# Remote Sensing and Satellite Image Technology: Capabilities and Implementation

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## Introduction

Satellite remote sensing of rural resources is now approaching middle age. The first dedicated earth monitoring satellite (Landsat 1 (originally known as ERTS)) produced its initial images in 1972. The data provided by the Multi-Spectral Scanner on this satellite gave us a unique view of the landscape: enabling views of large regions every 18 days and, importantly, giving us a look at the near-infrared part of the electromagnetic spectrum. These first images promised great things for agriculture with the synoptic, holistic and repeatable images informing farm management in a way never before possible. Indeed these images were very useful for regional planning, but the cost and level of expertise required to interpret the information stifled the adoption of the technology into every day agricultural practise. Since Landsat 1, satellite remote sensing technology, both the sensors and processing techniques, have developed continually. In the late 1990's two new groups of sensors made an impact on remote sensing technology; high spatial resolution and hyper-spectral sensors coupled with rapid advances in computing technology have us poised on the brink of a great chance to improve our agricultural systems.

This paper details the resolution of these new satellite systems and briefly explores the potential for these data to inform agricultural decision making.

## The basis for remote sensing of crops

Like most vegetative surfaces, crops have a small reflectance peak in the green portion of the spectrum ($\approx$ 530 nm), which is why they appear green when viewed in visible wavelengths (Figure 1: adapted from Van der Rijt *et al.* 1992). A significantly greater proportion of the sunlight is reflected in the near-infrared band of the electromagnetic spectrum, wavelengths that are beyond the limit of human perception. By comparison, bare soil and dead vegetation (in this case wheat stubble) exhibit a smooth increase in reflectance with increasing wavelength, and no appreciable hump in the green or the infrared wavelengths. Stubble and soils have significantly different spectral signatures from typical crop vegetation and different crops also have different spectral signatures.

It has been demonstrated that the near-infrared reflectance of vegetation is more sensitive to changes in plant health than in the visible wavelengths (Campbell 1996). Near-infrared images of plants therefore offer more information about plant health and vigour than visible colour images. Furthermore, digital near-infrared images can be processed by computer to enhance and map small changes in the plant signature over the entire surface of a target.

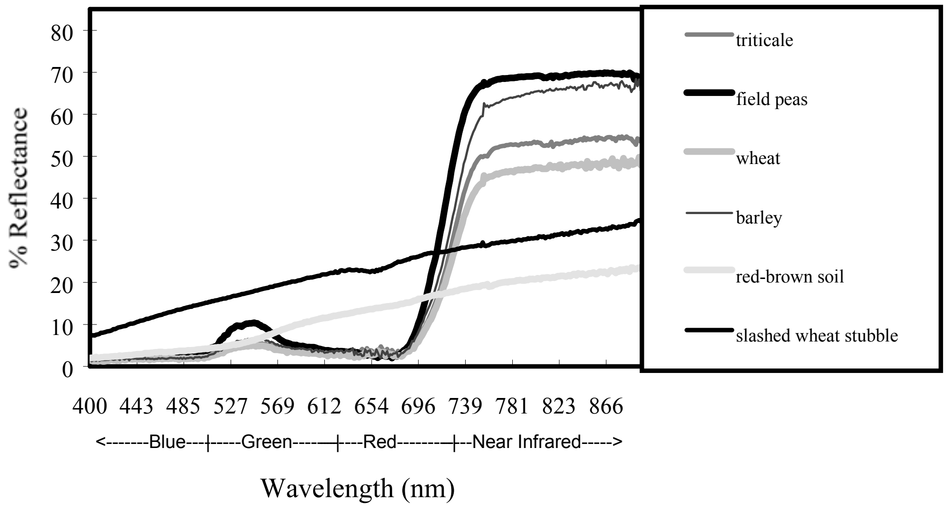


Figure 1. Spectral characteristics of some crops, crop residue and soil.

The improved contrast between plant and soil or stubble is an important aid in delineating relative amounts of plant biomass against a soil or stubble background in a field. Generally, the influence of plant diseases, pests, nutrition and available moisture will affect plant biomass or leaf spectral characteristics, or both.

Spectral vegetation indices reduce multiple-waveband measurements to a single numerical index, and many have been developed to highlight changes in vegetation condition (for example Wiegand *et al.* 1991, Price and Bausch 1995). For example, Normalised Difference Vegetation Index (NDVI) images are created by transforming each multispectral image pixel according to the relation:

$$\mathrm{NDVI} = \frac{(\text{near infrared}) - (\text{red})}{(\text{near infrared}) + (\text{red})} \qquad \text{(Rouse } et\ al. \text{ 1973)}$$

where 'near infrared' and 'red' are respectively the reflectance values in each band. The NDVI quantifies the relative difference between the near infrared reflectance "peak" and red reflectance "trough" in the spectral signature. Appropriate index or multi-band colour-infrared images of agricultural crops can be an important indicator of crop health and development.

Remote sensing can only be used for monitoring crops when:

(i) appropriate biophysical parameters influence the spectral signature of the crop canopy;
(ii) and the remote sensing instrument has the appropriate spatial, spectral and radiometric resolution to detect variations in spectral signature.

The remote sensing system itself must:

(i) provide cost-effective data;
(ii) be capable of acquiring and providing information in timely manner;
(iii) and have user-defined spectral characteristics to allow tuning to specific pre-defined crop indicators.

The required spatial resolution of the image will depend on whether the target is characterised by a continuous variation in condition or cover-type, therefore requiring “data thresholding" to discriminate and map particular levels, or whether variations in condition occur in discrete patches. The former case will require a considerably finer spatial resolution than the later. Obviously a spatial resolution comparable in size to the expected size of the variability is a starting point (Atkinson and Curran 1997). Recent research, related to precision farming in Australia, has shown observed variations in crop parameters occur on a scale as small as tens to hundreds of metres (Bryceson 1998, Cook and Bramley 1998), and even less for weeds (Cousens and Mortimer 1995) and pest/disease damage (Lamb *et al.* 1998). This range sets the context against which the appropriate spatial resolution of agricultural remote sensing instruments should be evaluated.

Until recently, commercially available satellites provided multi-spectral images with spatial resolution ranging from tens of metres (SPOT1-4, Landsat TM, IRS-1B) to kilometres (AVHRR) (Campbell 1996). The widths of the near-infrared and red bands of these satellites range from 60 nm to hundreds of nanometres wide. Comparing pairs of spectral bands allows discrimination between soil and vegetation, but this comparison is generally inadequate for delineating species of low density or for typing an impure population. A combination of large pixel size and relatively broad spectral bands increases the chance of data averaging (Everitt *et al.* 1993, Campbell 1996, Jensen 1996).

## High Resolution Satellite Systems

There are now several high spatial resolution satellites providing commercial, publicly accessible data. Table 1 gives a summary of the resolution of three of these sensors. The great advantage they offer over older satellite data is the very high spatial resolution down to sub-metre and the increased frequency of possible repeat coverage.

**Table 1: Summary of the resolution of three currently available high-resolution satellite images.**

| Satellite/Sensor | Spectral Resolution | Spatial Resolution (m) | Maximum Repeat Coverage (days) |
|---|---|---|---|
| [1]Quickbird/Multi-spectral | Blue, Green Red and NIR | 2.44 | 1-5 |
| [1]Quickbird/Panchomatic | Blue to NIR | 0.7 | 1-5 |
| [2]Ikonos/Multi-Spectral | Blue, Green Red and NIR | 4.0 | 1-3 |
| [2]Ikonos/Panchomatic | Blue to NIR | 1.0 | 1-3 |
| [3]Spot5/Multi-spectral | Green Red, NIR and SWIR | 10 | 2-3 |
| [3]Spot5/Panchomatic | Blue to NIR | 2.5 – 5.0 | 2-3 |

1.http://www.digitalglobe.com (accessed 13 July 2004)
2.http://www.geoimage.com.au/ (accessed 13 July 2004)
3.http://www.spotimage.fr/automne_modules_files/standard/public/p229_fileLINKEDFILE_satp_en.pdf (accessed 13 July 2004)

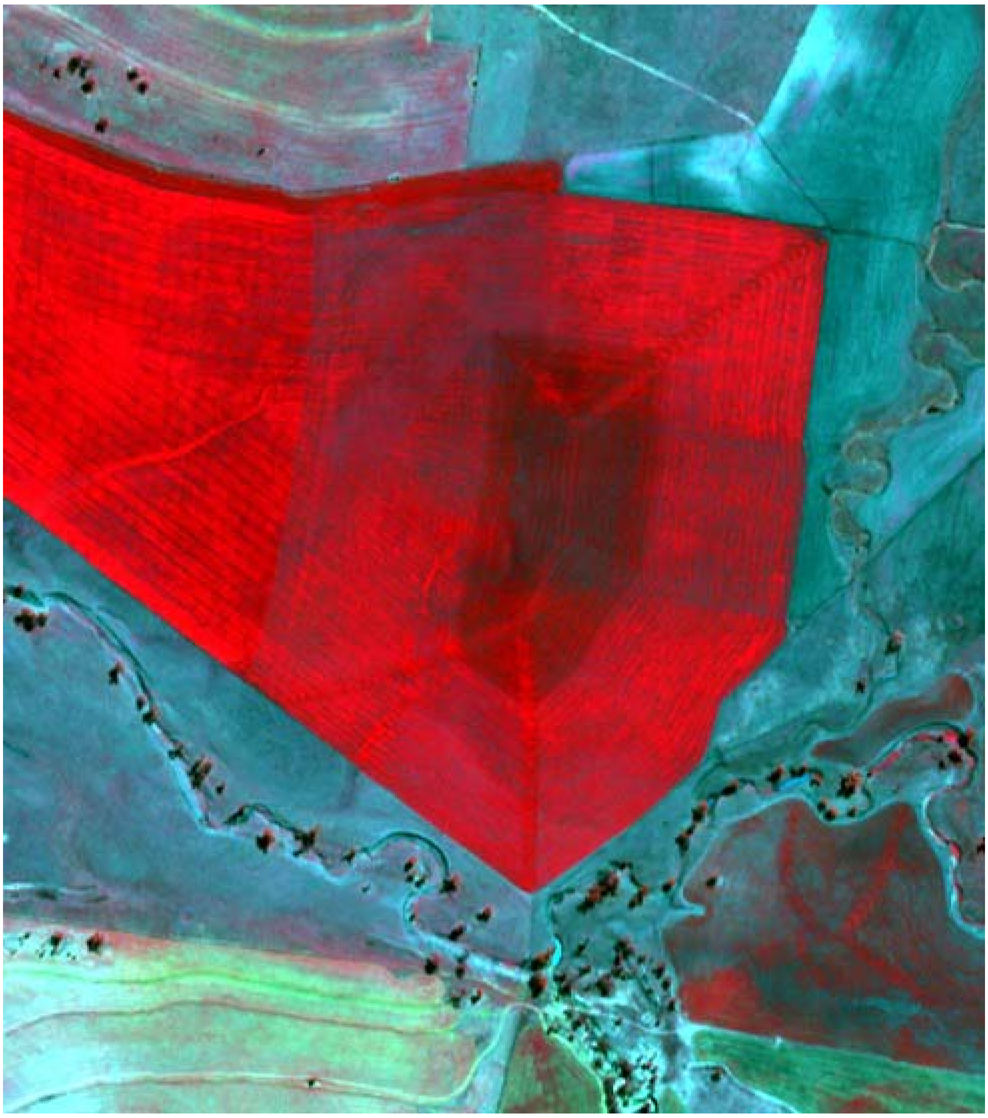

Figure 2: Quickbird image over section of McMasters Research Farm (near Warialda).

The high-resolution satellite images approximate the fine spatial resolution achieved with aerial photography (Figure 2). However, with multi-spectral capabilities, including infrared, and repeat coverage possible every day or two, the potential for mapping and monitoring crops and pastures at a sub-paddock level is dramatically improved. Figure 2 shows a section of a Quickbird multi-spectral image over an agricultural area to the north west of Warialda (NSW). This figure shows that the data are able to detect features as small as individual small trees, on-farm tracks and roads and variations in crop health due to uneven application of fertiliser and sowing rates.

There are several studies that indicate that these types of images can be used to produce accurate maps of green plant biomass (eg Yang and Anderson 2000, Hall 2003, Leon *et al*. 2003). This basic information often correlates strongly with yield, nutrition, quality or health information. However, to date there has been no detailed study that has demonstrated the robustness of these techniques across agricultural commodities, geographic regions or time.

## Hyper-spectral Sensors

Where multi-spectral sensors capture approximately 3-8 broad bands of electromagnetic radiation, hyper-spectral sensors may capture over 200 fine bands of information allowing for very subtle variations in spectral reflectance to be measured. These sensors offer potential to improve our ability to identify variations in crop/pasture condition. Several studies indicate that these fine spectral resolution data are able to produce accurate maps of crop quality and nutrient status (Basnet *et al.* 2003, Mutanga and Skidmore 2004).

Hyper-spectral remote sensing has been used to study water stress, net primary production and carbon fluxes in vegetation, and also to quantify lignin, carotenoid, chlorophyll, nitrogen and starch concentrations in leaves.

At this stage research into this field is developing. The majority of currently available systems are either too coarse in terms of spatial resolution (eg MODIS data) or designed for research use.

## Crop development and nutrition

Crop spectral signatures are a dynamic throughout a growing season. Early in the season the spectral signature is influenced by the underlying soil and residue. The signature is subsequently modified by the appearance of, and gradual increase in, surface coverage of crop. For example, the reflectance of winter cereal crops in the visible spectrum decreases significantly during the juvenile stage as the amount of biomass and chlorophyll increases, while an increase is observed at senescence as chlorophyll decreases. In the near infrared spectrum, a significant increase in reflection appears in the juvenile stage due to increases in biomass, and the number and size of leaf cell layers. At senescence, the near infrared reflectance decreases as the crop dries out and the internal plant structure in changed (Broge *et al.* 1997).

The distinctive absorption of incident visible and near infrared sunlight by photosynthetically active tissue in plants means vegetation indices developed from spectral properties in these wavebands tend to correlate highly with plant physical parameters such as leaf area index (LAI), chlorophyll content, wet and dry biomass and percent ground cover (eg Weigand *et al.* 1991, Clevers *et al.* 1996, Cassanova *et al.* 1998). However, care must be taken when interpreting such data as any relationships may be confounded by the influence of variability in background soil and crop residue, particularly in the early stages of crop development (Bellairs *et al.* 1996).

Measuring and mapping crop nutrient status by remote sensing is attracting interest because of the emergence of variable-rate fertiliser application technologies. Plant nitrogen status influences chlorophyll content and, since pigment-induced crop reflectance is dominated by chlorophyll (Thomas and Gausman 1977), researchers have targeted pigment-based reflectance indices or the position of the chlorophyll red-edge (eg Broge *et al.* 1997) in an attempt to remotely quantify N status. When canopy cover is incomplete, Chlorophyll A indices are mainly a function of leaf area index. Discriminant analysis based on pigment indices has allowed a clear separation of N-deficiency from well-fertilised plots at the canopy level (Filella *et al.* 1995, Blackmer *et al.* 1996, Fouche *et al.* 1997).

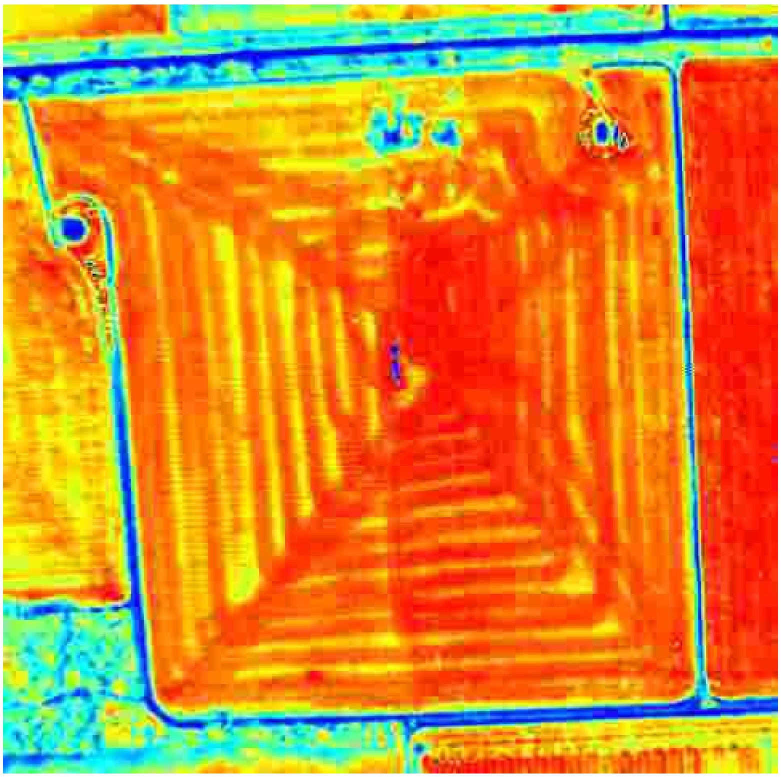

**Figure 3.** NDVI image of a canola field showing striping characteristic of uneven fertiliser broadcasting over the width of the spreader and/or inaccurate spreader navigation.

Remote sensing is potentially a useful method of monitoring the response of crops to the application of fertilisers. Figure 3 is an NDVI image of a canola field showing striping characteristic of uneven fertiliser broadcasting over the width of the spreader and/or inaccurate spreader navigation. In this case, variations in vigour correspond to urea application rates varying from 100 kg/ha to 0 kg/ha.

The potential for monitoring the fertility status of fields is not limited to nitrogen alone. Researchers have reported varying levels of success in correlating remotely sensed data with other metallic elements such as K, P, Na, Ca, Mg, Zn, Fe, Mn, Cu, and B (eg Milton *et al.* 1991, Yang *et al.* 1998).

## Discussion

Satellite remote sensing imagery is now of sufficient resolution to be able to inform on-farm decision making. Old impediments to adoption such as insufficient spatial resolution and lack of repeat coverage have now been removed by the new generation of commercially available satellite imaging systems. In addition to these new high spatial resolutions systems is a set of hyper-spectral imaging systems. Research studies have shown that these systems are capable of mapping plant biomass, yield and nutrition status. The challenge now is to develop robust systems that allow farmers to access these data to improve their management regimes.

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