **2**(3): p. 529.
49. HGCA, *Black-grass: solutions to the problem*. Agriculture and Horticulture Development Board Information Sheet, 2014. **30**: p. 4.
50. Lambert, J., et al., *Evaluating the potential of Unmanned Aerial Systems for mapping weeds at field scales: a case study with Alopecurus myosuroides*. Weed research, 2018. **58**(1): p. 35-45.
51. Mahlein, A.-K., et al., *Spectral signatures of sugar beet leaves for the detection and differentiation of diseases*. Precision Agriculture, 2010. **11**(4): p. 413-431.
52. Veys C, C.F., AlSuwaidi A, Hibbert J, Hansen M, Bernotas G, Smith M, Yin H, Rolfe S, Grieve B, *Multispectral imaging for presymptomatic analysis of light leaf spot in oilseed rape*. Plant methods, 2019.
53. Fennell, J., et al., *A method for real-time classification of insect vectors of mosaic and brown streak disease in cassava plants for future implementation within a low-cost, handheld, in-field multispectral imaging sensor*. Plant methods, 2018. **14**(1): p. 82.
54. AlSuwaidi, A., B. Grieve, and H. Yin, *Feature-Ensemble-Based Novelty Detection for Analyzing Plant Hyperspectral Datasets*. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2018. **11**(4): p. 1041-1055.
55. Tillett, N., T. Hague, and S. Miles, *Inter-row vision guidance for mechanical weed control in sugar beet*. Computers and electronics in agriculture, 2002. **33**(3): p. 163-177.

56. Cordill, C. and T. Grift, *Design and testing of an intra-row mechanical weeding machine for corn*. Biosystems engineering, 2011. **110**(3): p. 247-252.
57. Mahlein, A.-K., et al., *Recent advances in sensing plant diseases for precision crop protection*. European Journal of Plant Pathology, 2012. **133**(1): p. 197-209.
58. Thenkabail, P.S., J.G. Lyon, and A. Huete, *Hyperspectral remote sensing of vegetation and agricultural crops: knowledge gain and knowledge gap after 40 years of research*, in *Hyperspectral remote sensing of vegetation*. 2016, CRC Press. p. 698-763.
59. Shearer, S.A. and R. Holmes, *Plant identification using color co-occurrence matrices*. Transactions of the ASAE, 1990. **33**(6): p. 1237-1244.
60. Tillett, N., et al., *Mechanical within-row weed control for transplanted crops using computer vision*. Biosystems Engineering, 2008. **99**(2): p. 171-178.
61. Chen, Y.-R., K. Chao, and M.S. Kim, *Machine vision technology for agricultural applications*. Computers and electronics in Agriculture, 2002. **36**(2-3): p. 173-191.
62. Brodie, G., et al., *Microwave weed and soil treatment in agricultural systems*. AMPERE Newsletter (Association for Microwave Power in Europe for Research and Education), 2017(93).
63. Chui, M., et al., *Notes from the AI frontier: Insights from hundreds of use cases*. 2018, McKinsey Global Institute. Retrieved from McKinsey online database.
64. Annoni, A., Cesar, R.M., Anzai, Y., Hall, W., Hardman, L., van Harmelen, F., Heintz, F., Motta, E., De Heaver, M., Ten Holter, C., Keene, P., Ott, I., Perrault, R., De Prato, G., Sun, Z., Tan, T., Tang, C., Zhao, Z.,, *Artificial Intelligence: How knowledge is created, transferred, and used*. Elsevier AI Resource Center, 2018.
65. DEFRA, *The Future Farming and Environment Evidence Compendium*. UK Government Statistical Service 2018: p. 68.
66. AHDB, *Preparing for change: the characteristics of top performing farms*. UK Agriculture and Horticulture Development Board, 2018: p. 44.
67. Purdy, M. and P. Daugherty, *How AI boosts industry profits and innovation*. 2017, Accenture.
68. King, B. and K. Wong, *The 2017 CGIAR Inspire Challenge: Innovation strategies for digital agriculture*. 2017.
69. FAO, *Macro Statistics, value of agricultural production*. FAOSTAT, Food and Agriculture Organisation of the United Nations, 2019.
70. Laczkowski Kevin, P.A., Rajagopal Niranjana, Sandrone Paolo, *How OEMs can seize the high-tech future in agriculture and construction*. McKinsey Global Institute, 2018.
71. COPA, C., CEMA, Fertilizers Europe, CEETTAR, CEJA, ECPA, EFFAB, FEFAC, ESA, *EU Code of conduct on agricultural data sharing by contractual agreement*. 2018: p. 20.
72. Tilman, D., et al., *Agricultural sustainability and intensive production practices*. Nature, 2002. **418**(6898): p. 671.
73. Klerkx, L., B. Van Mierlo, and C. Leeuwis, *Evolution of systems approaches to agricultural innovation: concepts, analysis and interventions*, in *Farming Systems Research into the 21st century: The new dynamic*. 2012, Springer. p. 457-483.
74. MacMillan, T. and T.G. Benton, *Agriculture: Engage farmers in research*. Nature News, 2014. **509**(7498): p. 25.
75. Lasi, H., et al., *Industry 4.0*. Business & Information Systems Engineering, 2014. **6**(4): p. 239-242.
76. Vasisht, D., et al. *FarmBeats: An IoT Platform for Data-Driven Agriculture*. in *NSDI*. 2017.
77. Matthias, B., et al. *Safety of collaborative industrial robots: Certification possibilities for a collaborative assembly robot concept*. in *2011 IEEE International Symposium on Assembly and Manufacturing (ISAM)*. 2011. IEEE.

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RE: Conflict of Interest Declaration

Dear Sir or Madam,

As the corresponding author for the paper "The Challenges Posed by Global Broadacre Crops in Delivering Smart Agri-Robotic Solutions: A Fundamental Rethink is Required". We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author and which has been configured to accept email from bruce.grieve@manchester.ac.uk

Signed by all authors as follows:

Signature:  Date 14/04/19

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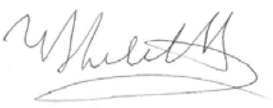
Signature:  Date 15/04/19

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Yours sincerely

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