UK Research and Innovation

AFN Network+

Briefing: AI - what are the risks and opportunities for reducing emissions in agri-food?

Based on an AFN Network+ webinar, held 13.12.24

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About the briefing & speakers

About this briefing:

This briefing is based on a webinar discussion with Andrew French, Paddy Tarbuck and James Strong, given to the AFN Network+ community on the 13th December 2024. It was written and collated by Nina Pullman, food systems writer for AFN, and edited by Jez Fredenburgh, AFN's knowledge exchange fellow; the transcript has been lightly edited to paraphrase in parts. You can also watch the webinar.

About the webinar topic:

Artificial Intelligence (AI) is fast opening up a world of new possibilities in multiple areas – and a lot of questions, too. For food and farming, a big question is whether and how it can help us reduce emissions faster, in what is a critical decade for tackling climate change.

Alongside this, AI also raises other issues for discussion, such as; are there risks of using AI in agriculture, and might there be unintended consequences and trade offs? It also begs the question – what needs more attention, resourcing and research to ensure we can make the most of AI while also guarding against any risks and negative outcomes?

In this webinar, our three speakers take us on a whistle stop tour of what AI might mean for crop and livestock production. AI is an emerging technology that is developing rapidly and may raise more questions than answers.

About Andrew French:

Andrew French is a professor of Computer Science at the University of Nottingham, where he leads the Computer Vision Lab. He has worked closely with plant scientists on a wide range of image-based data analysis challenges for nearly 20 years. Of course, today this means developing an array of AI-based approaches to image analysis of plants and crops. Andrew also leads the AI in the Biosciences community building network, along with a team of co-leads from around the UK.

About Paddy Tarbuck:

Paddy Tarbuck is Innovation Lead in Agri-Food Sustainability at UK Agri-Tech Centre, where he drives sustainability towards net zero and biodiversity goals by fostering collaboration across academia, industry, and the third sector. With a BA in Politics and an MA in Climate Change, his career spans civil society, finance, trade associations, and the UN. Before joining the UKATC, he co-founded two seaweed ventures in Southeast Asia, embedding sustainability principles and securing funding. Paddy's expertise includes carbon and nature markets, regenerative farming, and climate finance. He is passionate about addressing the climate and ecological emergency by focusing on evidence-based, holistic solutions for sustainable agri-food systems and land use.

About James Strong:

James Strong is a Research Software Engineer at Aberystwyth University, currently working on the Miscanthus AI Net Zero project, where his role involves investigating how AI models can support plant breeders in selection and breeding processes. His research background lies in bio-inspired AI, exploring how biological systems can inspire innovative approaches to navigation and problem-solving.

Summary of key points

Andrew French outlines the risks and opportunities of using AI, as well as explaining what the term AI encompasses.

AI is an umbrella term for a broad range of models and techniques

- AI ranges from data analysis to machine learning, which means that rather than writing lines of code to do very specific tasks, an algorithm allows a computer to learn from data.
- The definition of AI is broad but it is all about turning data into more meaningful and useful information.
- AI can be applied across different data sets, including numerical, text or images. Chat GPT, for example, is a large language model and a form of generative AI, which means it generates text out of data.
- AI is very good at analysing large data sets and seeing patterns that humans wouldn't see. However, creating AI and training an algorithm still relies on humans to gather the initial data and label it, so that the computer knows what it's looking for.

The technology can help detect disease in crops or map root systems

- An example of using AI in agriculture is identifying wheat heads in a complex image with varying lighting, shadows and background crops. From identifying an image and labelling it, AI can then map out a region that is affected by disease to extremely high levels of detail.
- For breeders or research projects, AI can create very detailed categorisation, for example a root system, including root lengths or angles of emergence.

There is a skills barrier as AI continues to develop rapidly

- Every year there are more advances in even more efficient research systems and software apps. As with any new technology, there's an understanding and training barrier alongside that growth.
- The skills are not just about developing it as a coder, but understanding where AI can be used, where it can't, or where one model is more suitable than another.
- Data collection is another barrier, especially in specialised areas like livestock. A huge amount of data is necessary to ensure algorithms and data sets work in other field settings.

James Strong explains the method and findings from the Miscanthus AI Net Zero joint project between Aberystwyth, Lincoln and Southampton Universities.

Miscanthus has robust growth and strips carbon out of the atmosphere

- The aim of the project is to find out how AI can improve predictive modelling to accelerate the miscanthus breeding cycle. Historically, breeders make crosses, take measurements, and update their models.
- Instead, the AI project aims to combine genotypic and phenotypic data using random forests for feature selection and modelling to predict yields, but also other elements like cellulose and lignin.

Testing and deploying AI has limited success with incomplete data

- The project faced challenges with overfitting data and generalisability, but achieved higher prediction accuracy than previous methods.
- A key finding was that care needs to be taken when testing, deploying and reporting on AI models to make sure they are accurately identifying, reading and applying data.

Paddy Tarbuck explains his role at the UK Agri Tech Centre in bridging the gap between AI innovation and adoption, and looks at the social costs of implementation.

Livestock is still a major greenhouse gas emitter despite successful reductions in emission intensity

- The agricultural sector accounts for an estimated 12% of total greenhouse gas emissions in the UK, including 71% of the UK's nitrous oxide emissions and 49% of its methane emissions (mostly from ruminants). [Please note these are the latest government figures, which were released post-presentation, and so may be different to those in the transcript below].
- New reports are helping to shift the narrative and look at how livestock, particularly grazing animals, can be used in the right farming systems to maximise resource use, circularity and carbon sequestration.
- According to a recent government study, 62% of farmers consider greenhouse gas emissions important for farm business decisions.
- The emissions intensity from the livestock sector has decreased, through efficiencies, innovation, circularity, management and precision farming, but it's not moving the dial fast enough.
- There is further potential for reductions and removals, and AI is one enabling technologies to help support that.

AI is already in practice in animal health and welfare on farms

- Animal health and welfare is one of the most readily applied areas for AI on farms, but the technology is also helping to monitor movement patterns, behaviour, temperature and productivity in real time.
- An example of AI for animal health diagnostics is Hoof Count (www.hoofcount.com), where an image of the hoof is taken and the AI imaging tool detects anomalies. The large language model supports that by explaining possible causes for lesions, suggesting interventions and connecting farmers to a vet.
- A project with poultry farms is detecting and using sound to indicate poor welfare and broiler systems.

Simplifying the data burden for farmers is a possible benefit of AI

- There is already a data overload at the farm level. AI systems should help simplify, rather than add to this.
- Data provided by AI should help farmers make decisions, not disempower them.
- An example of a potential evidence-based solution supported by AI could be soil and water management, to reduce resource consumption, increase efficiency, reduce runoff risks and decrease emissions.
- AI could also help improve feed efficiency by analysing each animal's nutritional needs, working alongside automated feeding systems to dispense customised feed portions.

Risks include safeguarding data and high energy demands of AI tech

- Data sharing and ownership needs to be safeguarded as AI begins wider deployment.

- AI processing systems have a huge energy demand, which prompts wider ethical questions around matching AI with the right problems rather than looking at it as a silver bullet solution.
- Job security, in particular for the rural communities that represent the majority of the farming sector, are at risk of impact or displacement from AI taking over farm-based tasks, education and training.
- AI models are only as good as the data fed into them. Data that is biased or incomplete means that the model may not be accurate.

Ethical concerns around animal welfare, access and cultural identities

- A key ethical question and research gap is what would farmers do if AI provides insights that prioritise efficiency over animal welfare.
- The economic viability and scalability of AI limits adoption for all farms. Small farms might not have the risk capital available to access AI technology.
- AI models are subjective in a number of ways, so upskilling sustainability professionals and social scientists to make sure that different worldviews are represented within those models is important. Some AI models are presented as black and white, without social components built in.

Key points from the audience Q&A

AI could optimise SFI by collectivising data around ecosystem outcomes

- Using AI to optimise the SFI payments could mean collectivising outcomes. For example, monitoring what a cover crop means for biodiversity and carbon.
- There's an opportunity to get a more standardised, effective answer on how SFI is additional to some of the ecosystem service outcomes.

Quantum computing could turbocharge AI advances

- In theory, the advances in quantum computing will provide more computer power and that is something that AI is very reliant on.

Using AI generates emissions but could also help reduce emissions in farming

- There's a high energy demand on the application of AI but if that avoids emissions at a farm level, then perhaps there's a positive trade off. This could be compared to the energy demand of cryptocurrency, which uses high amounts of energy without helping to reduce emissions elsewhere.
- Training an AI model is where a lot of the energy in computing is used. Using it via a smartphone or mobile device generally uses less energy and where development is focused for farming.

Job displacement in rural communities is a real-world impact of AI

- AI has a consequential social impact that needs to be evaluated as part of the transition to data-driven decision making.
- Farmers make decisions based on intergenerational knowledge, culture and ties with the land that are stripped away through data-driven support models. Integrating that local, indigenous knowledge into AI models is a gap.
- There is a role for government in promoting ethical AI use and supporting research and adoption, with a focus on collaboration and upskilling.

Webinar transcript

Speakers: Andrew French (AF), James Strong (JS), Paddy Tarbuck (PT). Chair: Jez Fredenburgh (JF).

The speakers discuss definitions, applications and impacts of AI, in relation to farming and net zero targets.

AI offers agriculture opportunities but is also raising questions about the risks

JF: Today's topic, Artificial Intelligence or AI, is fast opening up a world of new possibilities in multiple areas, and a lot of questions too, along the way. So for food and farming a big question is whether and how it can help us reduce emissions faster in what is a critical decade for tackling climate change. Alongside this, though, of course, it's also raising a lot of questions and a lot of issues for discussion, such as are there risks of using AI in agriculture? Might there be any unintended consequences, and what also might be the trade offs? It also begs the question; what needs more information resourcing and research to ensure that we can make the most of AI and guard against any risks and negative outcomes. So I think today we might end up raising more questions than we answer, which I think is absolutely fine.

AI is still very much an emerging technology. It's changing rapidly, and we're trying to keep up with it. So let's go into this webinar with a sense of inquiry, and not worry if we don't end up answering all the questions. But I think it's really important to be raising all these questions at the moment. So what we're going to do today is, we've got three speakers. So Andrew is going to kick us off in a minute looking at more general questions around risks and opportunities of using AI, and particularly with crops. And he's going to give us a really good introduction to AI, get us all up to the same understanding. Then James is going to come in and offer us a case study, so a project that he's been working on using AI machine learning related to Miscanthus as a by-crop.

And then Paddy will come in and again look at risks and opportunities research gaps,but looking more at livestock and net zero. So Andrew French is a Professor of Computer Science at the University of Nottingham, where he leads the computer vision lab. He has worked closely with plant scientists on a wide range of image-based data analysis challenges for nearly 20 years. This means today developing an array of AI-based approaches to image analysis of plants and crops. Andrew also leads the AI in biosciences Community Building Network, along with a team of CO leads from around the UK.

AI can mean anything from data analysis to machine learning to generate text or images

AF: As Jez said, I'm a computer scientist, so I'm not a core livestock or crop person. I'm a developer of computer vision techniques, really. So I've been doing that for about 20 years or so, and for most of that, we've been working with plants and crops in different forms. So I definitely have some knowledge of the crop possibilities of AI. And what I wanted to do today was really just to provide a pretty general introduction, as Jez said, just to set everything else in context and get you thinking about some potential, applications and some things that we need to think about when we're working with AI.

So in the news this week, I was reading that Amazon has released the top questions people ask Alexa in 2024 and this was up there. So people don't know what AI is, and in general what it means when we're talking about artificial intelligence. I would say AI is a pretty subjective term, so people have got different ideas about what it means. When you work in different areas, you use it in different ways. And I think my interpretation of it is definitely coming from a computer science background, and it's also pretty broad. So for me, when we're talking about AI, we mean learning from data. So that's not actually every single AI technique. But these days, most of the ones that you read about, most of the cutting edge ones that people are using, is a form of what we call machine learning, which means that rather than very prescriptively writing lines of code to do very specific tasks, instead we provide a framework that allows a computer an algorithm to learn from data. What it's learning from that data is pattern recognition.

So what AI is really good at is looking for potentially quite complex patterns in data, so seeing things that perhaps we can't see as humans in really, really large data sets. And it does this via a series of different algorithms and approaches. So as I said, AI is a as an umbrella term, and there are loads of different models or algorithms, tools, if you like, for getting this information out of our data. So there isn't one tool in the toolbox, if you like. There's a whole collection of different computational approaches that we can use that all fall under the umbrella term of AI. So it's very broad and covers a variety of techniques and models, and some of these come from statistics, machine learning, computer science and maths, but they're all to do with working with data and turning that data into much more meaningful and useful information.

Faster computers and better software have turbocharged AI in the last few years

A lot of AI that we talk about today, those tools are things like deep convolutional networks, CNNs, large language models. So CNNs are a way of looking at, in particular, image data. So I work in developing techniques that work with images, but you can apply AI across all kinds of different data sets. So numerical data, text data, image data, data to a computer is data, right, but there are different ways of thinking about it. So images in particular have got certain properties that perhaps a list of numbers don't have. So some of these approaches are really good at working with images and deep convolutional networks is one example of an algorithm that will do that if we're talking about text.

Obviously we've got large language models, things like chat GPT, which are really ecent and have just come out in the last couple of years, really, into the public domain. Large language models are a form of what we call generative AI generative, meaning it generates something. So text in the form of Chat GPT, but you can get image generation approaches as well. But that's not to say that's all there is. There's a host of other techniques and other kinds of models that are coming along quite rapidly, and allowing us to analyse data in different ways. And all of these approaches build on probably 50 years of development, and different kinds of development in computing and maths and those backgrounds.

But I think what's changed recently, and what's really allowed AI to become mainstream, if you like, is a couple of things. One is software related, so we've got better programmes that we can use to develop AI, and the second one is computers. So we've got a lot more computer power now, which is what a lot of these models will use. I talk about pattern recognition and interpreting things in data, and so one really general way that a lot of these models work is they turn the raw numbers or pixel values and images into more useful intermediate information. So here we've got an image of a leaf, and we're turning it into highlighting the edges. So we're highlighting using an algorithm where the edges around the leaf are. Now any AI system will do things like this. It will turn an image into more useful features, right? And this is what our eyes do as well, right? And our brain, we pick out information like boundaries around objects and patches of texture and things like that.

So a lot of these AI approaches will again, look for these patterns that represent higher level details about the image, edges, lines and even all the way up to concepts and things like that. And this allows us to solve pretty complicated problems. So here's an example of a wheat data set which is available online, and we're trying to categorise or locate where the wheat heads are. In the image, you can see it's quite challenging thing to do. I think one of the dramatic things about AI is even, even five, certainly 10 years ago, identifying where the heads of wheat were in an image like that, it's really, really hard. You've got a lot of complexity in these agricultural images. You've got challenging lighting and shadows. You've got things like weeds in the background, stuff like that. It's really, really hard to do it. What AI allows us to do is this really complicated insight into these really challenging data sets. And that works for images, but also, as I say, numerical and other kinds of data as well.

In practice, AI models still require human collection and input of data to train the models

So what AI is giving us, whatever the tool is, is more insight into really large data sets. So how does this work in practice? Just to overview how it would work if you were developing AI techniques, as I say, you have to build on data sets. So we have to collect a lot of data and label it often by hand. So in order to train these algorithms, we need annotations and labels collected by experts, perhaps via bespoke software tools, so that the computer knows what it's looking for in the images. In this case, there's normally some coding involved, so we need to develop algorithms which are going to build these models, or networks, as they're sometimes called, that are actually going to do the work of doing the pattern recognition, doing the extracting of features from images and things like that.

And once we've done some coding, we need to train the models. So that means that the models need to look at all the data that you've captured. So looking at all the images that have been labelled and trying to learn what it means to mark out regions of these images or detect certain bits of the image. So that training process can take a long time. It's quite computer intensive. So these days, we have a lot of dedicated hardware that allows us to do that training which is the most computationally intensive part of AI. Of course, once you've got a network, you need to test it. You can't just assume it's working, so we test them on dedicated test data sets that haven't been seen during this training process, so we can evaluate how well it would work in the real world.

Mapping agricultural images can help detect crop disease or monitor root systems

And often, then we want to build these algorithms into a tool that we can then deploy for people to use. So the idea of these networks is they go from pixel information, where we've got quite raw and noisy colour information in an image, along to, in this case, a classification problem. Classification problems, where we're applying a label to an image. Is it a leaf? Is it an ear? Is it something else? So we're teaching an algorithm to apply a text label. Other tasks that AI can do is mapping out regions of images. So again, here we're still with the wheat ear example. But actually we could be marking out regions of disease or something like that. And when you've got a region, you can measure things about the region. So you could measure the area or the width or the length, or things like that.

So you can do much more fine grained analysis as well. So perhaps more of interest to breeders and growers or research projects is you can get really detailed categorisation of, in this case, a root system. And so we're able to get out a lot of measures here about the length of all the different roots, the angles of emergence and things like that, again, all via an AI algorithm. And these things work really well. So another task you might want to do is to pinpoint things on an image via a heat map, so marking particular regions. And in this case, we've trained a system to mark the tip of the wheat here. And actually, what the AI said was, well, actually I think there's two tips of ears here. There's one there and there's one there. And actually, if you look really closely at the image there's actually two ears on top of each other. And again, 10 years ago, that would be a really challenging problem for us to solve, but here we've got AI systems that are able to look for those patterns in the data and really do quite impressive things like that. So you could use a system like this, for example, to identify maybe disease or pests or any feature that you want to train it to recognise.

So a few things to think about, some perhaps opportunities around AI in agriculture and crops in particular. Perhaps we've seen through these simple examples how you can get quite a lot of insight into really complicated to interpret images and data. One thing that AI will allow us to do, as will many other algorithms that you can develop in computer science, but perhaps the end goal is automation. So perhaps using robotics to capture data or sensors mounted on UAVs or tractors or whatever it is that we're doing, we can collect a lot of image data or other sensor data, the challenge is then analysing it. And a lot of these AI systems, because they can work so well at detecting these really complicated patterns, we can automate some of that process, and that gives us a way to monitor in a detailed way, things like fields or glass houses.

AI is still developing rapidly and training and data collection will need to keep pace

I think another really big opportunity of AI is just how fast it's developing. So, you know, every year there's more and more advances, more things that we can try and use to try and build more efficient research systems and software apps that can help us. Obviously, it comes with some challenges, as with any new technology, there's an understanding and training barrier. So not just in terms of developing it, you really need to be a coder, but even using the tools, you need to understand where they can be used, where they can't, where one model might be suitable versus another model. So there's definitely a training element to this, and a feeling that we need to, we need to understand as a community what AI is and what it can do for us and what it can't.

I've mentioned data. We need a lot of data. We need a lot of labelled data to make these things work. And that obviously comes as a barrier collecting these data sets, especially in quite specialised areas. You might not be able to find any images for one particular crop in a particular situation. So if you want to build a system, you might have to collect your own data to do that, and how well a model that you've built will work on another field, another farm, another data set is an open question, and something that we need to test when we're developing this software. Some of the algorithmic approaches are getting better at being generalisable. There's certain tricks we can use to help generalise data sets into other domains. But we want to build models that work across the biggest set of data that we can.

Equality of access to AI. So that means everything I've talked about really, the training, the understanding, but also computers. So I said it takes quite a lot of computers to train these things, and certainly some of the really big, especially generative, AI models that are coming out. It's not even within the realm of universities to train these things, right? So some of the really big models, the data sets are just so big and the model is so powerful, it's really down to real specialists like industry to train models, and then we can adapt them and reuse them in different ways. So in this context, I'm also part of the AI and Biosciences Network, and part of our aim is to try and help with some of these things. So to get us thinking about training and raising awareness and events, thinking about how we can use AI in different situations, of which crops, livestock and agriculture, are definitely some areas that we're interested in.

Although we're much broader than that, and go across the whole remit of BBSRC. So we've been going for about a year, and we've got a team from around the UK, and we're putting together events, talking to other networks at the moment, trying to do things like this and raise awareness of AI and get people more involved in the community when they might not have otherwise been. So I'm probably out of time, so I'll leave it there. More than happy to answer any other questions about AI in biosciences or AI at the end. So with that, I think I'll wrap up, and I'll pass over to James.

AI models can support plant breeders in selecting and breeding processes

JF: Thanks, Andrew. That was really good. Okay, we will move on to James. James is a research software engineer at Aberystwyth University, currently working on the Miscanthus AI Net Zero project, where his role involves investigating how AI models can support plant breeders in selecting and breeding processes. His research background lies in bio-inspired AI exploring how biological systems can inspire innovative approaches to navigation and problem solving.

JS: So I wanted to speak to you today about the project that we're working on, which is a joint project in Aberystwyth, Lincoln and Southampton Universities. It's funded by the EPSRC, and we're looking basically at how we can improve biofield features in Miscanthus. Our work stream is specifically looking at how AI can help with that. And today I was just going to speak to you about our implementation as a case study to show how AI can help. I'm going to speak to you about our specific aims, give you some background and context so you can appreciate what it is we're trying to do and how we're trying to achieve it. Spend a little bit of time on some light implementation of how we've gone about it, and then speak to you about the success and the problems that we've had with our results.

The Miscanthus AI Net Zero Project uses genotypic and phenotypic data

So a very specific research aim is basically looking at how AI can improve the predictive modelling and use that to accelerate the Miscanthus breeding cycle. So historically, when breeders are looking at crops, they're going to make crosses, they're going to take measurements, and they're going to update their models. And what we're hoping is that AI can step in and look at using and leveraging genotypic and phenotypic data to speed up this process. Our particular workstream is looking at combining snips and nurse data using random forests for feature selection and modelling, and we're able, or hopefully able, to predict yields, but also other elements like cellulose and lignin.

We're working on a data set that's called the two TT data set. It was 136 genomes that were planted and collected at Aberystwyth University. And the reason that we're interested in Miscanthus is because it has a large biomass. It's got robust growth, so it'll grow in maybe not ideal soil conditions for other plants, and it's a C4 grass, so it strips carbon out of the atmosphere. And then I'll quickly go through the two different sets that we're dealing with. So we've got nurse data, which is near infrared spectroscopy data. And what we're basically doing is we're using near infrared light to quantify the composition of plant material. So we have an example of five genomes, the data you'd get out of them using nurse. And that's basically like a waveform.

And we're really interested in nurse because it's non destructive, so we don't have to pull plants out of the grounds to get those readings, and it's relatively cheap and easy to collect, comparing it to other genotypic data. So we're currently looking at attaching nurse cameras to drones that can fly over fields and get the collection of data that we need. And then quickly just to cover off the genomic data, what we're basically looking at is variations at single positions along the DNA sequence. So this is a tiny little example of the data set. The whole data set is 50,000 features, and basically these markers are used to identify the differences genetically between each plant. So we combine these two data and the genomic data is the more classical way of looking at these problems. So I did mention previous results, and people have already looked at this dataset, and they used ridge regression to see if they can predict dry matters, dry matter, which is our yield cellulose and lignin levels.

And so you might be thinking, if the nurse is so good at predicting, why do we want to combine? And the reason we want to combine is because we know that the genomic data is heritable and the nurse data is environmentally impacted by local features where it's grown. So we want to try and leverage those two predictive abilities and ensure that we're not just getting good at that, we're predicting heritable traits in plants, basically. So the implementation we've been using is random forest. The project was interested in using random forests because they have a degree of human readability, which I don't want to get into a massive debate about right now, but they have this element of human readability, and they've been shown to previously be successful in dealing with noisy and biological data.

But really simply, the way that this random forest is working is we create a decision tree based on the information we have about the objects that we're trying to classify. And we make hundreds of these small trees on subsets of the data, and then we combine them into what we're naming a random forest. And we take the selection of decisions that each tree makes and come up with a final decision on a particular object. So it gives us a complex way of classifying, and the classification is the more standard approach. We're actually using random forests for regression here, but the same approach applies.

Testing and deploying AI techniques can have limited generalisability if data is incomplete

So the reason we're using something like this is because the data sets are quite challenging. The samples are quite highly correlated. The target variable distribution is problematic in the sense that we have very few examples from the lower range and the higher ranges of yield for this example, and we have a large number of features, but with a small number of samples. So the nurse data has over 1000 features, the snips, we're talking 50,000 features, and we end up with a problem that you might have, or a definition for this problem that you might have heard before, which is big, P, little n. So we have a lot of predictors, and not a huge amount of things to predict which can be really problematic for AI and machine learning.

So the normal approach here would be to try and reduce the dimensionality, to remove the number of features, or squash the number of features. And those typical approaches weren't successful with this data set. So what we decided to do was use a method called iterative feature reduction. So we used the way that the random forest creates its feature importance to rank the overall features of the data set and start to iteratively remove features that weren't contributing to predictive results, and we would expect to see the predictive ability increase until the performance plateaus, and then we're relatively confident that we've reduced features down to ones that are important for the targets that we're trying to predict. And this was relatively successful for our nurse data, we saw a higher prediction accuracy than that was previously achieved in the ridge regression. But one of the challenges, or one of the problems with using this technique is that you can lead to a problem called overfitting, where what we're doing is not very generalisable to new data.

We have a small amount of data points that we're trying to prove, and we've overfitted, and we're very good at predicting those, but not very good at predicting new ones. So we did some permutation testing, and we held back some data to verify that these results were legitimate, and although we saw a slight decrease for new unseen data, overall, the results still held. However, when we moved this process across to the snip data, we found that the same processes just didn't hold up. The additional data size based on the input features meant that we weren't able to achieve the same level of prediction that we would have been able to achieve with a nurse, and that we were overfitting to data means that our results aren't legitimate. So we saw that the two techniques worked really well with one data set and weren't applicable for another data set. So one of the conclusions that I'd like you to take from this is that we need to be really careful with how we deploy, report and test models.

Land use and emissions from livestock is still a key climate issue despite sustainability efforts

JF: Thank you. James. Paddy Tarbuck is Innovation Lead in Agri-Food Sustainability at the UK Agri Tech Centre, where he drives sustainability towards net zero and biodiversity goals through collaboration across academia, industry and the third sector. His career spans civil society, finance, trade associations and the UN and Paddy's expertise includes carbon and nature markets, regenerative farming and climate finance.

PT: It's been really interesting to see James and Andrew's real world applications of AI, particularly Miscanthus there. So don't expect that from my presentation. I'm certainly not an AI expert. I'm coming at this from more of a livestock and net zero perspective as more of an interdisciplinary sustainability professional, so climate and social science looking at the social costs of implementation. Some of you might be familiar with the UK Agri Tech Centre, at least some of our legacy centres. We recently merged earlier in the year to form the largest agri tech organisation in the UK, really trying to drive strong across sector collaboration and creating a larger ecosystem where we work at that intersection between academia, industry and government.

So we're really trying to bridge the gap and drive innovation and adoption throughout the agri tech sector. We've got a range of capabilities across the UK, ranging from respiratory chambers for measuring methane emissions all the way through to our stock bridge and vertical farming facilities, so we can connect you with those capabilities as well. So AI net zero, some of the risks and opportunities. So quick sort of framing of the problem, and we're probably all very familiar with the impact and the well established impact of the livestock sector on environmental impacts. It contributes 10% of total greenhouse gas emissions in the UK, of which 71% of nitrous oxide emissions and 49% of all methane emissions within that ruminants, through internal fermentation, represent over half of UK methane emissions. So pretty sizable and we've had reports, such as FAO's Livestock's Long Shadow, looking at the impact beyond that.

But now we're shifting the narrative a little bit from this long shadow to how livestock, particularly grazing animals, can be used in the right farming systems to maximise resource use, circularity and carbon sequestration. And we've seen that with farmers as well, where 62% farmers in the recent government study consider greenhouse gas emissions important for farm business decisions. So it's really empowering to see that, and the emissions intensities from the livestock sector on the whole have decreased, and we've done that largely through efficiencies, innovation, circularity, renewal, management, precision farming, all great tools, but not moving the dial fast enough.

So we really need to accelerate that and we're seeing this through some of the recent studies coming out looking at the role of large animals in climate change mitigation, the potential soil carbon sequestration potential of that. Just a note here that 70% of land in the UK is farmland, and there is further potential there for reductions and removals, and we need the right enabling technologies to support that. One of those enabling technologies is AI.

Animal health and welfare is where AI is already being applied on farms

I should start by saying, when you mentioned AI to a livestock farmer or a livestock sector, it's probably further down the pecking order than artificial insemination and avian influenza.

So worth mentioning that we are talking about artificial intelligence when we speak to livestock farmers. And Andrew's covered this off pretty well, but effectively we're talking about large data systems and processing of those data systems to make predictions, prove efficiency, productivity and sustainability in the sector. And it's really that machine learning component that I'm probably going to focus a little bit more on here. But some of those large language models and advanced AI tools really summarising all of the wealth of data on farm and packaging. To understand trends and patterns and provide insights direct to farmers throughout the supply chain as well. So a really useful tool, and we're still figuring out ways to do that.

There is a real data overload. I guess the bigger picture here is that there is a data overload at the farm level, and it's a burden for farmers, so we need to recognise that, and we need to have the right support and tools to support advisors, farmers and everyone throughout the supply chain. So we can simplify this through AI. The application of AI in farming is pretty well applied. We saw the presentation just then from James, but it is already in practice to manage the livestock health. It's one of the indirect or direct forms of climate action that we can see, and we're involved in a project just to highlight this with hoof count. It's quite simple, I guess. An image is taken, photos taken of a hoof, the AI imaging tool detects anomalies. So in this case, the lesion and the large language model will support that by explaining possible causes for lesions, suggesting interventions and connecting farmers to a vet, for instance.

Bespoke nutrition and water management are other examples where AI is being deployed

In terms of the opportunities and the risks, the big picture is that all solutions are here to support farmers and empower data-driven decision making. So we don't want to take that away from farmers. We want to support them through evidence-based solutions. One of those is soil and water management. So monitoring soil and water usage helps farmers reduce resource consumption, increase efficiency, reduce runoff risks and decrease emissions. So you've got the example, potentially of irrigation systems and a crop system, how that can be used and utilised by AI precision farming. I guess the one that most people will go to, is, how do we process complex amounts of data to be able to deliver the right insights and optimise precision farming?

Feed efficiency is quite an interesting one, not to displace any nutritionists on the call, but looking at automated feeders so you can analyse each animal's nutritional needs, so you can work alongside feed troughs and some of the automated feeding systems there to potentially dispense customised feed portions. And that's obviously particularly for the monogastric sector, a massive proportion of their carbon footprint. So a real opportunity there as well. Animal health and welfare is probably one of the most readily applied in the livestock sector in terms of AI, but looking at monitoring health, movement patterns, feeling behaviour, temperature and productivity in real time. And as we saw, early detection of diseases or stress, or heat stress, for instance, which empower and enable preventative actions.

I'm aware of a project with poultry farms, looking at detecting sound, and using sound to indicate poor welfare and broiler systems. Breeding mentioned earlier in terms of the crop would be identifying genetic traits and better feed to product ratios so it contributes along, so sustainability there. Carbon footprinting is particularly interesting, I guess, and we've covered this in previous AFN webinars, but looking at collectivising and harmonising some of those methodologies and how we can build in some of the accurate emissions tracking at the farm level, rather than some of the maybe higher IPCC level global figures to represent data in different format. And then, of course, policy design supports evidence-based regulations and incentives. So we can look at how SFI payments, for instance, are empowering farmers to create sort of sustainable farm systems.

Ethical concerns around AI include data ownership, energy use and cultural knowledge being replaced with machine learning

But within that, I guess we also have some of the some of the risks, some of which have been highlighted already. But data sharing ownership - safeguarding the ownership and value of that data, we need to make sure that that's safeguarded. I think the one perhaps to focus on here is the energy costs when we talk about net zero.

There is, of course, a huge amount of data running through some of these systems, and the processing systems and that creates a huge energy demand. We're already outstripping that energy demand. So there's a wider ethical question of, is this sustainable as a solution, and matching AI with the right solutions, rather than looking at it as a silver bullet solution. We don't want to create more work and more energy demand where we don't need to. Job security, in particular for the rural communities that represent the majority of the farming sector and the agricultural sector. What's the impact and the job loss and the job displacement, potentially, from AI and doing some of those farm-based tasks, education and training.

So I think the crucial thing with AI is, yes, it's a complex data processing system and all the different tools we have available there, but we are still reliant on human interventions and training to develop those models as well as ensure effective data collection and monitoring. Leading onto the data bias piece, that it's only as good as the data fed into them. Data that is biased or incomplete means that AI is not as accurate. So we need to keep that in mind as well. And then the ethical considerations, which probably leads to Q and A a little bit.

But, for instance, what if AI provides insights that prioritise efficiency over animal welfare? This is a key question and where do we place ourselves and position ourselves when that is presented, in terms of the research gaps? We spoke about it there, but the limited availability of high quality data, and particularly here, livestock emissions data by breed, by feed, there is more evidence and practice needed. There is also the economic viability and scalability, which limits adoption for all farms. We want to represent and try and drive adoption on smallholder farms, as well as some of the larger farms - they might not have the risk capital available to be able to get this on farm. There's also inconsistencies and gaps in quantifying and verifying long term impact of AI interventions on greenhouse gas reductions.

And of course, it would be remiss of me to not mention the integration of local knowledge and diverse data streams into models. So for instance, for biodiversity, how do we look at bio-acoustics alongside remote sensing, and how do we integrate that with what the farmer sees? In terms of that local knowledge, isn't that that real cultural knowledge? There's also requirement for us to work cross sector here. So while AI might be a little bit less down the line in terms of application in the agriculture sector, we might see a huge amount of financial sector. So there's opportunities to cross sector collaborate, and it was mentioned before in terms of building the models and the computer science expertise related to that.

But the models that we build are subjective in a number of ways, so we need to make sure we're upskilling sustainability professionals and upskilling social scientists to make sure that that data is represented and that worldview is represented within some of those models. You see it quite a lot in terms of how some of those models are presented in a quite black and white format, perhaps without a view of how social components are built in. And then beyond Net Zero is how can AI support some of the biodiversity and nature targets, and we're seeing that quite readily as well. Just a quick plug, I guess, on the UK Agri Tech Centre. We do support that innovation. We support through funding support, bid writing, project delivery, and we do have a commercial farm network as well where we're utilising some of the AI machine learning components within that.

Questions from the audience

JF: Could you elaborate on the opportunity to use AI to optimise SFI?

PT: You're punching data in, so you're looking at some of the attributional data. What are the farm practices that are being incentivised through SSIs? Take, for instance, the cover crop, and then monitoring what that means for biodiversity, what that means for carbon, what that means for all these different things. If you ask us to try and collectivise all of those different data points, it's very difficult, but if we build a model around that, and probably through machine learning system, then perhaps there's an opportunity for us to get a quicker answer and a more standardised, effective answer on on how SFI is additional to some of these ecosystem service outcomes.

JF: At the recent Agri Tech e-conference, Dr Elliot Grant identified farm business model optimisation as a key opportunity for the use of AI in the future. How can farmers make the most of AI in their businesses without feeling overloaded?

AF: I can talk a bit about how AI can be used in optimising things. So it's a method by which you might be able to learn what parameters of a model can be used to improve outputs or efficiencies or things like that, just as any other computational tool can be. So the way I would see it used in the future, is, I would think it would be built into existing systems, existing workflows, much like we're getting AI built into things at the moment to help us do tasks. I think that will happen more and more, either overtly or behind the scenes, whatever systems are used to try and help optimise or plan efficiencies and things like that. We could use these as a tool to try and do that.

JF: Considering Google's recent developments in quantum computing, could you elaborate on the potential synergies between quantum computing and AI? How might these technologies complement each other in practical applications? Can you also explain the term quantum computing?

JS: In theory, the advances that we'd see in quantum computing are going to give us more computer power. If you're looking at how we compute now, we are basically making decisions in zeros and ones. So we're able to say if something is on or off. And quantum computing very simply, while overly simplified, is giving us more options than that. So it means that we can compute things at a higher rate. It's probably slightly outside of the context for this webinar, but the upshot of quantum computing for AI would be that you have more computer power, and that is something that the AI is very reliant on. All of these machine learning models, at their roots, are seeing a lot of success at the moment because of the increase in computer power. So things that were theorised 15, 20 years ago are now very doable because of the increase in that. So I think we would expect to see the increase, or successful quantum computing, give us a huge, huge extra amount of resource for AI.

AF: I would say that I think the advances that have been made are very theoretical, is my understanding. So we're definitely not at the point where there's going to be a quantum computing like immediately on the on the horizon, right? So it's a tool to think about for the future. And like James said, it has the potential to just add vast amounts of computer power. We can do a lot more calculations, but yeah, definitely not there yet.

JF: Why is there a limited availability of high quality data on livestock emissions?And what can the research community do to increase that availability of data that is freely available to all?

JS: What I mentioned by limited availability of high quality data, is you often see, particularly in the livestock sector, livestock types presented in a certain way. Sowe've got a range of emission factors for beef. You might see on Our World in Data, it presented in one format, maybe the higher range or the low range or the medium range. There's a study that recently came out on slurry storage, where we are potentially looking at a five-fold increase on what we have in our inventory, which means we're effectively under reporting the emissions associated with slurry. So there's a requirement for the research community to be able to create high quality data. And where I think that the gap potentially is, is communicating that high quality data down through to proxies and measurements. So there's a real burden on the carbon footprinting community and the carbon calculators to try and include that in recent versions, and for policy and regulation to ensure that we're updating inventory in the right formats.

JF: What are the challenges around equality of access to AI and how do we stop AI becoming the preserve of big agri business? What does this mean for small farmers and the power balance within the food system?

AF: I think it's important to recognise that not everyone has the same access to AI tools, either developing them or using them, and there's a variety of reasons for that. You just might not have access to the data that you require to build some of these models. And as I said, some of some of the real cutting edge models that are out there are so big that unless you have access to billions of images, you know, it's that scale, you're not going to be able to build them. Luckily we're at a position where we can reuse models in different ways and fine tune them into different domains. But there's definitely an availability of data, and even on a much smaller scale, you might not be set up to collect, annotate and train your own AI models. So that speaks to the training and expertise bit as well.

And then I know there was a question about the environmental impact of computers as well, and the balance of that with emissions. And that's totally fair. Normally, most of the computers are in AI is when you're training the models. So you can train it once, and then once you release it and deploy it to smartphones or whatever it is you're doing, those user models are much more lightweight, right? That's why we can run AI on our phone without having to have it connected to a big GPU system, right? Because the lighter weight, which means there's less computer, it's using less electricity. So access to computers is probably more of an issue for being able to build and train your own models, rather than using them in practice. And there's definitely been a line of research around what we call lightweight or mobile models, which are specifically built to do smaller, easier tasks and run really, really quickly on quite low computing.

So from my perspective, the equality of access is: do people have access to expertise, to the data and to the computer needed to build it? And if you can't build your own, what access do you have to other systems? In computer science, we're used to publishing and sharing models and sharing data. But if you're developing something commercially, you might not want to do that. So there's an academic route, and there's an industrial route to developing these things. Like anything else that gets developed, I think there'll be lots of different versions of things. So there'll be free versions, lower cost versions, and versions that only top end users can use. So I think it's a wide enough domain that there will be that spread, but it's definitely something that we need to think about.

JS: The only thing that I can maybe add is that one of the things that we are doing in Aberystwyth University to try and make sure that people have more access to training and expertise is we run summer schools that deal with AI, so different departments can come and learn tools. But it's not a simple or a straightforward process. It is a really difficult, complicated process to understand the problem in the first place and then define it and learn how you'd solve it. So pushing that out to, in this scenario, agriculture, I can see, could be really challenging. It's not a straightforward, easy fix.

JF: As AI uses so much energy, does it actually make sense to use that AI to reduce emissions?

PT: It's almost cyclical, isn't it? Because you're utilising your AI to potentially provide insights, and if you plug in the right LCA data within that, maybe there's an opportunity. Yes, there's a high energy demand on the application of AI and the computing costs Andrew mentioned, but if that avoids emissions at the front end, then perhaps there's a positive trade off there. Whereas if you look at perhaps the energy demand of something like a cryptocurrency, not to put them in a different bucket, but maybe not as useful in terms of application, in terms of reducing emissions on farm.

I think you've got to think about the whole system, haven't you? So we often talk about the computer cost of the training, because that's where a lot of the heavy lifting of the computer does exist. But then if, on the user side, actually the end model allows you to analyse things more efficiently, so either quicker or using less power, and gives you more insight into the problem. Then that's weighing against that initial investment in computing. So it's a difficult question for sure, but yeah, something we're definitely aware of in the field.

JF: What are the risks of using AI in terms of displacement of jobs? What could AI mean for rural jobs and cultural identity?

PT: Yeah, I did mention it to my nutritionist colleague, and she said don't tell everyone, because I'll be out of a job. But, yes it's a real world impact, and it's a consequential social impact that we need to evaluate as part of this transition to data-driven decision making. A lot of farmers don't make decisions based on data. They make decisions based on intergenerational knowledge, on culture, on ties with the land that are stripped away through data-driven support models. So it's how we integrate some of that local, Indigenous knowledges into these models, is where the gap is, at least from, from where I see.

JF: What is the role of government to ensure that AI is used in an ethical and effective way? And how can government help ensure that we make the most of this technology to reach net zero?

AF: Our AI and bio-sciences network, which is funded by BBSRC, is a starting point to try and cover very broadly all the things we've talked about. The training, the consideration of ethics, making people aware of what's available across quite a broad remit. So there's initiatives like that, which are getting up and running, but I think everyone, government included, is still trying to figure out how we can use this tool. It's literally advanced so fast in the last five years that the potential is really exciting. But I think everyone's trying to work out how this all balances out. So I think it's all in flux, but there's some encouraging signs coming along.

About the AFN Network+

The AFN Network+ (UKRI Agri-food for Net Zero Network+) is a unique network of 2,000+ academics, researchers, third sector organisations, policy makers, and agri-food industry professionals
from farmers to retailers.

Together, we are working to identify key research gaps that may be holding the UK food system back from transitioning towards a net zero UK by 2050, while also enhancing biodiversity and healthy ecosystems, nurturing livelihoods, supporting healthy consumer habits, and minimising the environmental impacts of overseas trade. Our findings will inform the next decade of research
investments in this area by UKRI (our funder and the UK research councils umbrella organisation).

Alongside our core research, we run in-person and online events, produce topical resources, and give out hundreds of thousands of pounds of funding a year.

The AFN Network+ is coordinated by the University of East Anglia, University of the West of England, University of York, and University of Leeds, and is a £5m, 3-year project funded by four research councils; the Biotechnology and Biological Sciences Research Council, Economic and Social Research Council, Engineering and Physical Sciences Research Council, and the Natural Environment Research Council.

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