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DISCOVERING THE VALUE OF HYPERSPECTRAL DATA FOR NEW ZEALAND AGRICULTURE

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Abstract

Agricultural science in New Zealand has traditionally been well served by the classical science model. The model has enabled specialist agricultural research teams to extrapolate results from small samples to produce a significant knowledge return on investment.

The advent of big data in agricultural science is producing a radical transformation in the way value is generated from scientific research. Hyperspectral imaging (HI) technology is used by Massey University's New Zealand Centre for Precision Agriculture (NZCPA) in a variety of applications. Unlike traditional agricultural research, HI produces superabundant, multi-layered data early in the science process.

This study explores how the NZCPA is adapting its science processes in order to capitalise on the possibilities generated by the new data economy. The paper documents the iterative, cyclical science process being developed by NZCPA in order to refine value from the superabundant, versatile data. An example of how this non-linear process and a multidisciplinary approach, including farmers and scientists from other fields, have been used to extract unplanned value from hyperspectral imaging data is provided. The study highlights the need for agricultural science to adapt in order to maximise the value refined from the new data economy.

Introduction

Precision agriculture (PA) is rapidly evolving. Capturing and responding to real world variability is a defining objective of PA. While PA development has been established on an extension of existing agricultural technologies, i.e. variable-rate technologies (VRTs) and vehicle guidance systems, it is quickly moving into the diagnostic space (McBratney, Whelan, Ancev, & Bouma, 2005). In particular, hyperspectral sensing and imaging (HSI) promises to genuinely assist decision-making whilst also helping to achieve 'traditional' agricultural applications such as fertiliser, seed and pesticide placement (Grafton & Yule, 2015; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012).

The New Zealand Centre for Precision Agriculture (NZCPA) is a Massey University-based science centre working on a major project; a Primary Growth Partnership called "*Pioneering* *to Precision.*" The researchers are using airborne hyperspectral imaging (HI) to predict nutrient concentrations in plant tissue to guide and inform fertiliser decision making (Grafton & Yule, 2015; MPI, 2014). HSI produces highly versatile, real-time multi-layered data in extraordinary volume, which then needs to be refined into useful knowledge (Pullanagari, Yule, King, Dalley, & Dynes, 2011).

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The challenge of 'big data' for Precision Agriculture

Data-rich technologies are likely to bring forth both opportunities and new challenges for science teams (Sonka & IFAMR, 2014). For example, big data tools such as the proximal ASD FieldSpec® Pro spectrometer and airborne AisaFenix (Specim, Finland) hyperspectral imager are replacing the expensive, laborious and time-consuming data-collection methods with the non-invasive, rapid collection of high volume, versatile data (ASDInc, 2016; Pullanagari et al., 2011); we call this the 'new data economy'. Like many other big data applications, the data-intensity of HSI technology is providing challenges with regard to processing and extraction of value (Pullanagari et al., 2012; Sonka & IFAMR, 2014; Von Bueren & Yule, 2013). Early observations of the science process at NZCPA indicate that the linear, classic science model is not ideal for refining value from big data PA technologies.

The old data economy

Agricultural science in New Zealand has traditionally been well served by the classical science model. The model has enabled specialist agricultural research teams to extrapolate results from small samples to produce a significant knowledge return on investment (Alrøe & Kristensen, 2002). There are lots of variations on the model, but they generally follow a linear, efficient approach to the science process (see Figure 1).

Agricultural scientists have usually had to work on constrained budgets and sampling has been time-consuming and expensive (Huberty, 2015). Research projects are carefully designed so the data is received late in the process after planning on how best to structure the research so that it produces statistically significant results. In this old paradigm, agricultural scientists have gained 'big knowledge' through generalisation. This has been efficient, but the trade-off from this approach is the potential for inaccuracy. In the old paradigm, the research problem is decided at the front end of the process, often with a hypothesis that is to be proved true or false.

This linear approach means that only the bare minimum of samples are needed to get an output, and the results are extrapolated to other areas; we call this *data scarcity*. Note also that data is received late in the process; that is by design. Usually, there is a lot of work done in the research design and planning stages of the science process to ensure that the data (which is the most expensive part) is exactly what is needed to answer the initial research question only.

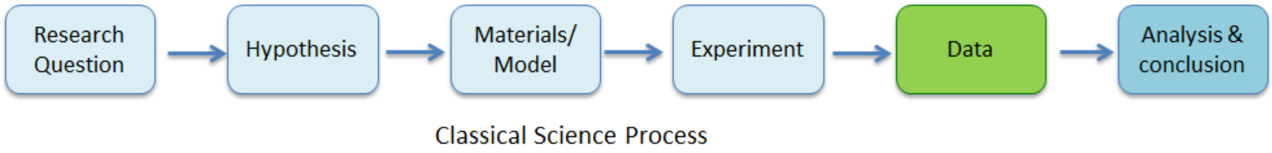

Figure 1: Classical Science Process

The new data economy

HSI technologies coming on-stream in agricultural science completely change the data economy because they produce a huge amount of multi-layered data quickly and cheaply. For example, with traditional soil testing methods, you would be lucky to take 30 soil samples over a 3,000ha area; with the AisaFenix, which has a pixel size (at 600m altitude) of approximately 1 metre you can take 30 million measurements in less than two hours (see Figure 2). We call this data *superabundance.*

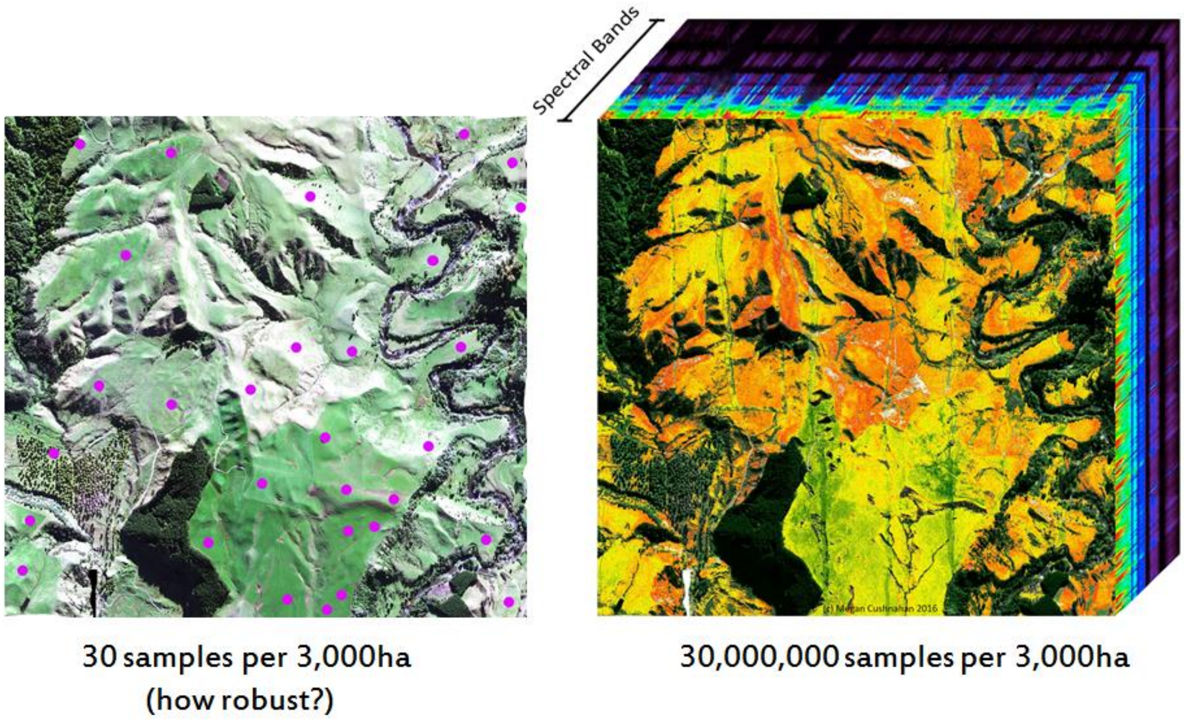

Figure 2: The new data economy.

Data collected in a single flight may be used not only to detect deficiencies of nutrients related to growth, but the versatility of the data also offers the potential to address cross-disciplinary problems (Alrøe & Kristensen, 2002), such as animal health (e.g. copper) problems.

An early observation of operations at the NZCPA indicated that the new data economy was disrupting their science process, and the classical science method was not the most suitable approach for the data-rich work they were undertaking.

'Disrupting' the science process

So what of the disruption? In the new data economy data has moved from a scarce commodity appearing late in the science process to upstream and superabundant (see Figure 3). The high-resolution, georeferenced data means that extrapolation is no longer an issue; we have hundreds of layers of data from every location. One data collection event not only provides data used to predict levels of nutrients related to growth, but the data carries so much information that it can be re-used to answer new research questions. This is rare in traditional agricultural science, which is accustomed to using data that is limited in both quantity and quality.

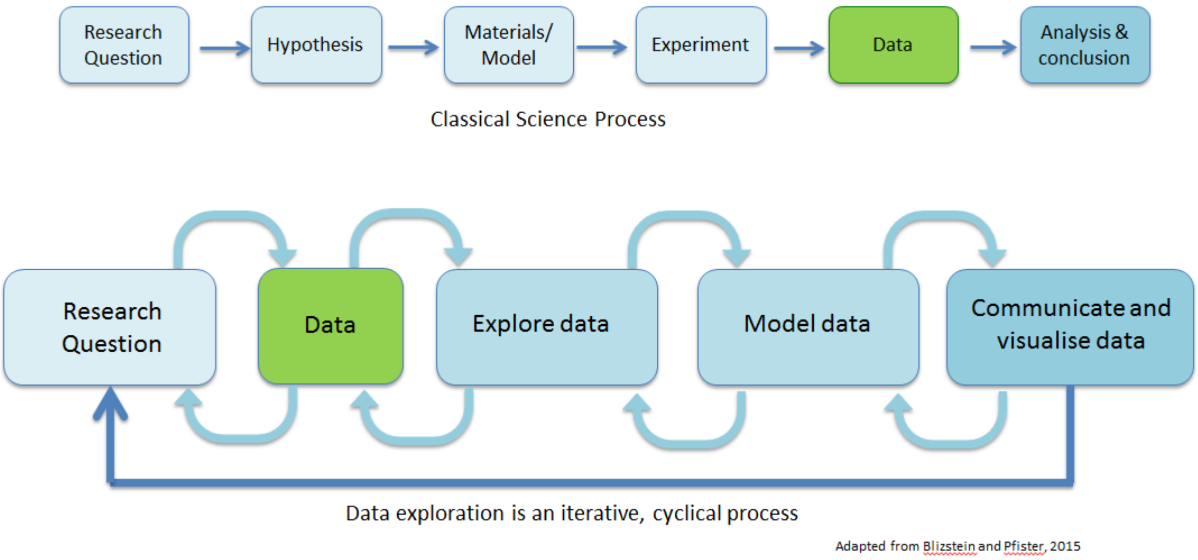

Figure 3: Disrupting the science process.

In the new data economy algorithms are used to refine the data into the valuable information but a cyclical, iterative approach may be required, and you may encounter unexpected science along the way. Data exploration is difficult because we are not always sure what we're looking for which is why it is important to use visualisation and questions that will guide the initial exploration to make sense of what is it that this data can tell us (Pfister & Blitzstein, 2013).

Big data ≠ big knowledge

A key challenge with big data technology such as HSI is that the value model does not emerge fully-formed from data itself; they are simply inputs to a production process that depends on human insight (Huberty, 2015). "Making sense" of massive amounts of highly variable and versatile data will require data exploration (Sonka & IFAMR, 2014), which may involve an iterative, cyclical process where the science-making team is not always sure what they are looking for (Pfister & Blitzstein, 2013). This approach is a far cry from the linear classical science traditionally promoted for agricultural science. Translating the data into valuable knowledge will require a multidisciplinary approach. There is also evidence that the science method traditionally used by specialist teams in agricultural research does not always meet the needs of cross-disciplinary research (Alrøe & Kristensen, 2002); this potentially limits the value that could be extracted from versatile, multi-layered data produced in superabundance by hyperspectral sensors. This conflicts with the way many Universities and research organisations fund and structure their science teams. Continuing to work in specialist teams may result in a widening gap between information and knowledge and there is a risk of missing out on what we call *surplus science*.

The story of copper

The lead author of this paper is embedded in the NZCPA undertaking a longitudinal study of precision agriculture researchers in a data-rich science-making environment. NZCPA is working on a major project, a Primary Growth Partnership called "*Pioneering to Precision*" funded by Ravensdown and the Ministry of Primary Industries. The researchers are using airborne HI to predict nutrient concentrations in plant tissue from the air to guide and inform fertiliser decision making (Grafton & Yule, 2015; MPI, 2014).

The project involved flying the AisaFENIX over eight test farms, with over 4,000 tissue and soil samples being sent to a laboratory for calibration. Data was then explored to see if relationships between the hyperspectral data and wet chemistry calibration samples could be found for the major pasture nutrients. Models were subsequently created from these relationships. A question arose during the process as to whether other minerals such as copper could be modelled from the data. In the classical science context, this question would usually be viewed as 'project creep' or as a whole new research project because another data collection process would be needed to provide the data needed to answer the new research question. The beauty of hyperspectral data is that the data from the original project can be re-used to answer new research questions (see Figure 4).

Using the original HI data, and calibrating using field measurements taken with the ASD FieldSpec® Pro spectrometer, and samples from the laboratory, Dr Rajasheker Pullanagari from NZCPA modelled the relationship to an acceptable level of confidence and produced a data visualisation of copper concentrations for feedback. The visualisation was presented to test farmers and members of the Ravensdown team as part of a feedback session for the original PGP project. Feedback from the session indicated that the farmers valued the copper map as they were supplementing stock without fully understanding the copper status of their property; importantly, they valued the information from an animal health perspective rather than a plant health perspective.

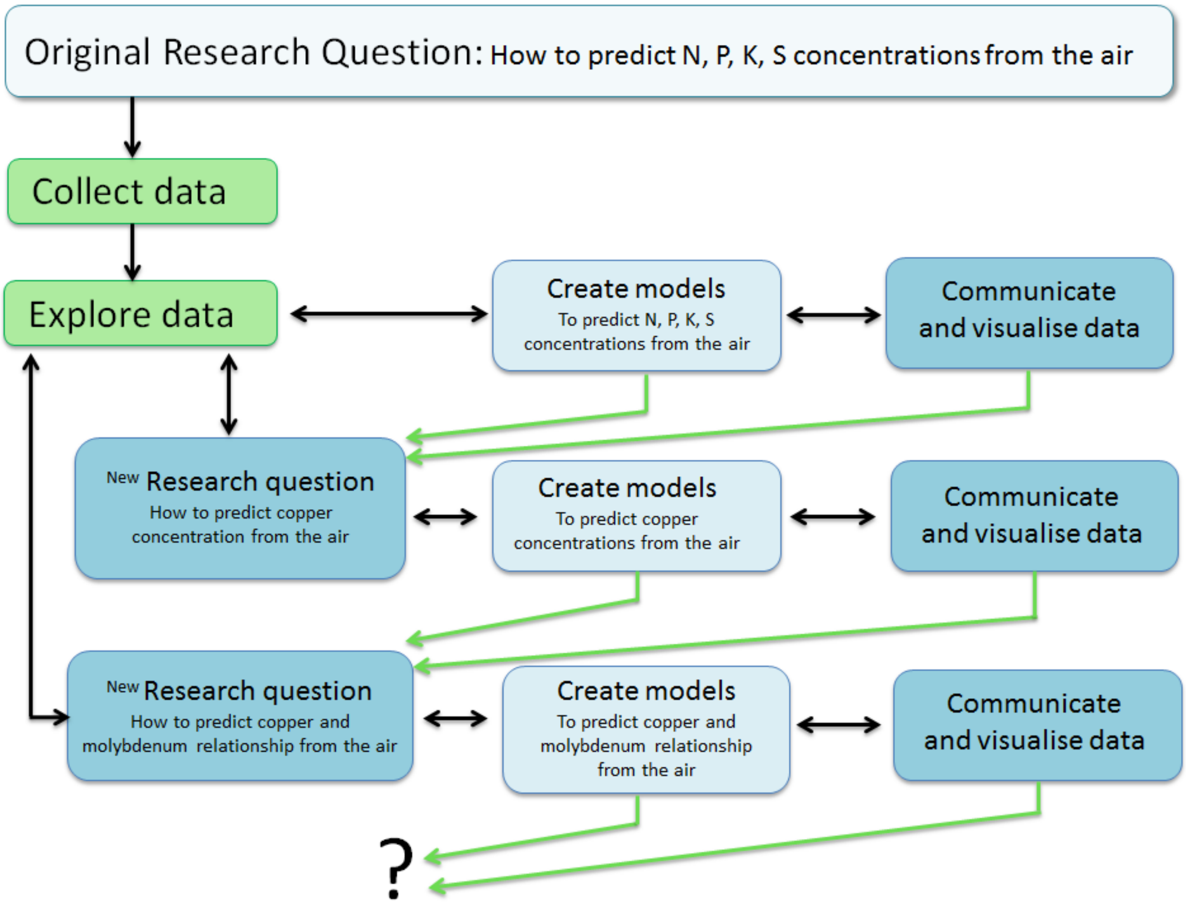

Figure 4: The iterative, cyclical science process used to generate additional value from a hyperspectral imaging project (surplus science)

After receiving the positive feedback, Dr Miles Grafton from NZCPA contacted his Massey colleague, Dr Rene Corner from Massey University's animal health team to see if she was interested in the findings and to see if she would like to collaborate, which she did. Dr Corner provided invaluable insight into copper deficiencies in animal health and proposed a third research question which meant the data was re-used yet again, this time to investigate if an antagonistic relationship between copper and molybdenum in the data could be found, which they duly did. In the end, the original HI data was used to answer three important and valuable research questions. It is unlikely that this additional value would have been realised from the data collection if a classical science process had been followed. It also highlighted the benefit of having a multidisciplinary team (or access to experts from other disciplines), who can view and shed light on new findings.

Conclusion

Hyperspectral sensing and imaging offers a unique opportunity to revolutionise precision agriculture; however a key challenge lies in extracting value from the data. An important characteristic of HSI data is that is versatile, superabundant and arrives early in the science process. The observations of the NZCPA science team indicate that this new data economy is not ideally suited to the classical science model, which is designed to extract an answer to a singular question from scarce data sets that receive data late in the science process. The centre has adapted their science method to follow a more iterative, cyclical process, and have utilised input from end-users and researchers from other disciplines to identify new opportunities and refine unexpected value from versatile data sets.

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