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NATURAL ENVIRONMENT RESEARCH COUNCIL

Identify the opportunities provided by developments in earth observation and remote sensing for national scale monitoring of soil quality

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BRITISH GEOLOGICAL SURVEY

Identify the opportunities provided by developments in earth observation and remote sensing for national scale monitoring of soil quality
Report OR/15/030

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Foreword

This report was commissioned by the Department for Environment, Food and Rural Affairs (Defra) under project reference SP1316 sub-project C. The report was largely prepared by staff from the British Geological Survey (BGS; NERC), with contributions from the Centre for Ecology and Hydrology (CEH) and ADAS.

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Glossary

DEM – digital elevtion model of the landscape

EO - Earth Observation using sensors above the ground surface

InSAR – Interferometric synthetic aperture radar – a type of radar-based remote sensing

IsBAS – a processing technique, called intermittent small baseline subset, applied to InSAR data

MIR – mid infra-red referring to the wavelengths of light between 2.5 and 25 microns

RS - remote sensing

SAR – synthetic aperture radar – a radar-based technique used in remote sensing

SLED - soil Euclidean distance; a method for computing a soil property index from remotely sensed images

UAV – un-manned aerial vehicle

VNIR **-** visible and near infra-red reflectance spectra which is a measurement of reflected light at different wavelengths from surfaces – in this case soil. The range of VNIR wavelengths is 0.35 to 2.5 microns.

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Summary

Defra wish to establish to what extent national-scale soil monitoring (both state and change) of a series of soil indicators might be undertaken by the application of remote sensing methods. Current soil monitoring activities rely on the field-based collection and laboratory analysis of soil samples from across the landscape according to different sampling designs. The use of remote sensing offers the potential to encompass a larger proportion of the landscape, but the signal detected by the remote sensor has to be converted into a meaningful soil measurement which may have considerable uncertainty associated with it. The eleven soil indicators which were considered in this report are **pH, organic carbon, bulk density, phosphorus (Olsen P), nitrogen (total N), magnesium (extractable), potassium (extractable), copper (aqua regia extractable), cadmium (aqua regia extractable), zinc (aqua regia extractable) and nickel (aqua regia extractable).** However, we also comment on the potential use of remote sensing for monitoring of **soil depth and (in particular) peat depth, plus soil erosion and compaction**.

In assessing the potential of remote sensing methods for soil monitoring of state and change, we addressed the following questions:

1. When will these be ready for use and what level of further development is required?
2. Could remote sensing of any of these indicators replace and/or complement traditional field based national scale soil monitoring?
3. Can meaningful measures of change be derived?
4. How could remote soil monitoring of individual indicators be incorporated into national scale soil monitoring schemes?

To address these questions, we undertook a comprehensive literature and internet search and also wrote to a range of international experts in remote sensing. It is important to note that the monitoring of the status of soil indicators, and the monitoring of their change, are two quite different challenges; they are different variables and their variability is likely to differ. There are particular challenges to the application of remote sensing of soil in northern temperate regions (such as England and Wales), including the presence of year-round vegetation cover which means that soil spectral reflectance cannot be captured by airborne or satellite observations, and long-periods of cloud cover which limits the application of satellite-based spectroscopy.

We summarise the potential for each of the indicators, grouped where appropriate. Unless otherwise stated, the remote sensing methods would need to be combined with ground-based sampling and analysis to make a contribution to detection of state or change in soil indicators.

Soil metals (copper (Cu), cadmium (Cd), zinc (Zn), nickel (Ni)): there is no technical basis for applying current remote sensing approaches to monitor either state or change of these indicators and there are no published studies which have shown how this might be achieved.

Soil nutrients: the most promising remote sensing technique to improve estimates of the status of **extractable potassium (K)** is the collection and application of airborne radiometric survey (detection of gamma radiation by low-flying aircraft) but this should be investigated further**.** This is unlikely to assist in monitoring change. Based on published literature, it may be possible to enhance mapping the state of extractable magnesium (Mg), but not to monitor change, using hyperspectral (satellite or airborne) remote sensing in cultivated areas. This needs to be investigated further. There are no current remote sensing methods for detecting state or change of Olsen (extractable) phosphorus (P).

Organic carbon and total nitrogen: Based on published literature, it may be possible to enhance mapping the state of organic carbon and total nitrogen (but not to monitor change), using hyperspectral (satellite or airborne) remote sensing in cultivated areas only. In applying this approach the satellite data are applied using a statistical model which is trained using ground-based sampling and analysis of soil.

Soil pH: Based on published literature, it may be possible to enhance mapping the state of soil pH (but not to monitor change), using hyperspectral (satellite or airborne) remote sensing in cultivated areas only. In applying this approach the satellite data are applied using a statistical model which is trained using ground-based sampling and analysis of soil.

Soil (peat) depth, erosion and compaction: based on some recent research, it may be possible using a new processing technique for InSAR (interferometric synthetic aperture radar) satellite data to monitor the change in surface elevation of peat soils (and overlying vegetation) as a proxy for change in depth. Further research is required to determine whether this approach could be applied to other (non-peat) soils. This approach is based on radar reflection from the Earth's surface and it cannot be used to quantify soil depth (status). However, this approach does not require field-based measurement of elevation to ground-truth the remotely sensed data. This technique can detect changes in surface elevation of as little as 1 millimetre over areas as small as one hundred square metres, so it may be possible to use it to monitor soil erosion in cultivated areas. This approach needs to be tested further and applied over large scales. Soil compaction also leads to small reductions in soil surface elevation so it may also be possible to detect compaction-induced changes through remote monitoring. Monitoring based on application of InSAR data needs thorough testing.

Bulk density: there are currently no remote sensing technologies which can contribute to improving measurement of status or change of soil bulk density.

1 Introduction

1.1 BACKGROUND

Defra last reviewed the opportunities for using remote sensing[1] (RS) to monitor soils in 2004 (Wood et al., 2004). This found, for the most part, that remote sensing could be used to monitor soil quantity and extent, but had only limited usefulness for those indicators that relate to soil condition (quality). Since then remote sensors have developed significantly and there have been a number of studies examining the potential use of remote sensing to measure the concentration of soil organic carbon across the landscape, and also possibly to monitor it. Given the high costs associated with soil monitoring, Defra wish to understand what the current opportunities to monitor soils remotely are, and what the potential is for remote monitoring to replace traditional field monitoring across England and Wales.

The UK Soil Indicators Consortium (UKSIC) identified the following eleven indicators for inclusion in national scale soil monitoring: **pH, organic carbon, bulk density, phosphorus (Olsen P), nitrogen (total N), magnesium (extractable), potassium (extractable), copper (aqua regia extractable), cadmium (aqua regia extractable), zinc (aqua regia extractable) and nickel (aqua regia extractable).** Since the UKSIC report (Black et al., 2008), **soil depth and, in particular, peat depth** has been identified as an important requirement for soil monitoring. There is also interest in the monitoring of **soil erosion and compaction**. However, we are not explicitly considering soil erosion monitoring, as a pilot project to establish a soil erosion network for England and Wales is currently underway. Combining the two sets of soil indicators above gives a total of fourteen that we consider in this report.

Soil monitoring activity is still at a relatively early stage of development. Optimal approaches to measuring state and change in soil may be quite different. The spatial variation of change in soil properties should determine the resampling strategy for monitoring, and this may be quite different from the baseline variation of that property's state (Lark et al., 2006). There are many examples of using remotely sensed data as covariates for reducing the uncertainty in predictions of soil properties such as organic carbon in combination with traditional, ground-based measurements (Rawlins et al., 2009). However, this, and other exploitation of remote sensor data depends on statistical correlations between the remotely sensed measurement and the soil property of interest. Such a correlation may have a direct physical basis (e.g. if the soil property directly influences the radiative properties of the land surface), but may also arise through secondary relationships (e.g. soil organic carbon may be correlated with clay content, which in turn affects soil water content and so the radiometric measurement). When we are concerned with measuring changes in the soil, a remote sensor variable that proves useful for predicting landscape-scale variation of baseline values may prove rather less useful, if its value in the former context is due to correlations with indirect rather than direct physical effects on the radiometric properties of the landscape. Our review of technologies therefore considers evidence for the relative importance of direct physical effects and indirect relationships in determining correlations of predictive value.

The aims of this report are to address the following questions:

1. What are the current and potential future opportunities to monitor any of the listed set of indicators using remote sensing? Defra wish to understand the potential to monitor both **state and change.**
2. When will these be ready for use and what level of further development is required?

[1] For the purpose of this study we consider remote sensing (RS) and earth observation [in relation to soil monitoring] to encompass airborne and spaceborne (satellite) sensor technologies (by means of propagated signals such as electromagnetic radiation) which can provide useful data or information for the purpose of soil monitoring.

3. Could remote sensing of any of these indicators replace and/or complement traditional field based national scale soil monitoring?
4. Can meaningful measures of change be derived?
5. How could remote soil monitoring of individual indicators be incorporated into national scale soil monitoring schemes (such as the Countryside Survey?)

In addressing these questions we have considered the full range of earth observation, satellite navigation and telecommunications tools available.

1.2 SENSOR PLATFORMS

In the context of remote sensing, the different sensor types can generally be mounted on either airborne or spaceborne platforms. Here, airborne platforms are differentiated according to whether the aircraft is manned (i.e. airplane or helicopter) or unmanned (i.e. UAV – un-manned aerial vehicle). The choice of sensor-platform combination is not only governed by the soil property of interest, but by several additional factors including the associated cost and practicality.

Irrespective of the application, the use of UAVs for remote sensing is somewhat restricted by the size and mass of the sensor payload they are capable of carrying. As a result, UAVs have traditionally been used as a platform for imaging systems for the acquisition of spectral reflectance data (Honkavaara et al., 2013; Torres-Sánchez et al., 2013), thermal infrared imagery (Berni et al., 2009; Zarco-Tejada et al., 2012), or for the derivation of photogrammetric digital elevation models (DEMs) (d'Oleire-Oltmanns et al., 2012). However, with recent advances in compact sensor technology, more potential UAV applications are emerging as some are now capable of carrying RADAR sensor payloads (Koo et al., 2012; Remy et al., 2012). After the initial outlay to purchase the UAV and any appropriate sensors, the cost of acquiring remotely sensed data from an unmanned airborne platform generally consists of the staff-time for only a single operator. Moreover, UAVs can be utilised to acquire very high spatial resolution data — typically on the order of centimetres — because they can be operated at lower altitudes than manned aircraft. However, imagery acquired at a very high spatial resolution usually covers a small spatial extent on the ground. As a consequence, achieving national-scale coverage using UAVs is likely to require considerable time and financial support. Accordingly, soil monitoring through repeat UAV surveys is arguably better suited to detailed local monitoring programmes.

The acquisition of various remotely sensed datasets (e.g., multi- and hyperspectral imagery, RADAR, LiDAR, radiometric, thermal) from manned airborne platforms is well established. Although having a higher operating altitude than their unmanned counterparts, manned airborne platforms can still be utilised to acquire high spatial resolution data — typically on the order of metres. Data acquired from manned airborne platforms also has the added benefit of it covering a larger spatial extent than that of UAV-acquired data, therefore providing a more practical means of acquiring data at regional or even national-scale. However, despite the advantages, the commissioning of manned airborne surveys is generally costly, particularly if considered for repeat surveys for national-scale monitoring purposes.

With many relevant sensors already in operation, spaceborne platforms offer an attractive means of monitoring soils at a national-scale, because image scenes typically cover large spatial extents and can be acquired at either no cost or for a relatively small fee. Although only a handful of scenes may be required for national coverage, spaceborne data do generally have a coarser spatial resolution than airborne platforms — typically on the order of tens to hundreds of metres. Nevertheless, with frequent revisit times, spaceborne platforms provide access to temporal datasets that can be readily used for monitoring purposes.

1.3 THE CHALLENGES OF REMOTE SENSING OF SOIL PROPERTIES

A recent review by Croft et al. (2012) highlights the major challenges to remote sensing and modelling of soil properties: "One of the greatest challenges facing the broad-scale adoption of remote sensing methods in soil science and soil organic carbon [SOC] studies is the site-specific nature of relationships between RS-measured variables and SOC."

Site-specific relationships between remotely sensed variables and soil properties can occur for various reasons:

1) Reported models are empirical in nature. These models are often only relevant for a particular instrument at a point in time and space, as the complex relationship between soil constituents and soil reflectance is not taken into account (Bartholomeus et al., 2011)
2) Sensor characteristics vary between sensors. The transfer of prediction models between one sensor to another can be complex, due to differences in spectral resolution, sampled wavelengths, location of spectral bands and the number of bands used (Bartholomeus et al., 2011).
3) The use of different numerical methods and data pools can also cause difficulties when comparing the statistical quality of mapped soil parameters (Selige et al., 2006).
4) Soil reflectance responds to temporally invariant factors (e.g. soil type, mineralogy, geology) and temporally variant factors (e.g. tillage, moisture, soil roughness, crop residue cover (Ladoni et al., 2010).
5) Inherent data accuracy of airborne and satellite data, which can be due to variations in illumination, changes in terrain and atmospheric attenuation (Ben-Dor et al., 2002). This can also cause problems particularly when, for example, SOC has low concentrations or a small range of SOC values, and measurement uncertainly can exceed spatial and temporal differences in SOC content (Stevens et al., 2008).

1.3.1 Challenges in northern temperate regions

In regions of northern latitudes, such as the UK (50-60 ºN), there are particular challenges for remote sensing of non-vegetated soils to measure their properties. The window of opportunity for remote sensors to measure soil surfaces is generally reduced because: 1) bare, or partially bare, ground exists mainly during the autumn and winter months, due to tillage practices, where soils are cultivated in the autumn and sown later that autumn; and in the case of grassland are seldom bare. 2) Cloud cover during the winter is common in northern latitudes, preventing clear-day skies, which are necessary for remote sensors to provide spectral reflectance data of soil properties. 3) Soil moisture can cause variation to spectral response, which during the winter can be very variable, including aspects of freeze/thaw and snow, which have a large effect on spectral reflectance. 4) During the winter, the angle of the sun is low, which also affects spectral response of remote sensors. To reduce spectral response variability in the visible and near infra-red, it is best to have a small azimuth angle[2].

Mulder et al. (2011) reviewed the use of remote sensing in **soil and terrain mapping** and summarised the various ways remotely sensed data offered possibilities for **extending existing soil survey datasets**. The suggested uses of remote sensing were:

1) Soil composition can be assessed by using remote sensing to segment the landscape into approximately homogenous soil-landscape units, which then aids the assessment of soil composition using classical or more advanced methods,
2) The spectral data measured by remote sensors can be analysed using physically-based or empirical methods to derive soil properties,
3) Remotely sensed imagery can be used as a data source to support soil mapping as described by (Grunwald et al., 2011), and (Minasny et al., 2013))

[2] The azimuth angle is the angle between the line from which the remote sensing instrument detects its signal from an observed point on the land surface and the line of shortest distance between the sensor and the land surface.

4) Remote sensing methods facilitate mapping of inaccessible areas, reducing the need for extensive time-consuming and costly field surveys.

1.4 MEASURING STATE AND CHANGE OF SOIL INDICATORS

The monitoring of the status of soil indicators and the monitoring of change in these indicators are two quite different challenges. Lark (2009) notes that the status and change of a soil indicator are different variables and their variability is likely to differ. For example, Lark (2009) considered the example of metal concentrations in the soil. The baseline status of a particular metal is likely to be primarily related to the underlying geology, whereas the change might be related to anthropogenic processes such as land use change and pollution. This example illustrates that a soil monitoring network that is suitable to monitor the status of a soil indicator might not be suitable to monitor the change in the property in two regards. First, the statistical design of the network might not be able to estimate the change in the indicator with the same precision as the status can be estimated. Second, a measurement method (e.g. a remote sensing technology) that is suitable to infer the status of the indicator might not be suitable to infer change in that property.

The design of a soil monitoring network refers to the configuration of locations and times at which the soil indicator is measured. The precision of an estimate of the baseline status of a soil indicator should improve with the sampling effort in space. This precision depends on the design and the spatial variability of the measurements of the soil indicator. If the variability of a particular indicator is well understood it is possible to estimate the precision with which a particular design will estimate the baseline status. Such a process was conducted by Black et al. (2008) when they considered the design of a UK soil monitoring network that would use conventional measurement methods. They used previous surveys of soil properties (the National Soil Inventory and Countryside Survey) to establish models of the spatial variability of key soil indicators, such as soil organic carbon, pH, copper and zinc. They then tested the precision with which different designs could estimate the means of these indicators. If the same process is to be used to determine the precision with which a soil monitoring network could estimate the change of a soil indicator, then it is necessary to quantify both the spatial and temporal variation of the indicator. Information about the temporal variation of soil properties tends to be less plentiful than spatial information, because of the expense of conducting a survey at multiple times and the time that must elapse before meaningful changes can be observed. Therefore, it tends to be more difficult to establish whether a monitoring network is suitable to monitor change with a specified precision. Black et al. (2008) only considered the precision with which changes in soil organic carbon could be estimated. Where temporal information about soil properties is not available it is necessary to conduct reconnaissance surveys prior to designing a soil monitoring network.

The second point about whether a particular measurement method is suitable to infer both status and change in a soil indicator is particularly pertinent for remote sensing technologies. Often these technologies do not directly measure the soil indicator of interest. Instead, they measure a property that is correlated to the indicator of interest and a statistical model is used to infer the indicator. If we return to the example of soil metal concentrations, it might be possible to use a radiometric sensor to identify variations in parent material and a statistical model calibrated to relate these variations to the metal concentrations. However, if the radiometric sensor is used to re-measure the soil at regular intervals then the information it gathers will still primarily relate to the variation in geology. It will say less about pollution or the changes in land use which might have caused changes to the soil metal concentrations.

One key question is "What is meant by a meaningful change in a soil property?" Meaningful could refer to a statistically significant change i.e. a change that is sufficiently large that we would not have expected it to occur by random chance. However, this is not always the most useful definition. The magnitude required for a change to be statistically significant decreases with sampling effort. If very intensive soil sampling is employed then it is possible that tiny changes to soil indicators might be statistically significant. However, these changes might be too small to cause a noticeable change to soil functionality. It is preferable to consider meaningful changes in terms of soil functionality. For instance, there might be critical thresholds in the concentrations of soil nutrients below which the soil is unsuitable to maintain production or heavy metal concentrations above which plant toxicity may occur. A meaningful change in the property could be said to have occurred if soil nutrient or heavy metal concentrations cross a threshold. Black et al. (2008) reviewed critical thresholds or ‘action levels’ for 13 soil indicators. A coupled question is how precisely the soil indicator and these action levels need to be monitored. Black et al. (2008) suggested that the development of such quality measures was urgently required, but to our knowledge, these have not been determined to date.

1.5 NATIONAL SCALE SOIL MONITORING AND INCOPORATION OF REMOTE METHODS

To understand the potential for remote methods to enhance soil monitoring it is necessary to clarify some terminology. We refer to ground-based soil sampling followed by laboratory measurements of soil indicators at national survey sites as *primary* observation. If a remote sensor makes a direct measurement of a soil indictor this is a *secondary observation*. Where we can establish a statistical relationship between a series of remotely sensed observations at a large number of sites where a series of *primary* observations have also been made, we refer to the former as a *secondary covariate*. Such a secondary covariate may have an indirect relationship with the soil indicator. For example, in their study on mapping soil organic carbon across Northern Ireland, Rawlins et al. (2009) stated that the two dominant factors which explained the negative correlation (indirect relationship) between SOC and gamma-radiation derived from potassium (^{40}K) decay were: i) the variation in mineral-K content which decreased with increasing quantities of soil organic matter, and ii) increased soil moisture resulting in greater attenuation of the gamma signal from the soil. The secondary covariate can be included in statistical approaches to predicting soil properties as a *fixed effect*.

To enhance soil monitoring, by contributing to the detection of a meaningful change in soil indicators, preliminary approaches are likely to utilise remote sensing as a secondary covariate to improve predictions of soil properties at unsampled locations. For example, in areas of cultivated soils of England, it may be possible to use either airborne (Selige et al., 2006) or satellite (Jaber et al., 2011) hyperspectral data as a fixed effect to predict SOC concentrations in topsoil across large regions.

The CEH Countryside Survey soil sampled a total of 396 sites across England and Wales in 2007 (Emmett et al., 2010), but it would only be possible to capture vegetation-free, remotely sensed data on soil reflectance for a subset of cultivated sites predominantly in southern and eastern England. If it was possible to establish a strong statistical relationship between the hyperspectral data for these sites and the primary measurements, this could be used as a fixed effect to make predictions (with associated uncertainties) for other areas of cultivated land for which hyperspectral data were available as a way of wider mapping of the status of soil indicators.

2 Methodology

Figure 1 shows our approach to address the aims of the project.

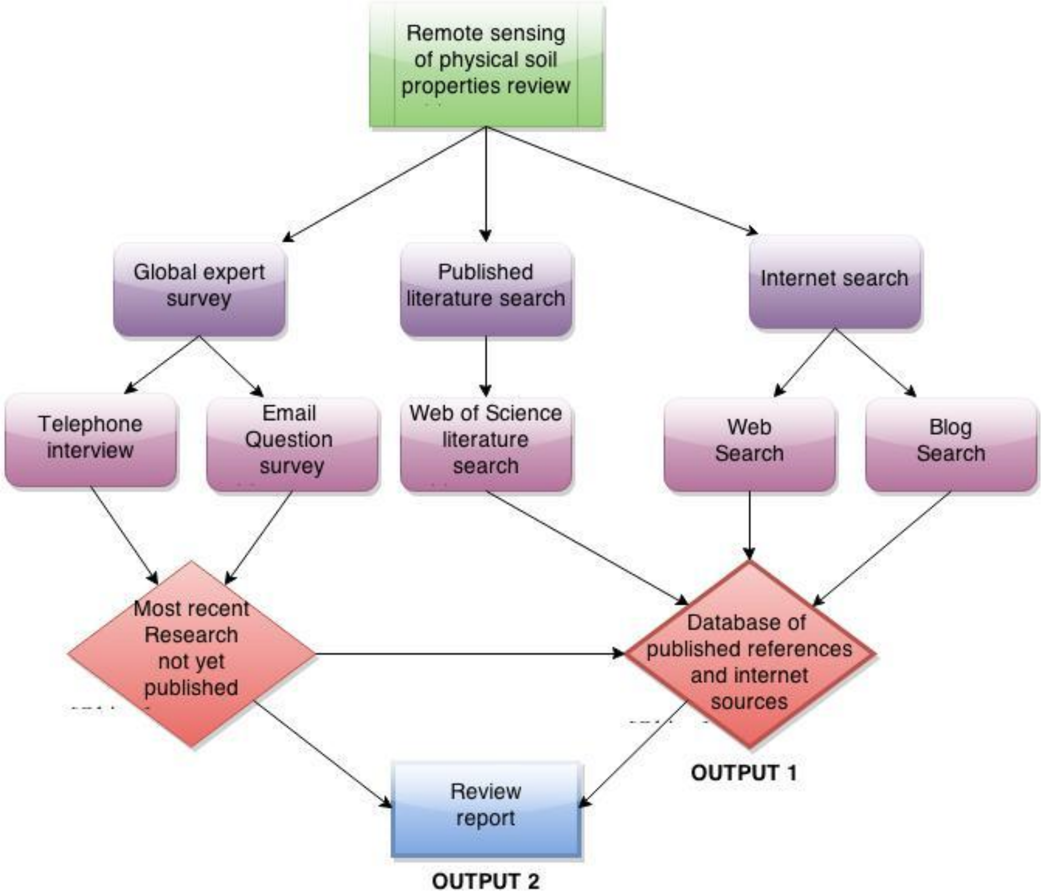

Figure 1 Summary of the approach used in this review study - Flow diagram of the literature review process to create a database of relevant literature and information (OUTPUT 1), which was then used to write OUTPUT 2: a review report of the most relevant findings of remote sensing and soil physical properties.

The literature review had three types of investigation to provide the relevant information and data for an up-to-date assessment. The literature review was divided into three searches: 1) Global Expert Survey, 2) Published literature search and 3) Internet search. These searches provided relevant published literature, internet data and sources, and the most recent up-to-date research from experts working in remote sensing. The data was compiled into a database to store and categorise the relevant material and is shown as Output 1, in Figure 1. The database was used to write the final review report (Output 2, in Figure 1).

2.1 PUBLISHED LITERATURE SEARCH

A literature search of published information was undertaken using the Thompson Reuters Web of Science literature search engine. A systematic topic search was done, using a combination of terms listed in Appendix 1 (Table 1), which provided 43 separate search criteria. The combination of search terms was considered in four 'fields': the first 'field' always used the term 'Soil'; the second 'field' was related to the terms 'remote sensing', 'satellite', or 'airborne' and more specific search terms relating to remotely sensed sensors, such as 'microwave', 'LiDAR' 'hyperspectal', 'thermal', 'radar' and 'unmanned aerial vehicle' and; the third field was related to a physical soil property, such as 'organic carbon', 'geochemistry', 'bulk density', 'soil depth'. Each time a search was done using a combination of terms, the number of 'hits': i.e. references found by the search engine were recorded (and are shown in Appendix 1, Table 1). If there were too many ‘hits’ (above 600 articles), more defined search terms were used and the search was run again. The search terms used in the published literature search are shown as grey rows in Appendix 1. A total of 2,885 published citations and their abstracts were downloaded to EndNote; a reference management software package, which manages bibliographies and references. All duplicate references were discarded and the final reference list in EndNote was 2,031 published references.

This final reference list in EndNote was then divided into three EndNote reference libraries and distributed to three experts, who then read through each reference and discarded those that were not-relevant. The criteria for keeping a reference were that the remote sensing method used monitored or measured one or more of the following:

1) SOC
2) Bulk density
3) pH
4) Soil depth
5) geochemical soil indicators: N, P, K, Mg, Cu, Zn, Ni and Cd
6) peat

Once all irrelevant published references were deleted, the three resulting libraries were merged to create a final reference EndNote library. The final merged library contained 307 published references.

2.2 INTERNET SEARCH

Two types of Internet searches were undertaken, using the Google Chrome browser to find relevant published references, website references, sources and blog sites relating to remote sensing of soil physical properties (shown in Appendix 1, Table 2). The first search was a Google Web search and used two search criteria: 1) ‘remote sensing’ + ‘soil’ + ‘physical’ + ‘properties’ and 2) ‘remote sensing’ + ‘soil’ + ‘monitoring’. Theses searches gave an enormous amount of hits (between 2 and 4 million), we therefore only searched the hits of the first 10 pages.

As the second search criteria provided only 1 useful reference, we only used the search criteria ‘remote sensing’ + ‘soil’ + ‘physical’ + ‘properties’ for a Google Blog search, which found 4 useful hits from the first 10 pages of the Blog Search.

In total, 44 useful references were found and added to EndNote. These references were added to the final merged EndNote library, providing in total 351 references.

2.3 GLOBAL EXPERT SURVEY

Based on our knowledge of the soil remote sensing community, we selected and wrote to six world experts (see list in Appendix 2, Table 1) to ask whether there were new techniques which had not yet been published that may be worthy of consideration in this review. The letter sent to these experts is also shown in Appendix 2. Where the experts provided new references relevant to our review we included these in our reference database and where they provided relevant, new insights we included these in our overall interpretation. We also undertook a telephone interview with members of a project team based at the newly established company Rezatec, who are currently undertaking a project to develop a peat spotter service, where the objective is enable accurate, cost-effective and appropriate (in line with international standards) methods for identifying the location of peatlands, quantifying their intactness and assessing their carbon content.

2.4 STRUCTURING AND ASSIMILATION OF INFORMATION

All the new (n=15) references from the Global Expert Survey were added to the final merged EndNote library (containing 351 references). This library was again divided into three smaller libraries and given to three experts who again discarded irrelevant references which were considered to be:

1) of no relevance in a UK environment (many of the references related to arid and semi-arid environments).
2) related to the monitoring of irrelevant physical soil properties.
3) using inappropriate remotely sensed techniques; for example many references were related to using spectral techniques proximally (at ground level) or in laboratory conditions.

The remaining total number of references was 186. These final references were then categorised using a 'tagging' procedure in EndNote. Each reference had a Keyword field which was 'tagged' using keywords, relating to the remote sensor and the physical soil property being measured. These keywords were the following:

1) Hyperspectral
2) SAR
3) Microwave
4) UAV
5) Thermal
6) Radiometric
7) Spectral
8) Soil texture
9) Electrical conductivity
10) Bulk density
11) pH
12) Soil depth
13) SOC
14) Geochemistry
15) Erosion

By using tagged keywords, the references were then categorised quantitatively to understand which remote sensor was mainly used to measure different soil properties and which physical soil property had been researched the most.

3 Results and their interpretation

We have presented our findings by first summarising the counts of the tagged keywords in the reference database through combining the information from the literature search, the internet search and the expert survey. Secondly, we have assessed each of the indicators separately through addressing the list of **5 key questions which were presented in the introduction**. We summarise the information in a table describing the most promising remote sensing approaches which might be used for each indicator and the practicality of implementation. We chose to combine some of the indicators into two groups: i) nutrients (extractable K, extractable Mg, Olsen extractable P, total N) and ii) metals (Cd, Zn, Cu, Ni).

3.1 TAGGED DATABASE SUMMARY

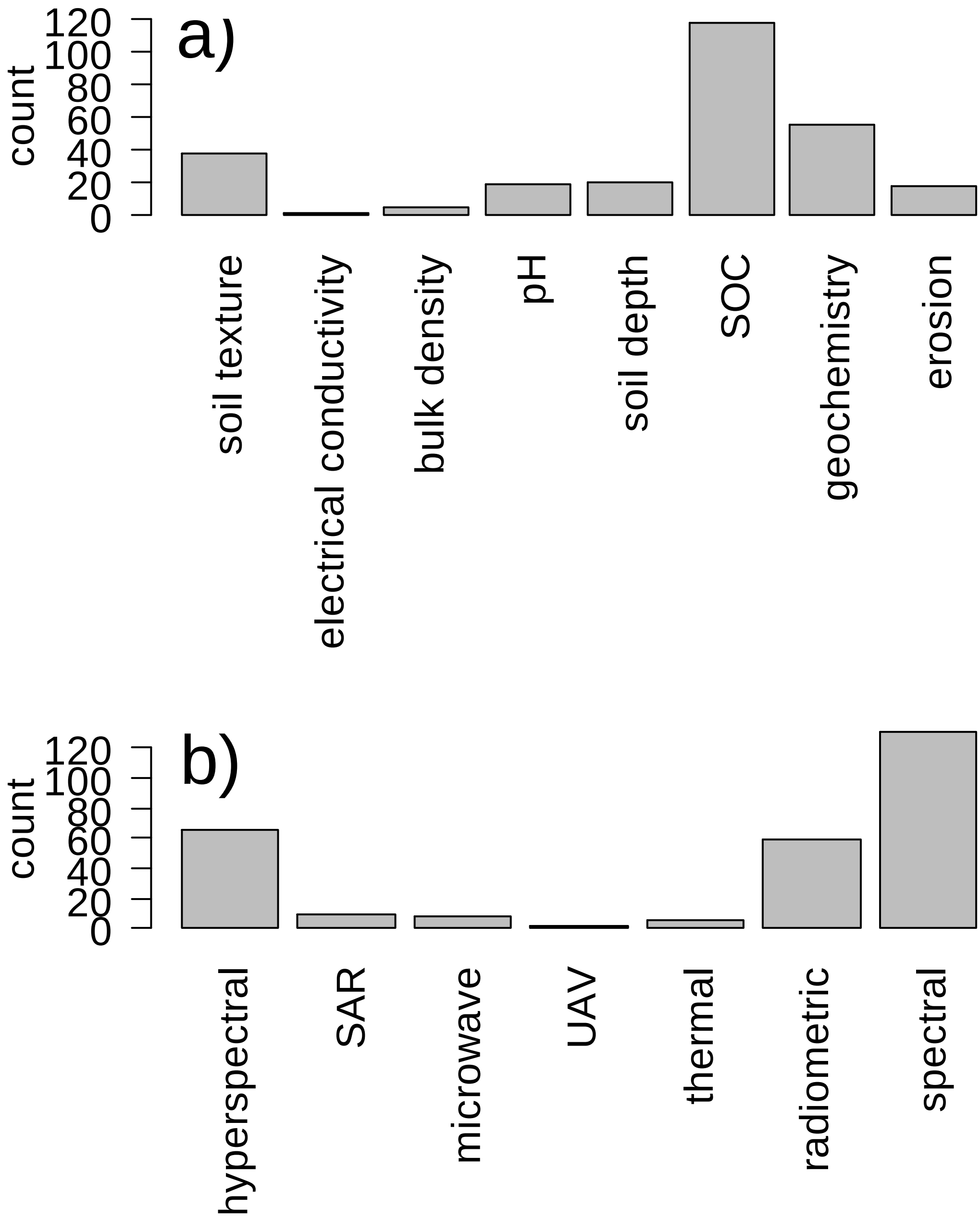

Figure 2 The number of soil monitoring and remote sensing studies which refer to or utilise the specified a) soil indicators, and b) sensors/platforms (based on a total of 185 references selected from peer-reviewed published literature).

Figure 2a shows that overwhelmingly the most common soil indicator which has been measured (or referred to) by soil remote sensing approaches is SOC (n=118 keyword citations). This dominance is likely for two main reasons: i) the importance of soil organic carbon as a mediator of global climate change and its general use as a soil quality indicator, ii) organic carbon signatures can be detected using hyperspectral data because the frequency of the associated bonds occur within the visible and near infra-red spectral range (0.35–2.5 µm).

3.2 SOIL ORGANIC CARBON (SOC) AND TOTAL NITROGEN (N)

SOC: There are many published studies which show that remotely sensed reflectance data can be used, via the construction of statistical models between the spectra and direct measurements of SOC, to make predictions of the concentration of SOC (status) at sites where soils samples have not been collected (Ladoni et al., 2010). The spectral reflectance (or spectral absorption) data encompasses the ultra violet (UV), visible (VIS), near infrared (NIR) and mid infrared (MIR) regions. However, there are currently few satellite-based observations that encompass the MIR range which typically have stronger correlations with SOC than the NIR range (Ladoni et al., 2010).

One of the problems of using spectral reflectance data is that mineral absorption features typically overlap with organic compounds so statistical models must be developed for particular regions and cannot necessarily be applied with the same confidence to other regions. Soil spectral reflectance and SOC relationships are not universal, and therefore require new statistical models to be constructed for each study area and field samples need to be collected and analysed (Ladoni et al., 2010). Weak statistical correlations may be observed between SOC and soil reflectance when soil samples are taken from large geographic areas with different parent materials or different landscapes where reflectance response is dominated by soil factors other than organic matter content (Henderson et al., 1992).

Gomez et al. (2008) used a combination of proximal spectrometer data and Hyperion hyperspectral information to construct a statistical model and map SOC. In their study, Gomez et al. (2008) concluded that predictions of SOC using ground-based spectrometer data were more accurate than the Hyperion spectra, although the SOC map predicted using Hyperion data showed similarity with field observations. Selige et al. (2006) showed that airborne hyperspectral remotely sensed data could be used to accurately map SOC concentrations at field scales,. In their study encompassing Europe, Stevens et al. found that the errors in predicting SOC concentrations from visible and near infra-red (VNIR) spectra were 5 times greater than for traditional soil sampling and laboratory analysis. The best spectral calibrations achieved a root mean square error ranging from 4 to 15 g C kg^{-1} for mineral soils and 50 g C kg^{-1} for organic soils.

A direct relationship between SOC and soil reflectance is only measurable when SOC is greater than 2%, otherwise the SOC signal is concealed by the presence of other biochemical components such as iron and manganese (Al-Abbas et al., 1972). Such low SOC concentrations can cause difficulty in deriving absorption features through visual inspection alone, due to a combination of overlapping absorption features. Consequently, more complex spectroscopic modelling approaches are needed to derive mathematical relationships between soil spectra and soil constituents (Croft et al., 2012).

Two reflectance bands (near infra-red and red) have been used from both airborne and remotely sensed imaging based on the ‘soil line’ concept. For any un-vegetated soil surface, there is an approximate linear relationship between the NIR and red reflectance bands referred to as the ‘soil line’ with which other soil properties are related. This shows bright soils are more reflective in both the IR and red, whilst dark soils are the least reflective in both reflectance bands (Richardson and Wiegand, 1977). As concluded by Baret et al. (1993) and Nanni and Dematte (2006), experimental results show that a “global soil line” does not apply and that the main factor of variation of ‘soil line’ parameters appears to be soil type. In their review, Ladoni et al. (2010) indicate that more recent research has shown that ‘SOC is correlated to a pixel’s location along the soil line’ using the soil Euclidean distance (SLED) technique (Fox and Sabbagh, 2002). Soil sampling and measurement of these samples for SOC provide a descriptive curve relating SLED and field SOC. This method has been shown to reduce field sampling and was found to provide good correlations with SOC (R^2 = 0.72 to 0.76) (Fox and Sabbagh, 2002). Both NIR and red reflectance bands are available from airborne infra-red cameras and satellite platforms that encompass the UK, but these data have not, to date, been combined with ground based analyses for application to national scales in England and Wales.

Based on a combination of ground-based sampling and airborne radiometric survey, Rawlins et al. (2009) showed that SOC concentration could be mapped with smaller prediction uncertainties by including measurements of radiometric K data as a secondary covariate, along with elevation data. This approach can only be applied from low-flying airborne or ground-based systems, so it may have limited applicability to national-scale approaches. All the published studies have demonstrated that remotely sensed data can contribute to improved mapping of SOC concentration [status], but none have shown that remote methods can monitor change, either with or without ground-based measurements. In their review, Ladoni et al. (2010) conclude that the main advantage of remotely sensed data (suggested by most researchers) is that "they can be used to design a sampling scheme for mapping SOC [status] with the smallest number of samples, and with greater accuracy". They also propose that:

1. Remotely sensed data should first be a guide for field soil sampling, rather than directly predicting soil properties.
2. Satellite data should be used as secondary information as geostatistical analysis has shown the potential to improve predictions of SOC.

Total N: There is a relatively restricted range of element ratios between total C (carbon) and total N (nitrogen) in soil organic matter and it is possible to use pedo-transfer functions (PTFs) to estimate total N on the basis of other measured soil properties, including soil carbon and bulk density, with only modest prediction errors (Glendining et al., 2011). However, errors for predicting total N based on the application of PTFs, using EO measurements of these soil properties as predictors, would likely be too large for practical use. It has been shown that total soil nitrogen can be predicted with reasonable accuracy based on statistical models of visible and near infra-red (VNIR) laboratory spectra (Viscarra Rossel et al., 2006) and also using airborne, hyperspectral remote sensing data in combination with ground-based measurements (Selige and Schmidhalter, 2005). There were two studies in which remotely sensed data had been used to enhance predictions of ground-based measurements of total nitrogen. First, a study by Wu et al. (2009) applied this approach in Hengshan County, the northern Shanxi Province of China, using Hyperion satellite data. Second, a study by Stamatiadis et al. (2013) applied the technique to three, 10 hectare fields in Greece. They showed that the greatest negative correlation coefficient (coefficient of determination R^2 = 0.77) was obtained between satellite NIR reflectance (0.5 metre multi-spectral World View 2 image) and soil N content. In both cases, it was necessary to develop statistical models for the prediction of total soil nitrogen, using primary field sampling in combination with EO (hyperspectral) measurements. The prediction errors for total soil N using the VNIR spectral range are typically somewhat larger than for total C (Viscarra Rossel et al., 2006). Based on the published literature, airborne or spaceborne hyperspectral soil reflectance measurement is the only current EO technique which is likely to provide reasonable predictions of total soil N. However, because the remote sensor must be able to detect reflectance directly from the soil surface, this approach requires non-vegetated soil which are most effectively calibrated by ground-based soil sampling and direct laboratory measurements of soil properties. Although we might expect statistically significant relationships between EO-derived vegetation canopy productivity indices and total soil nitrogen, there were no published studies which demonstrated that such relationships were sufficiently strong to accurately predict soil total N under a range of vegetation types.

Our findings relating to the most effective EO technique for predicting state or change of total soil N were very similar to those for SOC, the most promising technology is hyperspectral remote sensing.

3.2.1 Opportunities

The strong relationships between reflectance spectra and both SOC and total N, using multivariate statistical techniques, particularly laboratory and proximal (ground-based) approaches, illustrates their potential for improved mapping of their concentrations [state] (Croft et al., 2012). The larger uncertainties in statistical models developed to predict SOC and total N, using remotely sensed spectral information by comparison to ground-based (proximal or laboratory) methods, reflects: i) the site-specific nature of relationships between remotely sensed measured variables and target properties, and ii) atmospheric interference effects. However, the uncertainties in the prediction of soil properties such as SOC can be substantially reduced by combining digital mapping using combinations of spectral information and other data sources, such as soil and vegetation maps. Such an improvement in SOC prediction is shown in the use of digital mapping of SOC, which has quickly moved from a research stage to being operational, with maps of carbon concentration and carbon stock from field to regional scale (Minasny et al., 2013).

The review of Ladoni et al. (2010) suggests that given the uncertainty of direct measurements of SOC by remote sensing, there is a far greater possibility to use remotely sensed data to guide sampling schemes, rather than for direct measurement. Obtaining representative soil samples is useful for the application of geostatistical models, and remotely sensed data has been found to be advantageous in designing a sampling scheme for mapping SOC, with the smallest number of samples and with greater accuracy, at lower costs (Ladoni et al., 2010).

3.2.2 Can Earth Observation replace field sampling?

Based on current sensor technology, EO cannot replace field sampling but can complement it by: i) helping to improve sampling schemes, and ii) providing an exhaustive covariate (available across large parts of the landscape) that if used in a statistical model can substantially reduce the uncertainty in predictions of total concentrations. For mapping the state of these properties it would be possible to devise efficient sampling schemes to achieve a specified accuracy based on the analysis of a specified number of ground-based samples with associated analyses, thus reducing survey costs. In addition to spectral reflectance data, there are other environmental covariates which can reduce the prediction uncertainties of SOC and total N, such as terrain indices.

3.2.3 Can change be measured?

There have been no published studies to date which have demonstrated that a change in SOC or total N can be measured [at national scale], using only remotely sensed methods. We noted in the introduction that the challenge of monitoring change is quite different to mapping the state of soil properties. The errors associated with predicting SOC and total N concentrations by remotely sensed methods are substantially larger than for direct soil sampling and analysis, and it is therefore not practical to apply this approach to monitoring change for those areas where vegetation is sufficiently sparse for periods of the year for reflectance measurements to be made.

3.2.4 Integration with National Surveys?

The most promising technique for applying remote sensing of both SOC and total N is combining the use of hyperspectral satellite data with ground-based sampling and analysis of topsoils from a national survey (such as the National Soil Inventory or Countryside Survey) to improve predictions of SOC concentrations [state] at un-sampled locations. However, reflectance data will only be available for a subset of those sites which are cultivated annually, limited largely to eastern and southern parts of England. Without first testing this approach, it is not possible to state the magnitude of the improvement in prediction accuracy through using remotely sensed data. A number of other factors would likely influence this; the quality of the remotely sensed data (e.g. the extent of atmospheric interferences) and soil-dependent interferences between mineral and organic carbon and nitrogen absorption bands.

3.3 BULK DENSITY AND COMPACTION

The bulk density (of topsoil) is the mass of soil material per unit volume and is strongly related to the soil organic carbon concentration (and thus land cover type), land management and to a lesser extent soil texture (Hollis et al., 2012). Soils which have been subject to compaction have larger bulk densities than those which have not and so we consider compaction in this section.

There were no published papers in the scientific literature (nor was there evidence elsewhere) which showed that soil bulk density or compaction could be predicted on a defined scale with a specified accuracy using remotely sensed signals. In their study on prediction of soil physical properties using spectral approaches, Minasny et al. (2008) state that "soil physical properties that are based on pore-space relationships such as bulk density, water retention and hydraulic conductivity cannot be predicted well using [MIR] spectroscopy". The soil property which accounts for the greatest (typically around 65%) proportion of variation in bulk density is SOC concentration (Hollis et al., 2012). Hence, it may be possible to use pedo-transfer functions based on SOC concentration to predict bulk density with errors somewhat larger 0.17 gm cm^{-3} (Hollis et al., 2012) However, such large errors would mean that monitoring change by remote sensing would be impractical, and therefore it is advisable to use field-based sampling and analysis to monitor this property.

Given the current absence of effective techniques for measuring bulk density by remote methods, and no immediate prospect of this being addressed in the short-term by new technologies, we have not addressed the set of five questions relating to this indicator, but summarise them in Table 1. Soil compaction leads to small reductions in soil surface elevation so it may also be possible to detect compaction-induced changes through remote monitoring of elevation using the InSAR methods described in the study by Rawlins et al., (2014), however such an approach would need considerable research and testing before it could be deployed.

3.4 SOIL DEPTH AND SOIL EROSION

Soil/peat depth: In a recent study funded by the Welsh Government, interferometric synthetic aperture radar (InSAR) remote sensing data was used to monitor changes in the surface elevation of vegetated peat over an area of 10 km^2 (and other land cover types across a wider area) over a period of seven years (1993-2000; (Rawlins et al., 2014). This study involved the application of a new InSAR processing technique which considers pixels within the input radar stack that are only coherent for subsets of the total period of processing. The authors found that variations in the change in peat surface elevation across the study area were similar over shorter (24 hours) and longer periods (>100 days); the longer periods included periods of prolonged wet and dry weather. The standard deviation of the peat surface elevation change was around 5.5 cm, in both cases highlighting considerable movement which the authors consider may be caused by gas generation and loss in peat soil. The standard deviation in elevation change for other soil types with differing vegetation (grassland, forest, heather) was substantially smaller (1.7-3.2 cm). The mean elevation of peatland (and its vegetation canopy) did not appear to change markedly over the seven year period, but there was clearly a considerable amount of short-term variation. These data suggest that it would be possible to monitor peat canopy elevation over many years to detect change, as a proxy for measuring changes in peat thickness, assuming there were limited changes in vegetation canopy height. A substantial period of monitoring (>20 years) would likely be required to detect a statistically significant change in elevation of blanket peats, given the long timescales over which these soils respond to changes in local conditions.

The approach described by Rezatec (see expert survey) to develop a peat spotter service will be based on a combination of satellite-based interferometry and LiDAR techniques to quantify tropical peat depths and volumes, in combination with ground-based measurements using field sites in Indonesia. Based on the findings of this work, which are in the early stage, it is hoped that the methodologies might be transferable to temperate zones such as the UK.

Soil erosion: The current, Defra-funded pilot of a soil erosion monitoring network for England and Wales (project SP 1311), will utilise a fixed-wing UAV at a series of selected sites as a means of identifying the extent of erosion features, but there are no plans currently to process the captured images to quantify erosion losses. A fixed-wing UAV was used by d'Oleire-Oltmanns et al. (2012) to quantify gully and rill erosion in 2D and 3D for a region of Morocco, based on the creation of high-resolution Digital Terrain Models. In their review paper on monitoring, soil degradation by remote sensing, Shoshany et al. (2013) identified three RS technologies which were most likely to be effective: InSAR, LiDAR and close-range photogrammetry. For national scale erosion monitoring we suggest that deployment of *direct* approaches to detect either gully erosion features or overall lowering of parts of the landscape (with associated accumulation downslope) is the most promising approach.

3.4.1 Opportunities

InSAR methods applied to satellite data may be able to detect a lowering of surface elevation by millimetres or centimetres. This is a similar approach to that used by Rawlins et al. (2014) in their assessment of changes in peat elevation. After processing, the ERS satellite data used by Rawlins et al. (2014) had a support (ground footprint) of a square, with side length 100 metres. Although these data are costly, more recent satellites (TerraSAR-X and RADAR-SAT) have the potential for finer resolution imagery (square of side length 1 or 10 metres) which may offer greater potential for detecting changes within particular fields or identifying gully erosion features. The SAR data from ESA’s soon-to-launch (Spring 2014) Sentinel-1 satellite will be freely available at resolutions of 10 metres making this a practical means of obtaining the relevant data to assess the InSAR technique. One of the limitations of applying InSAR methods to the assessment of soil erosion/soil depth is the need to have a consistent (or preferably absent) vegetation canopy. The method could be applied effectively to cultivated land when crops have been removed, but it may be problematic to apply it in areas of grassland where sward heights change by season and between years. Another study also used a combination of LiDAR data, InSAR and air photographs for detecting landslides and erosional features evolving at rates similar to those represented by water erosion of soil (Roering et al., 2009). The approach was of sufficient resolution for the authors to compute downslope motion rates and also to estimate denudation rates.

3.4.2 Timing and further development

There are no current technical barriers to testing the use of a combination of InSAR with IsBAS processing for assessing changes in surface elevation as a means of estimating soil erosion in cultivated areas. To access the most appropriate data it would be necessary to make a scientific application to those responsible for satellite data capture to ensure the relevant scenes were acquired on a regular basis. It would also be necessary to ensure that areas where the technique is deployed are not subject to subsidence which could confound predictions of erosion loss or overall changes in surface elevation (Sowter et al., 2013).

3.4.3 Can Earth Observation replace field sampling?

Based on the evidence presented, we believe that a combination of InSAR with IsBAS processing for assessing changes in surface elevation, as a means of estimating soil erosion or change in soil depth, could replace field-based measurements such as terrestrial LiDAR. However, the method would need to be rigorously tested in areas where cultivated soils were known to have eroded to demonstrate that the method was fit for purpose.

3.4.4 Can change be measured?

Assuming there were no technical difficulties with access to and processing of the data, it should be possible to measure changes in the elevation of cultivated land, which could be attributed to erosion processes or changes in soil depth. However, this approach/technology would need thorough testing with ground-based validation before it could be implemented.

3.4.5 Integration with National Surveys?

There is currently no established national-scale soil erosion monitoring scheme, although a pilot is currently being undertaken (Defra SP1311). It may be possible to integrate earth observation with such a survey, although the InSAR technique is likely to be limited to vegetation-free, cultivated areas initially.

3.5 METALS

There is currently no technical basis for estimating the four total heavy metal soil indicators directly from remotely sensed data. Quantitative assessments of soil properties from remote sensing largely rely on the correlation of particular soil properties with infra-red spectroscopic reflectance measurements (Mulder et al., 2011) which relate to the chemical bonds within organic and inorganic compounds in the soil. The bonds that respond markedly to infra-red spectroscopy are predominantly between carbon, nitrogen, hydrogen and oxygen, which are present in substantial quantities in certain soil phases. The four heavy metal soil indicators (Cu, Zn, Ni and Cd) either do not exhibit diagnostic spectral features in the infra-red wavelength region, or in the case of extractable components, the relationships between the bonds and extracted phases are too complex to be resolved in a quantitative measurement. Nor do these indicators typically have simple relationships with common soil properties that can be identified by their infra-red spectral characteristics (Viscarra-Rossel et al., 2006). One study on soil heavy metals refered to the application of remotely sensed data (Chen et al., 2012), however, the hyperspectral imagery was used as a means of classifying land use, not as the basis for measuring or improving the prediction of heavy metal concentrations in the soil.

Due to a lack of appropriate methods, we do not consider it appropriate to separately address the five questions posed in our introduction. To summarise, there is no current or medium-term potential earth observation technique which could be deployed to monitor total (*aqua regia* extractable) soil heavy metal concentrations. It is likely that the only realistic approach is field based sampling and laboratory analysis, likely based on existing monitoring networks.

3.6 EXTRACTABLE NUTRIENTS

The three extractable nutrients (and the forms they are present in extracted solutions that concern us are: phosphorus (Olsen P), magnesium (extractable), potassium (extractable).

3.7 OLSEN P, EXTRACTABLE MG, EXTRACTABLE K

The extractable concentrations of these three nutrients inform us about the fertility of the soil. Extractable concentrations are quite different from total concentrations, because the former are held in ‘exchangeable’ forms associated with the surfaces of soil minerals and organic matter. The concentrations of extractable nutrients do not have such strong relationships with bulk soil properties, because they can reflect recent applications of manufactured fertilisers and organic materials or transitory soil hydrological conditions (e.g. wetting and drying cycles). The basis of predicting soil properties based on VNIR spectroscopy relies on the overall reflectance properties of the dominant soil mineral and organic phase composition, not the composition of ‘exchangeable’ elements on their surfaces. A review study by Ge et al. (2011) summarised approaches to estimate a range of soil properties by use of remote sensing including total P, total K and Mg, but not extractable concentrations. The bonds that respond to infra-red spectroscopy are predominantly between carbon, nitrogen, hydrogen and oxygen which are present in substantial quantities in certain soil phases, whilst bonds for P, K and Mg are much less responsive.

3.7.1 Olsen P

There were no published studies which showed that Olsen P could be measured using any remote sensing technique. Nor had any study shown that Olsen P could be predicted accurately from soil based spectroscopic measurements. A study by Baojuan (2008) in the USA showed that total soil P could be predicted using Hyperion hyperspectral, remote sensing imagery; the statistical model based on the spectra accounted for 67% of the variation in laboratory measured total P from field based sampling. However, although there are typically positive correlations between total P and Olsen P in soil (Owens et al., 2008), the uncertainties associated with predicting the latter based on the former are far too large for this approach to be practical.

3.7.2 Extractable Mg

Hyperspectral VNIR data have been used to construct statistical models to predict extractable Mg in soil. In a study using 750 diverse soils from South Africa, (Shepherd and Walsh, 2002) accounted for 81% of the variance in extractable Mg using VNIR spectra, suggesting this approach had potential for wider application. However, no studies have confirmed this relationship in temperate environments such as the UK. None of the other remote sensing technologies have been shown to have sufficiently strong statistical relationships with extractable Mg for practical deployment in predicting state or change.

3.7.3 Extractable K

The only study to have demonstrated that extractable K could be measured based on the VNIR spectra of soil samples was published by Daniel et al. (2003) based on 41 samples collected from a region of Thailand. In their study, Daniel et al. (2003) found that soil spectra accounted for 80% of the variance in extractable K; there was no attempt to relate the ground-based spectra to remotely sensed sources such as hyperspectral satellite data. A total sample size of 41 is a relatively small number upon which to develop and independently validate predictions of extractable soil K. It is somewhat surprising that, if there was a general relationship between soil VNIR spectra and extractable K, it has not been reported more widely given its potential importance for soil fertility and agricultural production. We believe that the relationship reported by Daniel et al, (2003) was unusual (confined to these local soils) and that if tested more widely, the relationship could not be deployed to accurately predict extractable K in soils across broad landscapes. Furthermore, the relationship with hyperspectral satellite data and extractable K would likely be even more tenuous.

By contrast, it is possible to accurately predict total K based on *airborne* radiometric survey data which relies on the detection of gamma radiation from ^{40}K emitted from the ground surface. Airborne radiometric survey data have been used to determine the distribution of plant available K at farm-scale (Pracilio et al., 2006); gamma-K concentrations accounted for 60% of the variation in bicarbonate-extractable K across three farms in Australia. Specific regions of England and Wales have been flown by airborne radiometric survey by the British Geological Survey, including parts of the Midlands (Rawlins et al., 2007) and Wales, the Isle of Wight, and in 2013 south-west England. However, the relationships between total and extractable potassium have not, to date, been investigated across England and Wales using these data. Such an investigation could be undertaken by combining the data from the original National Soil Inventory of England and Wales (McGrath and Loveland, 1992) with the airborne survey data held by BGS. This would establish if radiometric K is an effective predictor of extractable K at the landscape scale (i.e. to predict its state for mapping), and/or to infer change in this property.

3.7.3.1 OPPORTUNITIES

In general, there are limited opportunities to implement national scale RS techniques to contribute to monitoring changes in the three soil nutrients (Olsen P, extractable K, extractable Mg). In the case of Olsen P, there is currently *no technical basis* for successful application of remote sensing of this soil property. In the case of extractable Mg, there is some evidence that hyperspectral RS data might contribute to indirect mapping of this property (state), but there is no evidence to suggest it could be used to monitor change even in combination with a ground-based survey. In the case of extractable K, the most promising technology for mapping this property, in combination with ground-based sampling, is airborne radiometric survey. However, further investigation is required to establish the strength of statistical relationships between radiometric K and extractable K across the landscape; data are available to do this.

3.7.3.2 TIMING AND FURTHER DEVELOPMENT

There do not appear to be any major development opportunities or timelines for radical advances in the detection of the three extractable soil nutrients (P, Mg and K). One potential development is the investigation of whether radiometric K has a strong correlation with extractable K, which could be used to enhance the prediction of extractable K across the landscape.

3.7.3.3 CAN EARTH OBSERVATION REPLACE FIELD SAMPLING?

Based on the literature survey, it is *very unlikely* that earth observation could replace field sampling for the three soil nutrient indicators; it is possible that with further development the hyperspectral and radiometric RS approaches might be able to complement field sampling.

3.7.3.4 CAN CHANGE BE MEASURED?

Based on the available information it is *very unlikely* that change in these three soil properties could be measured directly using RS approaches.

3.7.3.5 INTEGRATION WITH NATIONAL SURVEYS?

There are technical and practical barriers which would limit the extent to which RS approaches could be integrated with national surveys to monitor soil nutrients. First, with the possible exception of extractable Mg, there is uncertainty over the strength of direct or indirect relationships between these soil properties and their (hyperspectral) remote sensing signal; this is likely to be insufficient for practical monitoring in combination with ground based measurements. The practical limitations of applying hyperspectral remote sensing are that for much of the year vegetation prevents direct reflectance from the soil surface which would severely hamper any attempt to apply these approaches to much of the landscape.

3.8 SOIL PH

Soil pH is a critical soil property which has importance for a wide range of soil processes concerning fertility and soil nutrients, water quality (acid deposition and buffering capacity), soil biology. Soil pH is controlled by a combination of soil mineralogy and land management (liming) and organic matter composition. Soil pH is typically measured using wet laboratory-based methods but there are strong relationships between VNIR spectra and soil pH.

3.8.1 Opportunities

The most promising approach for quantifying the state of soil pH using remote sensed methods is the application of hyperspectral remote sensing in combination with ground-based measurements (Lu et al., 2013). In their study, Lu et al. (2013) showed that using Hyperion imagery, 60% of the variation on pH was accounted for by a statistical model fitted between the measured pH of the field samples and the remote sensing data from the VNIR region. To robustly detect a change in soil pH, the method for its measurement would need to have a significantly smaller error than that which would be associated with spectral approaches that relay in ground-based calibration of remote sensed data which could have RMSE values as large as 0.3 pH units (Lu et al., 2013). So it is unlikely that hyperspectral imagery (in combination with field sampling) could be used to measure change of soil pH. Based on our literature survey, only one study has demonstrated that remote sensed data can improve the prediction of soil pH (state) and further studies are required across a range of soil types to prove that this approach is more generally applicable.

3.8.2 Can Earth Observation replace field sampling?

It will be necessary to use field sampling to develop the statistical model based on the remote sensing data for the prediction of soil pH.

3.8.3 Can change be measured?

It is unlikely that change can be measured based on current technology; there are no technologies in the pipeline that are unlikely to mean that change can be measured by remote methods at national scale.

3.8.4 Integration with National Surveys?

By capturing hyperspectral remote sensed imagery for periods when cultivated areas are largely free of vegetation, it would be possible to make more accurate predictions of soil pH in these areas, but only in regions where ground-based sampling has been undertaken. It would not be possible to use this approach in year-round, vegetated areas.

3.9 SUMMARY

Table 1 below provides a summary of the most promising earth observation techniques for each of the soil indicators.

Table 1 Summary of most promising remote sensing techniques for a range of soil indicators.

Indicator	Most promising RS technique (or none available)	Platform	Can detect state and/or change	Will also require ground-based soil sampling and analysis at national scale?	Further development required? Practicality or technical considerations to be addressed
Organic carbon and total N	Hyperspectral	Satellite	* State (not change)	Yes	Outcome: smaller errors in predicting concentrations in bare soil (partially vegetation free regions). New satellites (e.g. HySPIRI) may enhance spectral signal-to-noise ratios.
Bulk density	None available	NA	NA	NA	NA
Soil depth (and erosion)	InSAR (using IsBAS)	Satellite	Change	No	This technique needs further testing before it could be used to monitor either peat depth or estimate the magnitude and extent of soil erosion.
Total metals (Cu, Zn, Cd, Ni)	None available	NA	NA	NA	NA
Extractable K	Radiometric survey (gamma radiation)	Airborne	*State (not change)	Yes	This technique would need testing in a pilot study – there are sufficient data across England and Wales for this to be undertaken.
Extractable Mg	Hyperspectral	Satellite	*Maybe state (not change)	Yes	This approach needs to be explored further as there are currently insufficient data from England and Wales to determine whether it could be effective.
Soil pH	Hyperspectral	Satellite	*State (not change)	Yes	Smaller errors in predicting pH values in bare soil (or partially vegetation free regions). New satellites (e.g. HySPIRI) may enhance spectral signal-to-noise ratios.
Olsen P	None available	NA	NA	NA	NA

*the remotely sensed data would most likely be used here as a secondary covariate to reduce the uncertainty in the prediction of the primary indicator property (measured by ground-based sampling plus analysis) at locations across the landscape where the remotely sensed data was available, but the primary soil indicator had not been measured.

NA = Not applicable

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Appendix 1

Published literature search criteria

The Excel spreadsheet of criteria used in the Web of Science search engine to search for published articles related to remote sensing of physical soil properties is summarised in Table 1. The number of ‘hits’ are the published references found by each search. The references found for the Search terms shown as grey rows, were downloaded to Endnote to create a database of 3663 published references. If the search terms provided more than 1000 ‘hits’, this was considered too many ‘hits’ and the search was run again using more defined search criteria

Table 1 Excel spreadsheet showing the number of references found using 43 different search criteria (shown as 'fields').

SEARCH ID	Field 1	Field 2	Field 3	Field 4	Hits
1	Soil AND	remote sensing AND	organic carbon		184
2	Soil AND	remote sensing AND	geochemistry		22
3	Soil AND	remote sensing AND	physical OR	bulk density	51594
4	Soil AND	remote sensing AND	bulk density		39
5	Soil AND	remote sensing AND	soil depth		518
6	Soil AND	satellite AND	organic carbon		143
7	Soil AND	satellite AND	geochemistry		6
8	Soil AND	satellite AND	physical OR	bulk density	51594
9	Soil AND	satellite AND	soil depth		418
10	Soil AND	satellite	bulk density		20
11	Soil AND	airborne AND	organic carbon		130
12	Soil AND	airborne AND	geochemistry		53
13	Soil AND	airborne AND	physical OR	bulk density	51594
14	Soil AND	airborne AND	bulk density		10
15	Soil AND	airborne AND	soil depth		158
16	Soil AND	hyperspectral AND	organic carbon		55
17	Soil AND	hyperspectral AND	geochemistry		4
18	Soil AND	hyperspectral AND	physical OR	bulk density	51664
19	Soil AND	hyperspectral AND	bulk density		2
20	Soil AND	hyperspectral AND	soil depth		59
21	Soil AND	LiDAR AND	organic carbon		10
22	Soil AND	LiDAR AND	geochemistry		1
23	Soil AND	LiDAR AND	physical OR	bulk density	51616
24	Soil AND	LiDAR AND	bulk density		3
25	Soil AND	LiDAR AND	soil depth		50
26	Soil AND	Radar AND	organic carbon		26
27	Soil AND	Radar AND	geochemistry		8
28	Soil AND	Radar AND	physical OR	bulk density	51858
29	Soil AND	Radar AND	bulk density		24
30	Soil AND	Radar AND	soil depth		488
31	Soil AND	Thermal AND	organic carbon		539
32	Soil AND	Thermal imagery AND	organic carbon		7
33	Soil AND	Thermal imagery			239
34	Soil AND	Thermal AND	geochemistry		2
35	Soil AND	Thermal AND	physical OR	bulk density	51615
36	Soil AND	Thermal AND	bulk density		1
37	Soil AND	Thermal AND	soil depth		19
38	Soil AND	Microwave	organic carbon		57
39	Soil AND	Microwave	geochemistry		5
40	Soil AND	Microwave	physical OR	bulk density	51804
41	Soil AND	Microwave	bulk density		22
42	Soil AND	Microwave	soil depth		318
43	Soil AND	Unmanned Aerial Vehicle			23
TOTAL HITS USED FOR LITERATURE REVIEW					3663

The Excel spreadsheet showing the number of hits for two Web searches and 1 Blog search is summarised in Table 2. The overall number of references considered to be of relevance was 44.

Table 2 Excel spreadsheet showing the number of hits for two Web searches and one Blog search using different search criteria (shown as 'fields').

SEARCH ID	Field 1	Field 2	Field 2	Field 4	Search tool	Hits	Number of pages searched	Number of useful references
1	Remote sensing	soil	physical	properties	Web	2,180,000	10	39
2	Remote sensing	soil	monitoring		Web	4,110,000	10	1
3	Remote sensing	soil	physical	properties	Blog	8,910	10	4
TOTAL USEFUL REFERENCES								44

Appendix 2

Expert survey questions

Dear **named RS expert**

Monitoring soil indicators using remote sensing – request for small expert contributions

We are currently undertaking a review on behalf of UK government on the application of remote sensing of specific soil properties / indicators because they wish to know whether (and how) such approaches could contribute to soil monitoring. We consider you/your team to be experts on this topic based on your previous research. Our team at the British Geological Survey have used remotely sensed data in our research to examine spatial variation of soil properties, but as you will be aware, repeated monitoring to detect change is a more demanding requirement. Accordingly, there are relatively few systems and techniques that offer a reliable means of monitoring the various soil properties.

We have collated a database of published studies that have utilised remotely sensed data for soil applications, which monitor physical soil state and change. However, this cannot include the most recent work that scientists around the globe are developing. We are writing to ask whether you are using a new or novel approach that may not yet be in the published scientific literature (and so we would not be aware of), but which may have applications in detecting **changes** in soil properties or to enhance prediction or **state** of soil properties. We would be grateful of you could write a short description **(one paragraph maximum)** of any methods you have developed in the last 12 months that may have relevance to our study.

The list of soil properties or indicators we are considering are: soil organic carbon, soil depth, soil pH, bulk density, electrical conductivity, phosphorus (Olsen P), total nitrogen, magnesium (extractable), potassium (extractable). We are also interested in methods to assess soil erosion and compaction. Although we do not consider there is any sensor which can detect metals remotely, the following soil properties are also on our list of indicators: total copper, total cadmium, total zinc and total nickel

We do not wish to appear to be offering nothing in return for your contribution so we have made our reference database relating to "Soil+Remote Sensing+Monitoring" available to you via a link at the end of this email in various formats (Endnote, BibTex, RefMan RIS, .csv, .txt) so you can download it and use it yourself. The database is focussed on temperate environments similar to the UK but we have included studies relating to arid settings for completeness. The reference database can be found at the following location:

https://www.dropbox.com/sh/75en2inmnis6xmr/OwBMlEJpid

Thank you in advance for any information you can provide to our study. Any reply you make would need to be with us by Friday 28th February 2014 so that we can use it in our report. If you would like any more details relating to our study then please let us know.

Yours sincerely,

Barry Rawlins (bgr@bgs.ac.uk) & Nicole Archer & Stephen Grebby

Table 1 Expert survey participants

Institute	Expert
1.GFZ Potsdam	Prof S. Chabrillat
2.Wageningen University	Dr Harm Bartholemeus
University of Zurich	Prof M. Scheipmann
US Department of Agriculture	Dr M Moran
Tel-Aviv University	Prof E. Ben-Dor
INRA, FRance	Cecile Gomez