Complexity in Remote Sensing:
A Literature Review, Synthesis and Position Paper

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1 Introduction

In general, remote sensing is the act of obtaining information about an object from a distance. This can be applied in a number of situations, but in this paper I will focus on the field of *remote sensing and Earth observation* which is primarily concerned with the observation of the Earth's surface from a distance (usually by satellites or aircraft) with the aim of obtaining information about the surface of the Earth. Further to this, I will focus on passive remote sensing in the optical domain, that is, remote sensing which uses the sun as the source of the radiation (rather than creating any radiation from an artificial transmitter) and operates in the optical wavelengths (approximately 0.4–1.4μm).

Remote sensing and Earth observation is a growing field and has expanded significantly in recent years. There are now hundreds of Earth observation satellites in orbit around the Earth providing many petabytes of data a year, and data derived from remote sensing sensors are used in applications from precision farming (D'Urso et al., 2010) and climate modelling (Liang, 2007) to census data reconstruction (Watmough, 2010) and disaster management (Tralli et al., 2005). A number of authors are now stating that "Remote sensing has come of age" (Mather, 2010; Tang et al., 2009), but this has led to remote sensing data products being used with little thought to the process by which they were acquired and the inherent errors and uncertainties in the data.

Complex systems science is a relatively new area of scientific research which focusses on understanding systems which have many interactions which are difficult to model mathematically. I feel that complexity science is able to contribute significantly to the understanding of remote sensing systems and the complex interactions which occur within them. In this paper I will endeavour to establish what the remote sensing system is, show that it is a *complex* (as opposed to just a *complicated*) system, and examine some of the ways in which this complexity manifests itself. Finally, I will examine the applicability of complex systems simulation techniques to remote sensing problems.

2 Motivation

Remote sensing has developed significantly as a field since the first dedicated earth observation satellites were launched in the early 1970s and is now used operationally for a wide range of purposes. With this apparent success in the field, it may be difficult to appreciate what remote sensing may stand to gain from a complex-systems based approach. However, remote sensing data products are not perfect, and the procedures that are used to produce them often do not work as well as we would hope. Despite the best efforts of researchers in the field, simple 'point-and-click' methods of pre-processing and analysis do not tend to provide high quality results. In this paper I will argue that these problems are due to the complexity of the remote sensing system, and that applying a complex systems approach may help to provide some solutions.

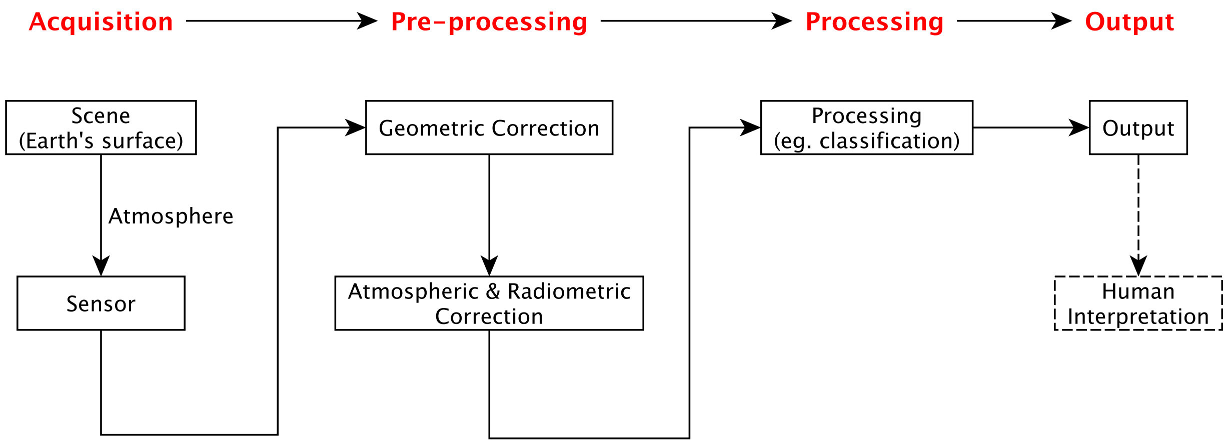

Figure 1 – The major stages in the remote sensing process, which can be thought of as the components of the remote sensing system

3 Is the remote sensing system a complex system?

3.1 What is the remote sensing system?

The image chain approach to remote sensing Schott (2007) splits the process of remote sensing into a number of individual steps which are joined to produce a chain leading from acquisition of the image to the final output of information to the user. This chain is a processing system which I will refer to as the *remote sensing system*, and each of the processing systems is a component of this system.

At its simplest level, this system consists of three major stages: the acquisition of the data (usually in the form of images), the processing of this data, and then the display of the output to the user. These steps can then be broken down into substeps which are present in almost all remote sensing projects, as shown in Figure 1. The pre-processing steps are particularly important, as they alter the image data in an attempt to make it better reflect the 'reality' of the situation on the ground (for example, by removing the effects of the atmosphere and the geometry of the sensor's view of the Earth). Figure 2 shows an outline of the stages involved in creating the GlobCover global land-cover map (Defourny et al., 2006) from a set of satellite images as an example of a multi-stage remote sensing system .

3.2 Is the remote sensing system complex?

There are a number of arguments for the remote sensing system being a *complex system*, as opposed to simply a *complicated system* (Amaral and Ottino, 2004), all of which approach the question from a different point of view.

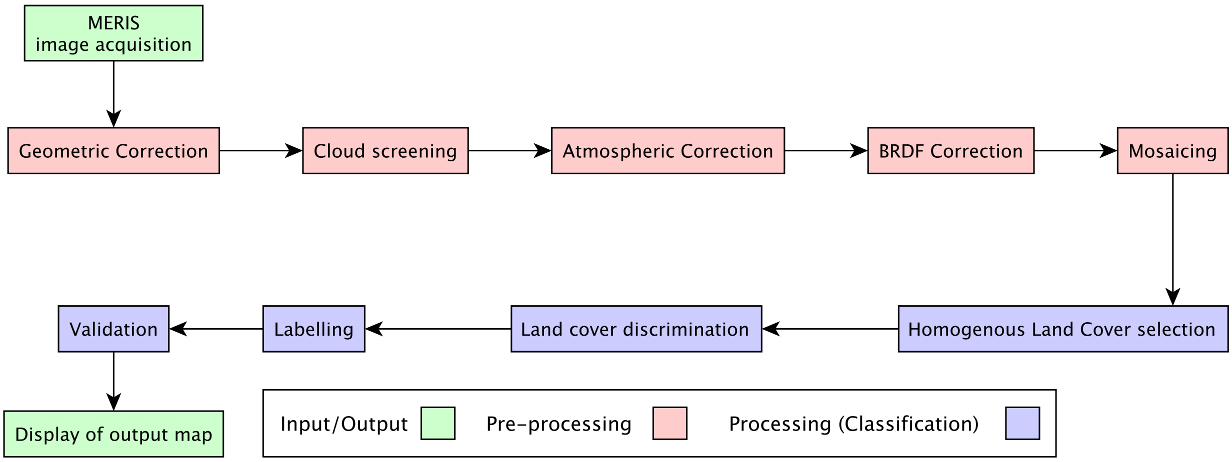

Figure 2 – The outline procedure used to create the GlobCover global land-cover map (Defourny et al., 2006)

3.2.1 Complex interactions between processes

The image chain approach (Schott, 2007) emphasises the linkages between different procedures carried out as part of the remote sensing process, but these linkages are described as being simply between adjacent processes. I would argue that there are, in fact, many more linkages than this, but that it is difficult to work out where these extra linkages are.

It should be remembered, of course, that Figure 1 is very simplified, and that each of the components in that diagram is likely to have many sub-components which may interact in a non-linear manner. For example, the atmospheric correction component is likely to consist of a number of processes such as those listed below (used in the ATCOR atmospheric correction software; Richter, 2007)

- Selection of haze, cloud, water and clear pixels
- Haze removal
- Shadow removal
- Calculation of optical thickness
- Correction of path radiance
- Water vapour retrieval
- Reflectance spectrum calculation
- BRDF correction

Within each of these steps there is a complex model which is unlikely to be driven by a simple set of linear equations. For example, the selection of haze pixels in the algorithm above is likely to be a complex system in itself possibly including a small simulation

Table 1 – Major assumptions held in remote sensing studies, from Duggin and Robinove (1990)

1.	Correlation between image and ground attributes is 1.00
2.	Sensor radiometric calibration is known *for each pixel*
3.	Atmospheric affects do not affect the correlation *or* atmospheric effects have been perfectly corrected for
4.	Sensor spatial response characteristics are accurately known and accounted for
5.	Sensor spectral response are accurately known at the time of image acquisition
6.	Image acquisition conditions were optimum with high radiometric contrast
7.	Image resolution is appropriate to detect and quantify features of interest
8.	Correlation between image and ground attributes is *constant across the image*
9.	Analytical procedures are appropriate and adequate to the task
10.	Imagery is analysed at an appropriate scale
11.	There is a means of verifying the accuracy of the quantification of ground attributes and this process has been performed *across the image*

model within it. The rules connecting these components of the atmospheric correction process change over the running time of the model, based on the parameters chosen and the results of the previous stages. Furthermore, the order in which processes are carried out will affect the results - leading to the question of whether, for example, performing geometric correction before atmospheric correction is the ‘correct’ order, or whether they should be done the opposite way around.

It is important to note here that the linkages between these processes are not necessarily explicit linkages where code in later procedures explicitly references values calculated previously. Instead, the linkages are often more subtle - involving the complex effects of results calculated earlier affecting the results at each subsequent stage.

These linkages can be partially explained as a complex uncertainty propagation process where major assumptions in each step of the process are not fully met, and these errors and uncertainties interact with each other. Duggin and Robinove (1990) examined a number of the major assumptions made in remote sensing studies, most of which are never entirely true, (listed in Table 1). As more of these assumptions are invalidated, the chain of interactions leading from radiation source to final output product becomes more complex.

3.2.2 Boundaries between complex systems

The remote sensing system is an observing system, and therefore by its nature it is at the boundary of a number of systems. In the case of an Earth observation system these boundary systems are the Earth surface itself (including the processes driving spatial and temporal change on it), the atmosphere through which the Earth is observed, and the human eye-brain system which is interpreting the image and/or map outputs. There is little disagreement that all of these systems are complex systems, and therefore the remote sensing system is at the boundary of three significantly complex systems.

This does not mean, of course, that the remote sensing system itself is complex, but it does suggest that:

- When the remote sensing system is considered along with at least one of its boundary systems (for example, the atmosphere) then the resulting system is definitely a complex system.
- The inputs to the remote sensing system will be from complex systems (the Earth and the atmosphere) and therefore 'stray complexity' can leak into the remote sensing system. For example, all input data is filtered through the atmosphere, but we don't fully understand the complexity of the atmosphere, so this input data has been modified in ways that we do not understand. This then leads to more complex interations (as detailed above), between the remote sensing system itself and its boundary systems.

3.2.3 Chaos in image processing

Many image processing algorithms are very sensitive to the initial image values provided to them. For example, a very small change in the value of one pixel in the input can lead to a large change in the output of a procedure such as unsupervised image classification. This can be a problem as image values are inherently uncertain, both because of the method of acquisition of the images and the pre-processing functions applied to the image.

Regardless of the quality of the sensor, the raw digital number (DN) recorded by the sensor is unlikely to be an accurate representation of the light reflected from the pixel in view. This is due to effects from the sensor itself (such as the point spread function, which describes how much of the light entering the sensor actually originates from outside of the pixel) and from atmospheric effects (which, for example, cause scattering of light into the sensor's aperture). Many procedures have been developed to try and correct these effects by changing the DN values. However, as these effects are very difficult to correct (partly because the processes causing the effects are, themselves, complex and chaotic), so the final DN values used as input to the main processing procedures could have significant errors.

It can easily be seen that small changes to the input DNs for a processing procedure (well within the boundaries of the error discussed above) can lead to very large changes in the outputs. This satisfies the common definition of chaos, where, in the words of Lorenz (in 2006, aged 89) "the present determines the future, but the approximate present does not approximately determine the future", with the present and future referring, in this case, to the input and output of a processing algorithm.

Chaos can also be caused not by image data as such, but by choices made in algorithm design. For example, decision tree classifiers use a hierarchy of rules to classify the image.

These rules are applied in a sequential manner, and therefore if the wrong decision is taken at the first rule, the end result could be erroneous - in complex systems terminology, the first decision is a *tipping point*. A wrong decision here could be caused by inaccurate image data (as above), or by bad choices for the conditions used for the rule. Regardless of the cause, a small inaccuracy in a choice made at the start of the processing has led to a large discrepancy at the end - an example of chaos

3.2.4 Intentional complexity

So far, complexity in remote sensing has been discussed in terms of a 'problem' that we want to solve, with the aim of creating better outputs from remote sensing analyses. However, complexity can be useful, and a number of remote sensing procedures depend on complex interactions to work. Many classification techniques are forms of machine learning or artificial intelligence, and these are therefore trying to mirror the workings of the human brain - which is a complex system. Therefore, these techniques use techniques based on complex systems including the concept of self-organisation, which is a key feature of many complex systems.

For example, one of the most common unsupervised classification techniques is ISODATA, the Iterative Self-Organizing Data Analysis Technique. As its name suggests, this technique involves self-organisation of data, that is, the evolution of a system towards a state of organisation, without any central authority imposing this organisation upon it. In the case of ISODATA, the data will end up organised into a number of classes within which the data is fairly similar. This self-organisation is key to the utility of the algorithm, and therefore the complexity underlying the formation of this organisation is very useful.

Similarly, neural networks such as the Multi-Layered Perceptron and Radial-Basis Functions have many applications within remote sensing (Mas and Flores, 2008), and these are based on evolving a network of complex linkages between neurons (during the training phase) such that the network can then be used for classification. This evolution is designed to mirror the evolution and reinforcement of linkages between neurons found in the human brain, and has been very successful in producing high classification accuracies.

3.3 Types of complexity in remote sensing

In the literature on complex systems a difference has been recognised between natural complexity and engineered complexity, with the latter being complexity that arises in systems that have been explicitly designed by humans (whether in the traditional engineering sense or not). Figure 3 gives examples of areas of remote sensing covered by both of these categories of complex systems, splitting engineered complex systems into those in which the complexity is intentional and those in which it is unintentional. This distinction is important, as in remote sensing we are often struggling to remove complexity which has

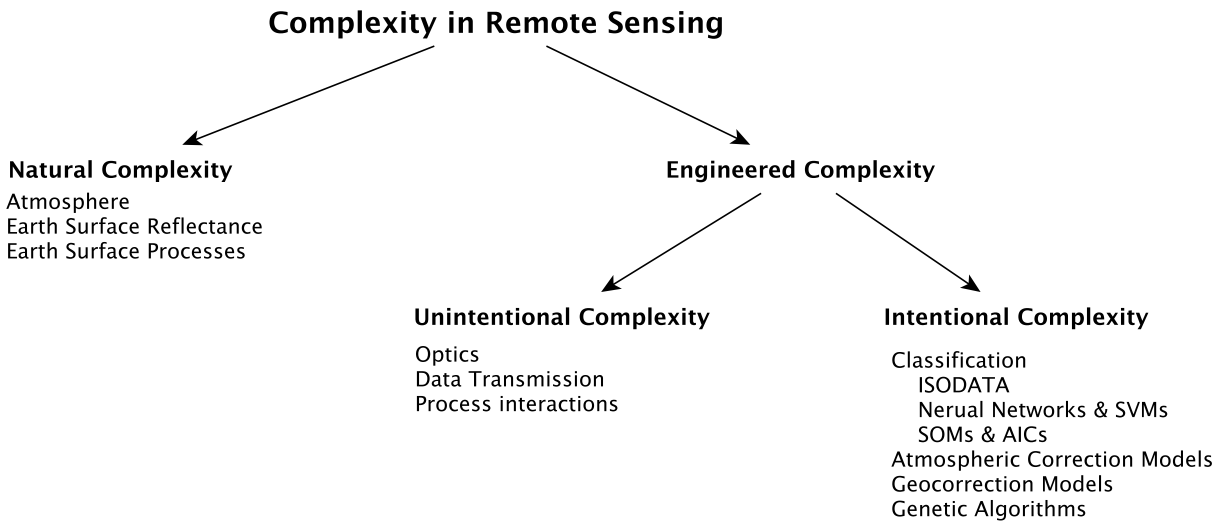

Figure 3 – The different types of complexity found within remote sensing, with examples of areas where they are found

unintentionally crept in to our systems and processes, but sometimes we are using the complexity in a system to do a useful job.

4 Case studies of complexity in the remote sensing system

4.1 Flow of complexity through image analysis procedures

Wilson and Milton (2010) developed a technique for automatically extracting suitable atmospheric calibration sites from satellite images. Their study is used here as an example of a simple analysis procedure which still has to deal with complexity issues, particularly complexity flow through the process.

A flow chart showing an overview of the procedure carried out by Wilson and Milton (2010) is shown in Figure 4. However, this flowchart does not show the details of the issues which may affect this procedure. Figure 5 shows the details of the site selection procedure which ran within eCognition (an Object-based Image Analysis program). These classification tests all depend on the data being correct, in terms of values and location, but this may not be the case. The assumptions listed in Table 1 are unlikely to be true in this study, and this will significantly affect the quality of the output.

I will take one example of an assumption which may not hold true for the image data used in this project, and show how the complex interactions based on this pass throughout the process. The images used were from the IKONOS satellite, which acquires images with a

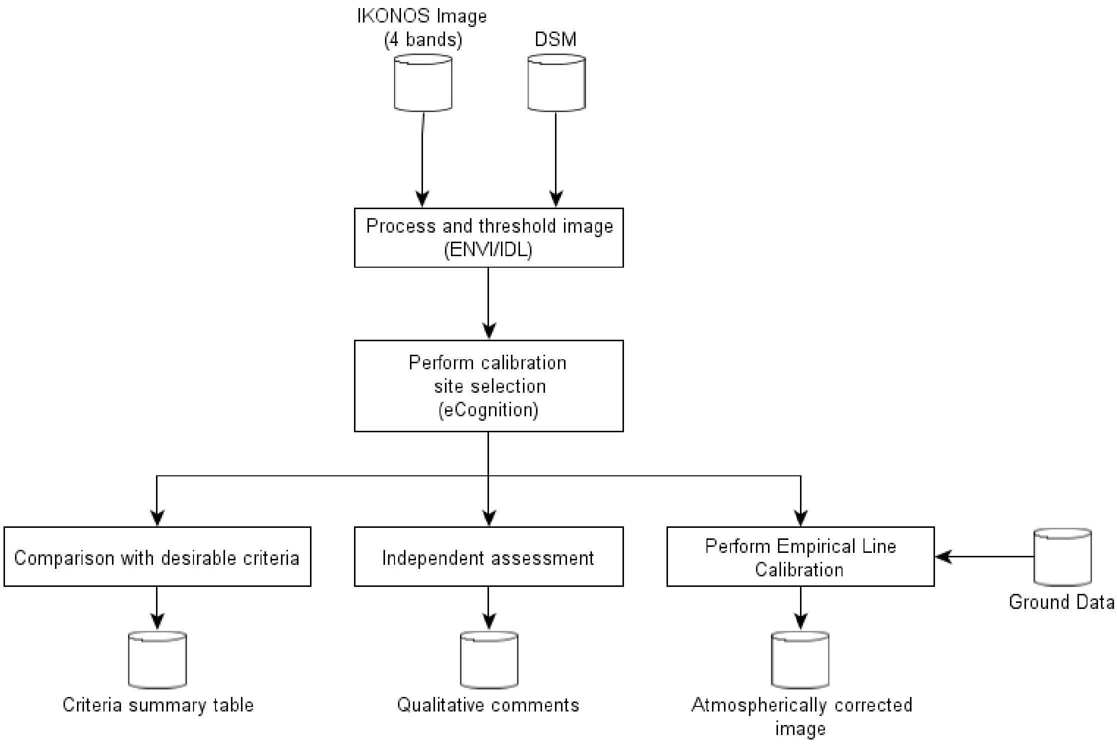

Figure 4 – Flow chart showing the procedures carried out by Wilson and Milton (2010)

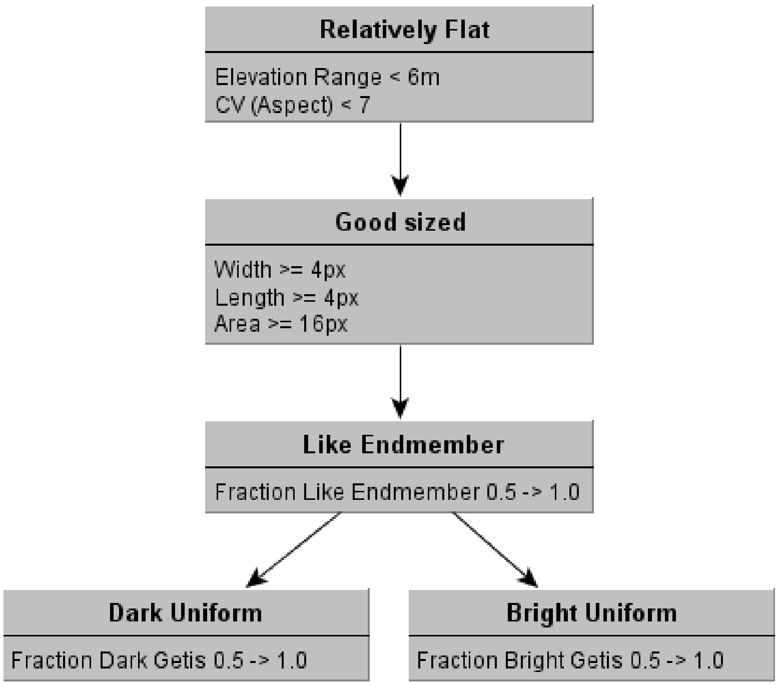

Figure 5 – Rules used for classification within eCognition

resolution of 4 metres from a 681km altitude. This is a high resolution to obtain from such a height, and therefore there are likely to be significant inaccuracies in terms of the area on the ground which contributes to the data stored in each pixel.

A method of quantifying this inaccuracy is known as the Point Spread Function (PSF), which describes which areas of the ground contribute to the radiance received at the sensor for each pixel. Nearly all sensors have a PSF such that some of the received radiance comes from outside of the specified Ground Resolution Element (GRE; the defined pixel-size on the ground), but this can vary between sensors. Table 2 shows the PSF for the SPOT sensor, and it can be seen that only 65% of the radiance received at the sensor, and therefore stored in the pixel corresponding to the GRE under observation, actually came from that GRE.

This obviously has implications for the analysis of the image. The uncertainties and inaccuracies in the data will, in some unknown way, affect the result of the various analysis procedures applied to the image. This is a form of complex interaction, as the uncertainties and inaccuracies of the original image data (caused by the *optical sub-system*) are affecting the *analysis sub-system* in a non-linear and unpredictable manner.

Referring to the list of assumptions in Table 1, the sensor spatial characteristics are definitely not accounted for, and this then makes a number of other assumptions false - for example, not knowing the sensor spatial response affects the ability to resolve fine detail

Table 2 – Point Spread Function for the SPOT sensor, from Ruiz and Lopez (2002). The central cell is the GRE under observation, and the value in each cell is the percentage of the radiance received at the sensor which is sourced from that cell.

0.09	0.16	2.36	0.16	0.09
0.16	0.31	4.48	0.31	0.16
2.36	4.48	**65.1**	4.48	2.36
0.16	0.31	4.48	0.31	0.16
0.09	0.16	2.36	0.16	0.09

in the image (assumption 7) and the correlation between image and ground attributes (assumption 1). The latter assumption is particularly troublesome as the relationship between image and ground attributes is usually assessed from the data in the acquired images, and if this data is incorrect (because of any of the other assumptions) then the calculation of the relationship between image attributes and ground attributes will be flawed.

The aim of the project was to select suitable sites for atmospheric calibration. These sites must fulfil a number of criteria: they must be flat, spatially uniform and temporally stable, amongst other requirements. Spatial uniformity is assessed using the Getis statistic (Bannari et al., 2005), which is calculated using a 3x3 window across the image. These Getis statistic values are then assessed within the segmented image objects in the image. Of course, if there is a wide PSF then the pixels representing uniform areas will be 'contaminated' by radiance from outside of the uniform areas, thus negatively biasing the Getis values for these image objects. This is an example of the *adjacency effect*, where adjacent pixels affect the radiance from the pixels under study.

This adjacency effect will not only affect the Getis statistic, but also the extraction of endmember abundances and any processing based on the spectral data. This, of course, includes the segmentation of the image before classification, which - as it may be based on a complex algorithm itself - may be significantly different due to the adjacency effects.

This may seem a simple uncertainty propagation problem, but the complex comes through the interactions of all of the procedures with the unknown errors which have occurred earlier. Unfortunately, this means that simple methods to deal with the adjacency effects are unlikely to work. Wilson and Milton (2010) performed an additional investigation to see if shrinking each image object by one pixel around its border before using it for analysis improved the results. It was thought this may be the case as the pixels around the edge of the object are those most likely to be affected by adjacency effects from the surrounding pixels in different objects, but this correction did not improve the accuracy. This suggests that the problem is too complex for simple measures like this to improve results.

4.2 Complexity in Object-Based Image Analysis

Object-based Image Analysis (OBIA) is a method of image analysis which involves breaking down an image into a number of *image objects*, each of which can be analysed individually. This provides more contextual information to image analysis techniques by operating at the level of sets of pixels rather than individual pixels.

The first stage of OBIA is image segmentation, where the image is divided into a number of image objects. A number of image segmentation methods exist, and they all aim to produce image objects that are representative of real-world objects. For example, in a high-resolution aerial photograph the segmentation may extract individual buildings as separate objects, and similarly for individual fields and roads. However, it is important to realise that the objects created from image segmentation do not necessarily have a one-to-one relationship with objects in the real world. This is one of the major assumptions of OBIA, and it is almost always incorrect. Figure 6 shows an IKONOS satellite image and the associated image objects produced by the segmentation process. It can be seen that the entire roof of the large building (a warehouse in an industrial estate) has not been extracted as a single image object, but has been split into a number of separate objects. These objects seem to represent the different segments of a sloping roof (it may be that the building has a 'sawtooth' roof). In some situations we may want to extract separate segments like this, but in many situations this would be a case of *over-segmentation*.

It is accepted that image objects do not always correspond to real-world objects on the ground, but can there ever be a one-to-one relationship between these? The surface of the Earth is complex and boundaries are often hard to define. For example, the boundary of a building is fairly easy to define (and is often a straight line), but where is the boundary between woodland and heathland? Or the boundary between a lake and a field? Surely this depends on the definitions of woodland and heathland, or the level of the lake when the measurements were taken.

Furthermore, landscapes are fractal (Goodchild, 1980; Gao and Xia, 1996), for example, it is well-known that there can never be a truly accurate measurement of the length of the UK coastline, as the resolution of measurement determines the length which is obtained - anything from one to infinity (Mandelbrot, 1967). Surely, however, this fractal nature applies not just to coastlines, but to any boundaries on the Earth system, leaving us with a situation where length of an object boundary can be infinite, and the location of the boundary is uncertain. How, then, can we expect extract meaningful objects from satellite images when we cannot even define their boundaries accurately on the ground?

The fractal nature of landscapes also creates an issue with levels of description, or, in more geographical terminology: scale and resolution. One of the defining features of complex systems is that they behave differently at different levels of description (Amaral and Ottino, 2004). In the case of remote sensing, the concept of 'behaviour' can be equated with the response of the image data to analysis procedures, and the quality of the resulting output.

(a) IKONOS image of an industrial estate near Manchester

(b) Segmented image showing image objects

Figure 6 – Example of over-segmentation

There has been significant work within the remote sensing and geographical information communities on the problems of scale in their research. The seminal paper by Strahler et al. (1986) defined two *scene models*: H-resolution and L-resolution, defined by the features under investigation being larger than the sensor resolution and smaller than the sensor resolution respectively. They suggest that these different scene types require different types of analysis, and are susceptible to different types of uncertainties and inaccuracies. Further to this, remote sensing has also played its part in the development of a *science of scale* (Marceau and Hay, 1999), a new field with many applications to complex systems research. Goodchild and Quattrochi (1997), writing from a remote sensing perspective, defines the three major research questions of this science of scale as:

- What is the role of scale in the detection of patterns and processes, and how does this affect modelling?
- How can we identify areas of invariance of scale and scale thresholds?
- How can we implement multiscale approaches for analysis and modelling?

There is no doubt that these questions are key in the understanding of complex systems, particularly when examining complex systems through the medium of simulation models. They are also important questions in understanding remote sensing analysis. For example, when using OBIA there are two separate scales: the scale of the original image and the scale of the segmented image objects. The choice of these scales has a large influence on the patterns which can be observed, and therefore on the relationship between the image attributes and the ground attributes that we are trying to infer (assumption 1 in Table 1). A major cause of this is the Modifiable Areal Unit Problem (MAUP; Openshaw and Taylor, 1979) which occurs when data (in this case image data) is aggregated into a number of different areas (in this case the image objects). Openshaw found that the choice of these areas (which is often arbitrary) significantly affects the results of the aggregation.

The MAUP, amongst other problems such as the ecological fallacy, show that the choice of scales do not just have an influence on the patterns observed but they control the data that we have, and the methods by which we can try and observe patterns.

5 Opportunities for complex systems simulation in remote sensing

In recent years there has been significant progress in using simulation modelling as a tool to understand complex systems. These simulation models can be split into two types (Murray, 2003): exploratory models which use simulation to explore the fundamental processes at the heart of complex systems, and predictive models which seek to model systems as accurately as possible to produce quantitative predictions. There is a place for both of these types of models in understanding complex systems, and the opportunities given below will include both types of modelling.

5.1 End-to-end simulation

Figure 1 shows the major stages in the remote sensing system, and it would seem sensible to attempt simulations of various parts of this system with the ultimate goal of producing a full end-to-end model of the system. This is a very ambitious task, and so it would seem to sensible to limit this to a simulation of a simple configuration of the system (for example, one satellite image acquisition from a well-characterised sensor with associated pre-processing followed by a simple classification task). This model would be of the exploratory variety, as it would be almost impossible (and probably not very useful) to produce a fully predictive model of the whole system. The aim of the model would be to investigate the effect of changing the parameters of various components. For example, if the atmospheric correction was changed, or a deconvolution filter was applied to attempt to remove the effects of the Point Spread Function, then the model would allow us to understand how the output would change.

This model would give an insight into the complex linkages within the image chain, but, as described above, each component of the chain has its own internal chain of complex subcomponents. Therefore detailed simulation models of individual components or closely linked components of the chain could be performed. For example, scene models (which would simulate scenes on the ground which sensors may observe) could be coupled with sensor models (which would simulate how the sensor observes the scenes it can see) to investigate how the parameters of the sensor and types of scene affect the resulting image data. This would be particularly useful when characterising new or as-yet-unbuilt sensors, and could be used to determine the utility of these sensors for certain types of work. This process is currently being carried out for the SkyDome sensor which is currently under development at the University of Southampton (Choi and Milton, 2011).

5.2 Investigation of ‘pre-packaged’ algorithms

Many remote sensing analyses require the use of ‘pre-packaged’ algorithms, such as those used for atmospheric correction, segmentation and classification. The exact details of the implementation of these algorithms is not always available, meaning that they cannot be studied mathematically or simulated in detail. Instead, investigation can be performed by modelling the parameter spaces of these algorithms. This involves running the algorithms many times using a number of different parameters and quantifying the results. Inferences can then be made about the effect that each parameter has on the output, and the interactions between each parameter can be observed. This type of modelling can apply dynamical systems concepts to these algorithms, plotting parameter choices as phase space diagrams and investigating the attractors of the phase-space of the algorithms.

5.3 Development of algorithms based on simulation

The alternative to investigating existing algorithms is to develop new algorithms based on simulation techniques. For example, atmospheric correction algorithms are just predictive models which are designed to give an accurate output. The development of these algorithms is a form of applied complex systems simulation: simulating a complex system (the atmosphere) with the purpose of inverting the model and using it for a practical purpose.

Although atmospheric dynamics was one of the first areas in which complexity and chaos were studied (Lorenz, 1963), many existing atmospheric correction models seem to ignore much of this complexity and use deterministic models based on solving standard atmospheric modelling equations. There appears to be a gap here which could be filled by simple atmospheric models based on complex systems simulation techniques such as cellular automata and agent-based modelling. These models would not necessarily provide the accuracy required for operational use in atmospheric correction, but they should provide a useful method by which the essential characteristics of such models can be explored.

Furthermore, current atmospheric correction models do not take into account temporal changes in the atmosphere. This is becoming more important as time series of satellite and airborne imagery are becoming more widely available, and atmospheric correction is needing to be performed across the whole set of images. When dealing with airborne imagery, even if temporal data is not explicitly used, different parts of the image are likely to have been collected at different times.This is because the aircraft normally flies a number of 'flightlines' as in Figure 7. Depending on the length of the flightlines the time of data acquisition for points 1 and 2 could be very different. As far as the author is aware, no atmospheric correction software takes into account the progression of atmospheric conditions over the time period of the acquisition of the set of flightlines.

Another area with many possibilities for complex systems simulation is the modelling of the atmosphere with clouds. Most atmospheric models only take into account high cirrus cloud and its haze-like effect on the transmission of radiation, but, of course, there are many other types of cloud which are present in imagery. One may argue that it is of no use for atmospheric correction algorithms to deal with cloudy skies, as these images are often discarded when choosing images to process, but there are a number of reasons why gaining an understanding of the effects of cloud on the properties of the atmosphere is important:

- **Clouds cannot always be avoided:** Although many studies discard images with high cloud cover and mask out clouds in other images, this is not always possible. For example, Watmough (2010) needed to use images of India during the monsoon season when it is almost impossible to avoid images with high cloud covers.

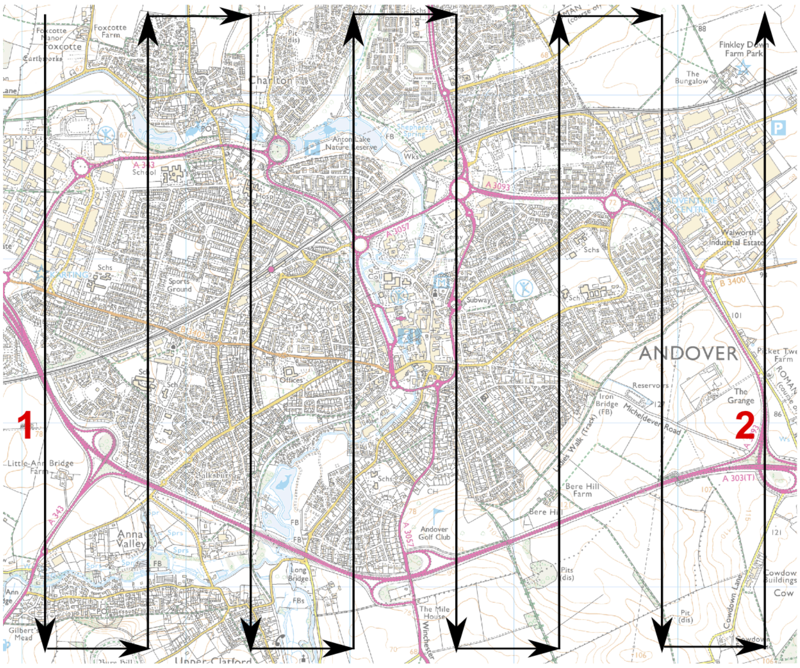

Figure 7 – Example of the flightlines that may be flown by an aircraft to collect aerial images

- **Clouds affect the optical properties of the whole sky:** Atmospheric correction algorithms use a number of parameters describing the optical properties of the sky, and one of these is the diffuse to global ratio. This measures the proportion of the brightness of the sky which comes from the solar disk compared to the brightness from the rest of the sky. However, clouds significantly affect this ratio and most models of the distribution of sky brightness used to calculate this ratio (such as Hooper and Brunger, 1980) are only designed to work with clear skies.

This is an area in which modelling techniques such as cellular automata could be used. Cellular automata have already been used for creating animated clouds (Dobashi et al., 1998), so it seems natural to try and extend these models to be useful for scientific purposes.

6 Conclusion

Until now there has not been a systematic study of complexity in passive, optical remote sensing. It is intended that this report will be the start of a detailed investigation into the linkages between complex systems science and remote sensing, and that this will lead to significant benefits to the field of remote sensing. This report has demonstrated that the remote sensing system is a complex system, and has provided some case studies of complexity in the system. It is now down to future work to extend this approach and produce results which will be useful to applied remote sensing projects.

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