CZECH UNIVERSITY OF LIFE STIENCE SCIENCE PRAGUE

FACULTY OF ENVIRONMENTAL SCIENCES

IMAGE PROCESSING TECHNIGUES FOR DETECTION OF SOIL FEATURES

MSc THESIS

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Jan Trenciansky

Land and Water Management

Thesis title

Image processing techniques for detection of soil features

Objectives of thesis

The aim of this study is to investigate the remotely sensed images and GIS techniques to rapidly and accurately identify the spatial location of roddon soil features. Based on review of existing methods and literature dealing with remote sensing of soil and differences in landscape for GIS applications a new methodology of roddon detection will be developed and applied.

Methodology

A methodology to detect roddon features will be developed and applied in a step-wise approach. Coincidental spatial images of UK-DMC2 base data products over one growing season will be used to determinate the spatial location of roddon soil features. Based on roddon difference in brightness to darker surrounding peat land an appropriate remote sensing technique with method to detect the boundaries of features where large in adjusted spectral contrast will be applied. To decrease the number of inaccuracies generated through process of roddon detection the mask technique will be developed. Further enhancement of the spectral difference (i.e. soil brightness of soil features) will be achieved by repeating the process over multiple images.

The proposed extent of the thesis

40 – 60 pages

Keywords

Agriculture, Digital Soil Mapping, East Anglia, Remote Sensing, Roddon, Soil Brightness Index, UK-DMC2

Recommended information sources

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CRANFIELD UNIVERSITY

JAN TRENCIANSKY

IMAGE PROCESSING TECHNIGUES FOR DETECTION OF SOIL FEATURES

SCHOOL OF ENERGY, ENVIROMENT AND AGRIFOOD
Land Restoration and Reclamation

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This thesis is submitted in partial fulfilment of the requirements for the degree of Master of Science

ABSTRACT

An image processing technique was applied to detect roddon soil features from UK-DMC2 base data. Roddon soil features represent former watercourses in English Fenland, now raised banks with altered soil composition. They can be clearly seen on remotely sensed imagery as bright features in contrast to the darker surrounding peat land. Based on difference in brightness of roddons and surrounding peat soil the Soil Brightness Index (SBI) was applied to detect the roddons. To identify the edges of these features where there is a large spectral contrast a non-directional filter was applied together with an image enhancing technique to better differentiate the roddons form other non-soil features. Understanding the location of roddons will allow adaptive farming practices that account for differences in soil properties, and help optimizing yields.

Keywords:

Agriculture, Digital Soil Mapping, East Anglia, Remote Sensing, Roddon, Soil Brightness Index, UK-DMC2

Word Count: 5450

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LIST OF ABBREVIATIONS

DEM	Digital Elevation Model
DSA	Digital Soil Assessment
DSM	Digital Soil Mapping
GIS	Geographic Information System
GPS	Global Position System
NDVI	Normalised Difference Vegetation Index
NIR	Near-infrared
NVI	New Vegetation Index
SARVI	Soil and Atmospherically Resistant Vegetation Index
SAVI	Soil-adjusted Vegetation Index
SBI	Soil Brightness Index
UK-DMC2	United Kingdom - Disaster Monitoring Constellition-2

NOTATIONS

This thesis has been prepared in the format used for the journal *Remote Sensing of Environment*. An extended literature review has been included following the requirements of *Cranfield University*.

Image processing techniques for detection of soil features

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ABSTRACT:

An image processing technique was applied to detect roddon soil features from UK-DMC2 base data. Roddon soil features represent former watercourses in English Fenland, now raised banks with altered soil composition. They can be clearly seen on remotely sensed imagery as bright features in contrast to the darker surrounding peat land. Based on difference in brightness of roddons and surrounding peat soil the Soil Brightness Index (SBI) was applied to detect the roddons. To identify the edges of these features where there is a large spectral contrast a non-directional filter was applied together with an image enhancing technique to better differentiate the roddons form other non-soil features. Understanding the location of roddons will allow adaptive farming practices that account for differences in soil properties, and help optimizing yields.

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1 INTRODUCTION

Identifying the spatial distribution of soils and soil features is a fundamental knowledge of today's soil science. Process of soil formation has been described by Jenny's (1941) brilliant equation (Jenny, 1941) and laid the foundation of soil mapping. Spatial distribution of soil has been described mainly by conventional methods including soil surveys and soil sampling. However conventional methods of soil mapping are slow and relatively costly (McBratney, et al., 2003) and therefore GIS and remote sensing techniques that recognise differences in soils and soil features allow better and faster approach of soil data extraction (Scull, et al., 2003).

Digital Soil Mapping (DSM) is a valuable and widely use alternative of soil mapping to conventional methods. This method involves remote sensing and GIS application and deployment of statistical models to predict the spatial distribution of soils and various soils characteristics. DSM provide numerous approaches and soil information for different data mining techniques and presets new framework called Digital Soil Assessment (DSA) a modelling tool designed to describe more detailed and difficult to measure soil attributes (McBratney, et al., 2003; Carré, et al., 2007).

Knowledge about soil distribution and the state of vegetation canopy has become favoured information to utilize in appropriate economic planning, crop yield prediction and optimising management and resource allocation for agricultural management (Bastiaanssen, et al., 2000; Haboudane, et al., 2004; Johanson, 2013; Moran, et al., 1997). The importance of remotely sensed information for agricultural management was rapidly up taken since remote sensed data become publicly available and their use was demonstrated widely in numerous research areas (Jakubauskas, et al., 2002; Ozdogan, 2010; Yan & Roy, 2014). Increasing demands on remotely sensed information produce more practical methods of data extraction. Today's image processing techniques working with high resolution space born imagery includes various sophisticated methods and are able to detect detailed land cover information (Jensen, 2006; Lillesand, et al., 2008). Implementation of precise processing algorithms on high resolution data is reflected in the ability to detect small differences in the terrain or soil characteristics (Weng, 2011). Digital Elevation Model (DEMs) analysis for GIS application are often used to detect differences in terrain and landform (Eshani & Quiel, 2009; Florinsky, 1998; Klingseisen, et al., 2008). However, identifying soil properties and soil features from satellite imagery rely more on differences in spectral reflectance of land cover (Dorigo, et al., 2007; Mulder, et al., 2011) rather than on DEMs analysis.

Mixing of different data mining techniques for soils and soil feature detection using satellite imagery can be useful, for example combination of DEMs with radiometric data for regional soil mapping (Dobos, et al., 2000) or using combination of vegetation transformation indices for vegetation detection (Das, et al., 2009). However most recent studies using satellite imagery as data input for land cover classification attempts to suppress the soil information and focus more on land cover information i.e. the vegetation canopy (Bacoura, et al., 2002; Huete, et al., 1984; Huete, et al., 1985; Schmidt & Karnieli, 2001). Consequently to describe phonological stage and state of canopy various vegetation indexes for example New Vegetation Index (NVI), Normalised Difference Vegetation Index (NDVI), Soil-adjusted Vegetation Index (SAVI), Soil and Atmospherically Resistant Vegetation Index (SARVI) have been developed (Deering, et al., 1975; Huete, 1988; Huete, et al., 1992; Huete, et al., 1997; Huete & Liu, 1994; Qi, et al., 1995; Gupta, et al., 2001; Rouse, et al., 1974). Until recently soil related research based only on the use of remote sensing data was, with a few exceptions, often overlooked. Kauth and Thomas (1976) and Kauth et al. (1979) described distribution of spectra for four band spectral data and introduced the concept of “soil line” from where the Soil Brightness Index (SBI) was developed. SBI is a widely used index for bare soil recognition and therefore can be used for soil feature detection or extraction.

Problems associated with soil information extraction from satellite imagery are often connected with signal noise, shadows and change in canopy, which overly underlying soil and therefore complicates the soil information extraction.

Moreover, remote sensing techniques of soil features detection or extraction are affected by many factors, such as vegetation phenology stage, time of satellite observation, spectral similarity of different land cover, variations in soil moisture and soil composition (Caloz, et al., 1988; Jensen, 2005). This is especially evident in agricultural regions with arable crop rotation where the vegetation canopy may change many times during the growing season depending on harvest and current management practice reflecting the crop utilization. On the other hand certain agricultural practise involving crop rotation includes periods with bare soil thus the opportunity to extract soil information. Various approaches of object extraction from satellite imagery has been developed (Mayer, 2008; Mulder, et al., 2011), but no methodology is directly applicable for soil feature detection or extraction from satellite imagery.

Anthropogenic and natural processes interact to reshape the physical characteristics of the landscape (such as soils or landscape features) (Eshani & Quiel, 2009) and give rise to relatively new soil features. One of the example of these soil features are called Roddons. Roddons (or also Roddamy, Roddens or Rodham (Coates, 2005) are mainly bright soil features of the Fenland of eastern England. Roddons represents mid to late Holocene tidal deposit creek networks, that are now raised banks with altered soil composition due to human activities (Smith, et al., 2010). The draining of the Fenland that has enabled the establishment of agriculture in the area, has resulted in wind erosion and oxidation of the surrounding peat and thus exposed the roddon features (Godwin, 1978; Waller, 1994). Roddons have been identified into three generations each representing a different in period of creation and distribution of clay, silt and sand deposition from a marginal salt-marsh environment. Roddons vary in composition, depth, width, size, cover brightness and location (Smith, et al., 2010; Smith, et al., 2012). Differences in soil composition i.e. sediments of roddons may affect how Roddons are displayed (brightness) in remotely sensed data and therefore complicates their detection, although difference in brightness of roddons to surrounding dark peat soil is significant and essential for this study (Palmer, 1996; Smith, et al., 2010).

The aim of this study is to investigate the remotely sensed images and GIS techniques to rapidly and accurately identify the spatial location of roddon soil features. Based on review of existing methods and literature dealing with remote sensing of soils and differences in landscape for GIS applications, a methodology of roddon detection was developed. The proposed methodology was applied to identify the spatial location of roddons based on roddons difference in brightness to darker surrounding peat land.

A semi-automated methodology of roddon soil features detection is presented. The methodology requires minimum training, data pre-processing, relatively small number of parameters and can be optimised to various scale applications and on features with similar remotely sensed attributes. Spatial map of roddons detection and processing images are delivered from remotely sensed UK-DMC2 data series images products. Results are delivered for 11, 858 km x 11.352 km (539 x 516 22m pixels) in a predominately agricultural region.

2 DATA AND STUDY AREA

2.1 Study area

The study area is located in English Fenland of Cambridgeshire. The area is well known for its unique geology of basal clay overlain by peat interspersed with roddons. The area has been extensively drained transforming the environment into intensive and productive agricultural land (Brew, et al., 2000; Pryor, 2013; Smith, et al., 2010). Roddon soil features are frequently distributed over the area of English Fenland, therefore the test area was selected representing an area of contrasting peat and roddons.

The test area was selected to demonstrate the presence of roddon features. The study area is located in predominately agricultural region near Littleport in Cambridgeshire covering mainly farmland of G's growers Ltd. Current agriculture management of G's growers Ltd. is based on crop rotation over years. Rotation cycle of different crops is mainly composed of vegetables (spring onion, lettuce, leek and bulb onion) and grain (wheat, barley and maize) (G's Growers, 2015). These crops require individual management practise and therefore optimising the current agricultural management through detailed land and soil knowledge would ensure sustainability of farming business and benefit the environment. The UK-DMC2 data series images composed of 539 x 516 pixels covering area of 11. 858 km x 11.352 km (52.389° to 52.494° North and 0.273° to 0.447° West) shown in Figure 2-1 represents landscape cover with specific features including agricultural land, communication networks, drainage channels, poly tunnels, roddons, solitary farms, urban areas and water bodies (Figure 2-2 (a)). Roddons can be clearly seen on remotely sensed imagery as bright river-like features in contrast to the darker surrounding peat land (Palmer, 1996) as shown in Figure 2-1 and Figure 2-2.

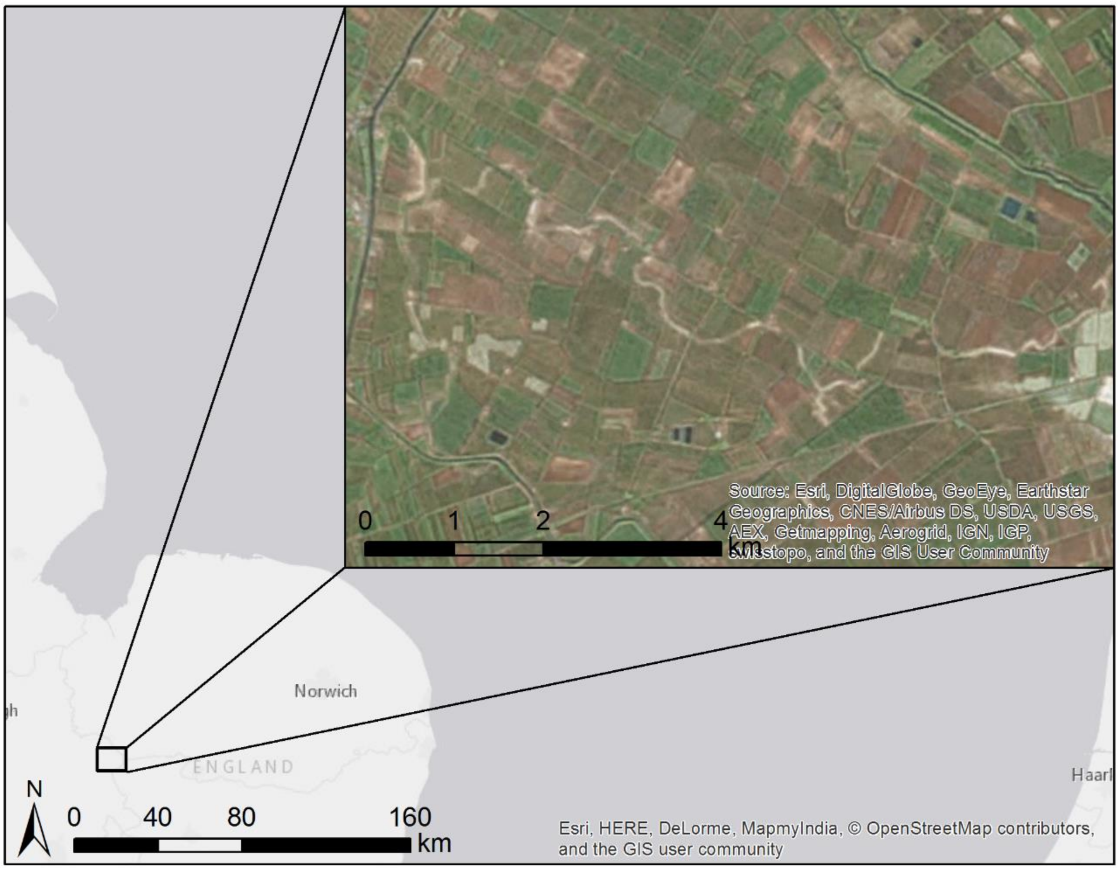

Figure 2-1 Spatial location of tested area (zoomed) delivered from UK-DMC2 data series image in East Anglia.

2.2 UK – DMC2 data sets

In this study the UK-DMC2 data subset over one growing season in 2013 were selected. The data series images are ortho-rectified DMC level L1R product. They were radio metrically normalised to a reference scene by linear regression of the co-change pixels between each image and the reference. The reference scene (u2003df.img) was first calibrated to top-of-atmosphere reflectance using the standard process described in the UK-DMC2 product manual. No-change pixels were automatically determined between images using the approach in Canty & Nielsen (2008). UK-DMC2 data series images where obtained from the DMC International Imagine Ltd. (http://catalogue.dmcii.com/). The base data are composed of 3 reflective bands Green, Red and NIR bands (0.77 - 0.90 μm NIR, 0.63 - 0.69 μm Red and 0.52 - 0.60 μm Green). The spatial resolution of pixel is 22 m covering the projection area of 539 x 516 pixels. Each selected image represents 7 cloud free different days over a growing period: 02/05/2013; 03/06/2013; 09/07/2013, 18/07/2013; 19/07/2013; 05/09/2013 and 24/10/2013. Figure 2-2 illustrates 4 examples of selected data across the growing season in 2013. Differences in imagery are caused due to change in vegetation cover as the vegetation cover matures and seasonal construction of poly tunnels. The UK-DMC2 base data have been selected considering relatively easy accessibility, simple pre-processing preparation, spatial location of study area and excellent compatibility with widely used Landsat 7 ETN+ (DMC International Imaging, 2013).

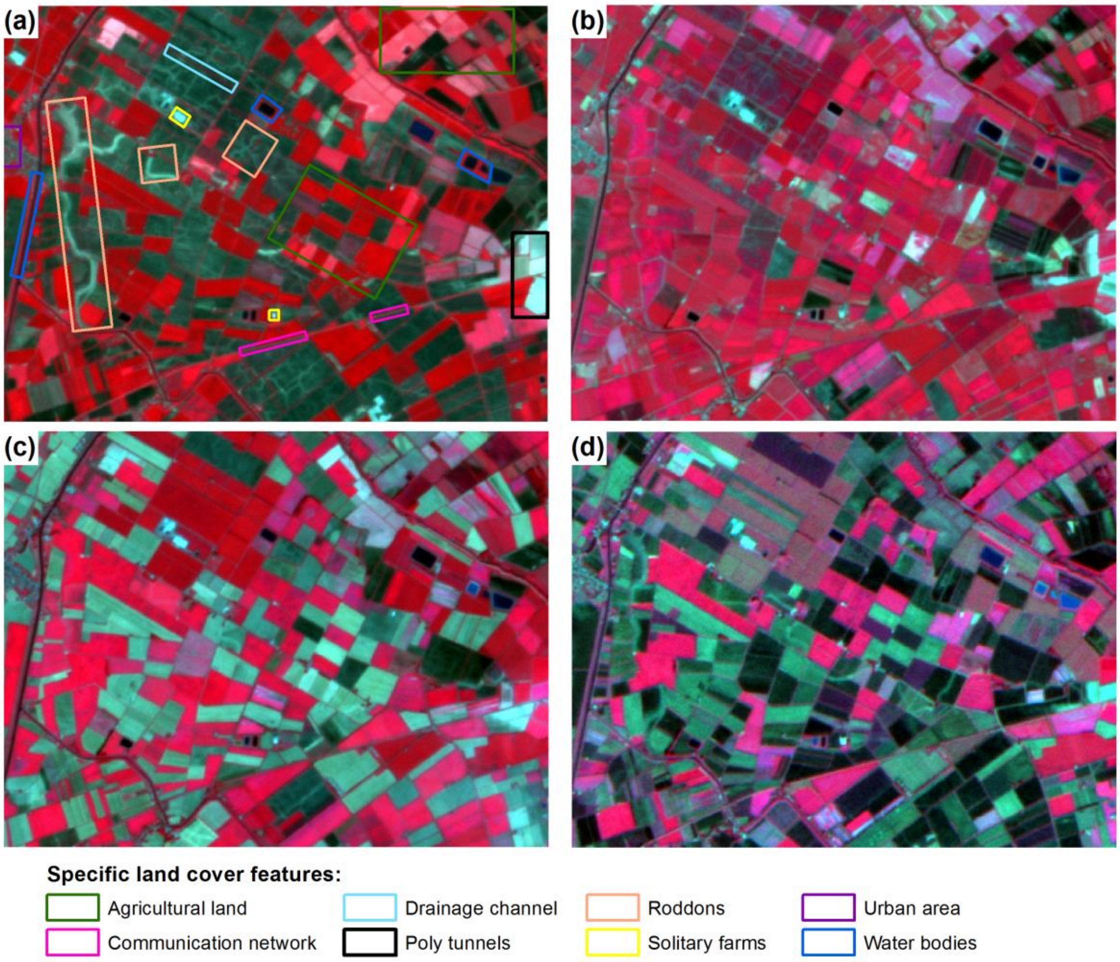

Figure 2-2 Comparison of input UK-DMC2 data series images. (a) 3rd June 2013, (b) 18th July 2013, (c) 5th September and (d) 24th October.

3 METHODOLOGY DEVELOPMENT

3.1 Methodology overview

A methodology to detect roddon features was developed and was applied in a step-wise approach. Coincidental spatial data of UK-DMC2 base data products over one growing season were used to determinate the spatial location of roddon soil features based on Soil Brightness Index (SBI) and non-directional edge filter (Section 3.2). To decrease noise from the SBI image from field edges a mask was developed from the normalized difference vegetation index (NDVI) (Section 3.3) and an edge filter was applied. Further enhancement of the spectral difference (i.e. soil brightness of soil features) was achieved using the sum of the masked SBI images over one growing season (Section 3.4).

3.2 Detection of features using the SBI

The remote sensing detection of soil features over the test area is based on defining attribute of roddons from UK-DMC2 base data products. Roddon soil features differ in brightness from the relatively dark surrounding peat soils (Palmer, 1996; Smith, et al., 2010).

3.2.1 SBI application

The Soil Brightness Index (SBI) in various modifications, depending on nature of the spatial data and band composition has been used to study soil phenomena (Caloz, et al., 1988; Sharma & Bhatt, 1990) including vegetation/crop detection (Das, et al., 2009; Choi & Yang, 2012) agricultural management (Deb, et al., 2010), soil mapping (Nicoletti, et al., 2003) and soil characteristics (Gore & Bhagwat, 1991). The spectral difference of roddons soil features was derived by the adaptation of the SBI (Eq. (3-1)) calculated from UK-DMC2 base data products. The SBI, derived as the sum of 3 bands (green, red and near-infrared), is based on enhancing the soil spectral difference over the other land cover (Kauth, et al., 1979; Kauth, et al., 1979). The index is defined as follows (Jensen, 2005):

$$SBI = (0.332 * green) + (0.603 * red) + (0.262 * \ infrared) \qquad (3\text{-}1)$$

In this study SBI was applied over seven images taken at different times in the growing season. Figure 3-1 and Figure 3-2 show examples from two different dates. Both large and relatively small roddon features in Figure 3-1 (b) are better visible after the application of the SBI. However, this effect is not repeated in other images as shown in Figure 3-2 (b). Therefore the change in the vegetation canopy during the growing season impedes the detection of roddons from the SBI image as the crop cover matures. Although the application of the SBI on UK-DMC2 base data leads to noticeable changes in roddon visibility some of the other features of land cover are evident and can be misrepresent as roddon features. To identify the edges of roddon features where there is a large spectral contrast between the roddon and the surrounding peat a non-directional filter was applied over all seven SBI images to observe change in edge feature visibility over the growing season in 2013.

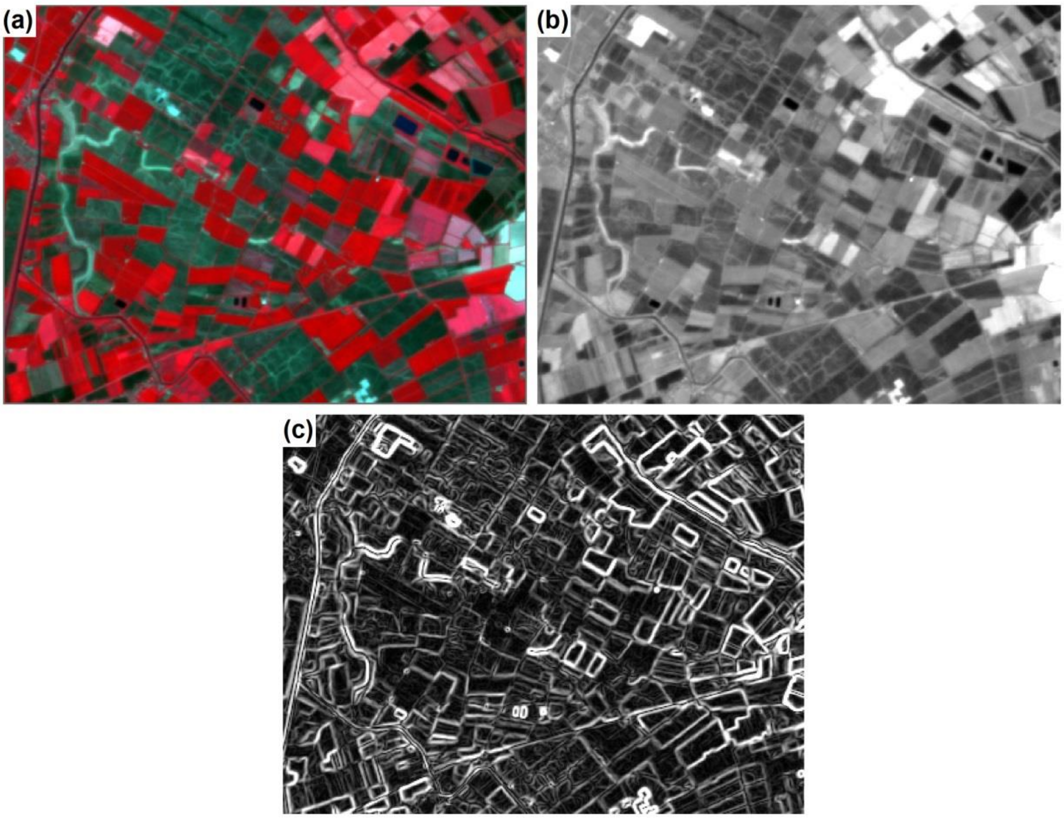

Figure 3-1 Process of roddon detection using SBI. (a) The UK-DMC2 base data set from 3rd June 2013, (b) with application of SBI, (c) edge filter.

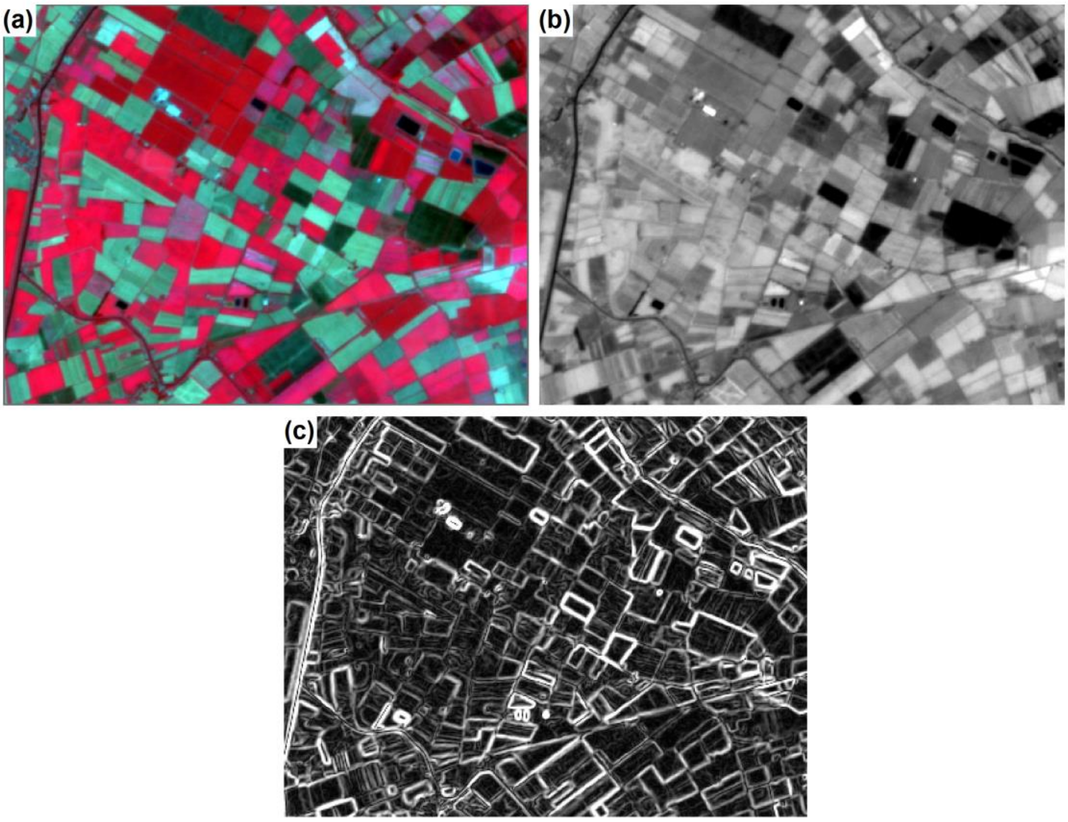

Figure 3-2 Process of roddon detection using SBI. (a) The UK-DMC2 base data set from 5th September 2013, (b) with application of SBI, (c) edge filter.

3.2.2 Application of edge filter

The spatial image defining the boundaries of features was obtained by applying the non-directional edge filter on the SBI image to define the probability of roddon features edges. The edge filter is based on Sobel edge detection Eq. (3-2) operating with convolution of kernels (Pratt, 2001). The equation is defined as follows (Maini & Aggarwal, 2009):

Sobel:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * I \ \ and \ \ G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I$$

(3-2)

Gradient Magnitude:

$$G = \sqrt{G_x^2 + G_y^2}$$

where G_x and G_y are gradient components in each orientation and I is the source image i.e. UK-DMC2 data series images after SBI application. The edge detection filter enhanced the edges (i.e. detect the areas with large adjacent spectral contrast) of land cover features. This resulted in separation of these objects in the SBI image and generated an image of edge features (Suresh, et al., 2014). Therefore, the edges of areas such as roddons with large spectral contrast to surrounding darker peat soil in the SBI image were detected. The Sobel method of edge detection is sensitive to noise and so derived images can include degraded information that is also obtained from the procedure.

Figure 3-1 and Figure 3-2 shows step by step application of SBI index and non-directional edge filter over two imagery dates. The boundaries of large and relatively small roddon features were enhanced as presented in detail in Figure 3-3. Large roddons features are spatially located over several agricultural field due to their large spectral contrast with surrounding peat land while relatively small roddon are more clustered on individual agricultural plots and separate by noise elements mainly vegetation edges or drainage channels. Although non-directional edge filter enhanced the edges of roddon features shown in Figure 3-1 (c) and also in Figure 3-2 (c), the filter also enhanced edges of all kinds of land cover features with adjacent spectral contrast including non-soil related ones as shown in Figure 3-3. To identify some of the non-soil related edges i.e. vegetation boundaries a development of a mask approach based on NDVI was applied, therefore this phenomenon is discussed in following section (Section 3.3).

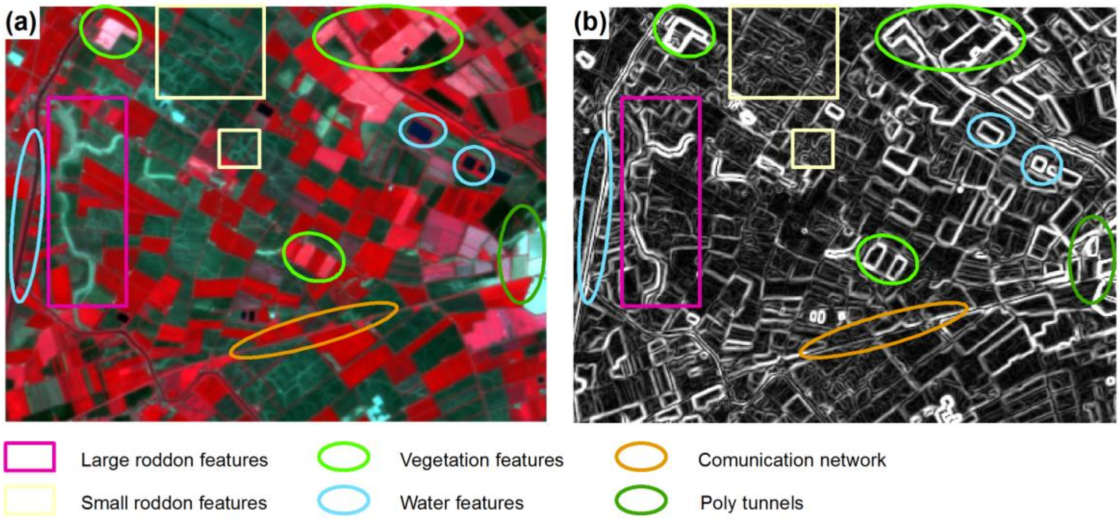

Figure 3-3 Examples of some features detected by edge filter application. (a) The UK-DMC2 base data set from 3rd June 2013, (b) edge filter.

3.3 Image cleaning

To reduce noise elements from the SBI image a further image cleaning technique was established. One major contribution of the noise on the SBI image after edge detection are field boundaries. This is due to the contrast of vegetated to non-vegetated areas at the edge of agricultural fields. Therefore, the Normalised Difference Vegetation Index (NDVI) (Figure 3-4 (b)) was generated from UK-DMC2 base data to identify some of the noise elements especially crop boundaries from SBI edge image (Figure 3-1 (c) and Figure 3-2 (c)). The NDVI is the most widespread vegetation index used to analyse vegetation cover or its state (Tucker, 1979) from satellite imagery. The NDVI indicates green live vegetation over the targeted area and is described as a simple ratio of NIR band and Red band in Eq. (3-3) (Huete, et al., 2002; Rouse, et al., 1974). The index is defined as follows (Jensen, 2005):

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{3-3}$$

where the NDVI enhances the effect of the vegetation canopies and facilitates the identification of changes in the response of the vegetation cover. The NDVI has been used to detect agricultural field boundaries (Yan & Roy, 2014) or to study various vegetation phenology (Fisher, et al., 2006). The crop plots from Figure 3-4 (b) generated by applying the NDVI are assumed to be agriculture field at different vegetation stage and field margins. The intensity of index indicates the amount of vegetation i.e. values less or close to zero represents sparsely or non-vegetated areas while values close to 1 are very dense green vegetated.

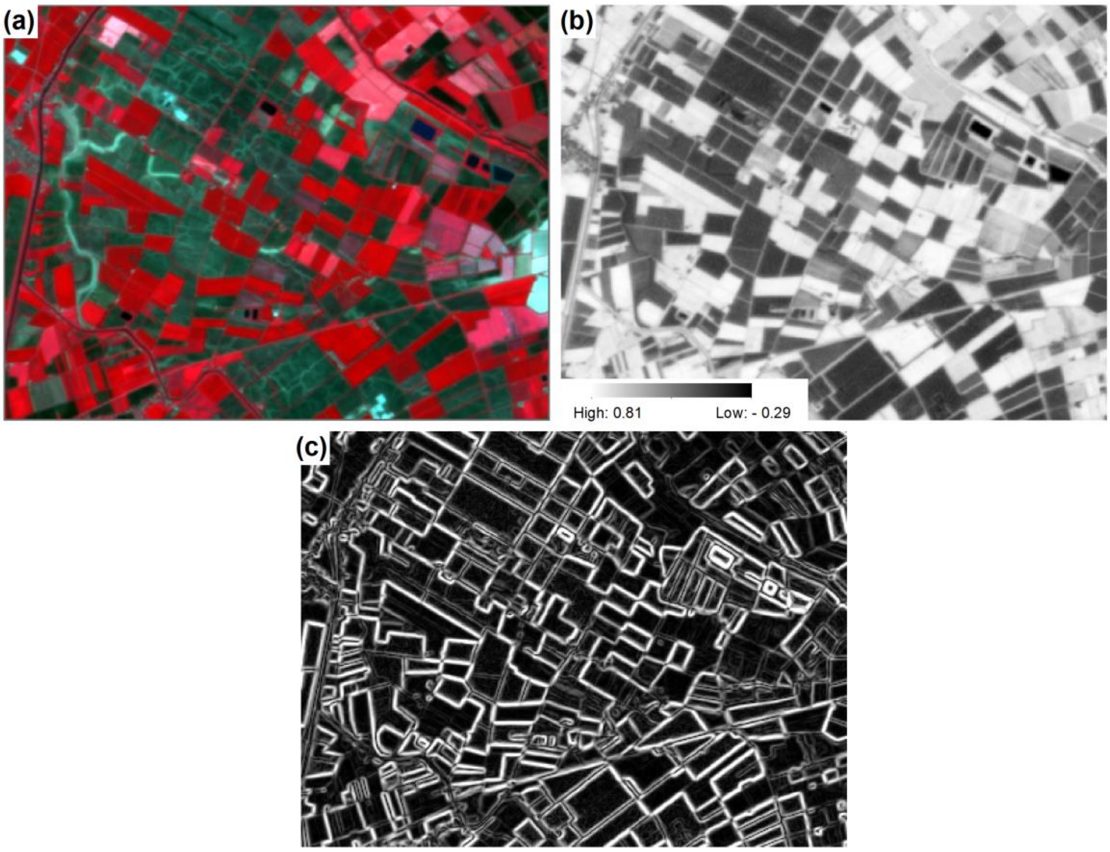

Figure 3-4 Process of mask generation. (a) The UK-DMC2 base data set from 3rd June 2013, (b) application of the NDVI, (c) edge filter.

To enhance field boundaries on NDVI image (Figure 3-4 (b)) the non-directional edge filter was applied following the procedure from previous section (Section 3.2). Figure 3-4 (c) shows an example of the edge detection for agricultural field boundaries. The agriculture field edges are visually evident. However, some other noise features edges such as communications network and drainage channels where enhanced through the procedure as well and this is described further in the discussion (Section 4). Figure 3-5 shows a comparison between SBI edge filter (a) and NDVI edge filter (b). Enhanced boundaries on example (b) are mainly vegetation edges and match with less bright vegetation edges on example (a). Consequently the NDVI places more emphasis on vegetation information and less on soil information whereas the SBI enhances the latter. Therefore, the edge filter applied on NDVI image detected mainly vegetation edges that showed high spectral contrast (Figure 3-5 (b)) and on the SBI image it detected soil features boundaries (Figure 3-5 (a)).

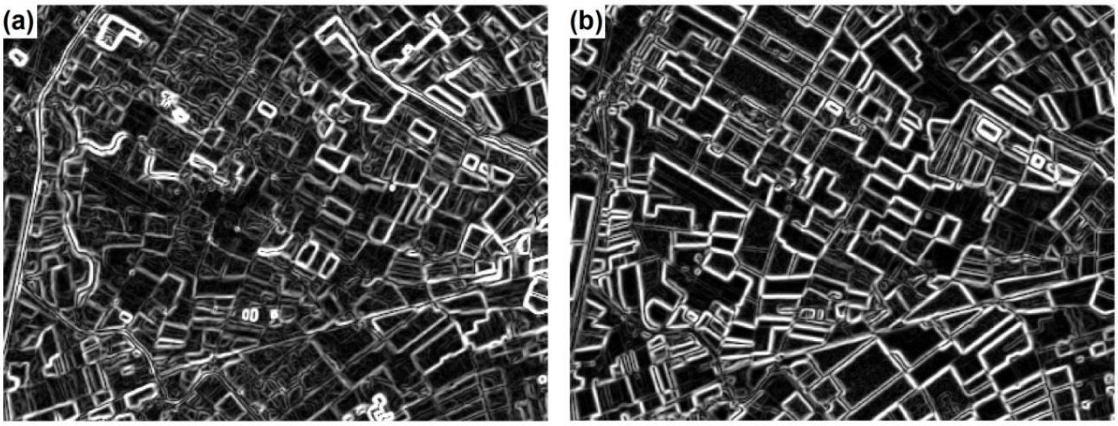

Figure 3-5 Application of edge filter over UK-DMC2 base data image from 3rd June 2013. (a) SBI edge filter, (b) NDVI edge filter.

To minimise the influence of field boundaries generated through edge detection on SBI image, the NDVI edge image Figure 3-5 (b) was used as a mask to clip out some of the non-soil edge features and clean up the SBI edge image (Figure 3-1 (c)).

To set up and an appropriate method to clip out the non-soil features boundaries from SBI edge image a mask has been developed. The mask procedure is based on creation of a binary mask from the NDVI edge image. Enhanced edges of the NDVI edge image have high brightness i.e. their pixel value lies between 0.1 and 0.6 Therefore all pixels higher than 0.1 where assigned a value 0 and all pixels lower than 0.1 where assigned a value 1. The mask is computed as follow:

$$I_M(i,j) = \begin{cases} I_{SBI}(i,j) \; if \; I_{NDVI}\,(i,j) < 0.1 \\ 0 \quad\quad\; if \; I_{NDVI}(i,j) \geq 0.1 \end{cases} \tag{3-4}$$

here $I_M(i,j)$ is the result image (Figure 3-6 (b)) after mask application based on the NDVI edge image, $I_{SBI}(i,j)$ is the SBI edge image (Figure 3-6 (a)), $I_{NDVI}(i,j)$ is the NDVI edge image (Figure 3-5 (b)) and (i,j) are vertical and horizontal coordinates for pixels. The resulting binary mask of values 0 and 1 was subsequently summed up with SBI edge image to achieve a cleaned SBI image and noise elements connected with vegetation where reduced. Figure 3-6 shows example of SBI edge image before (a) and after (b) mask application.

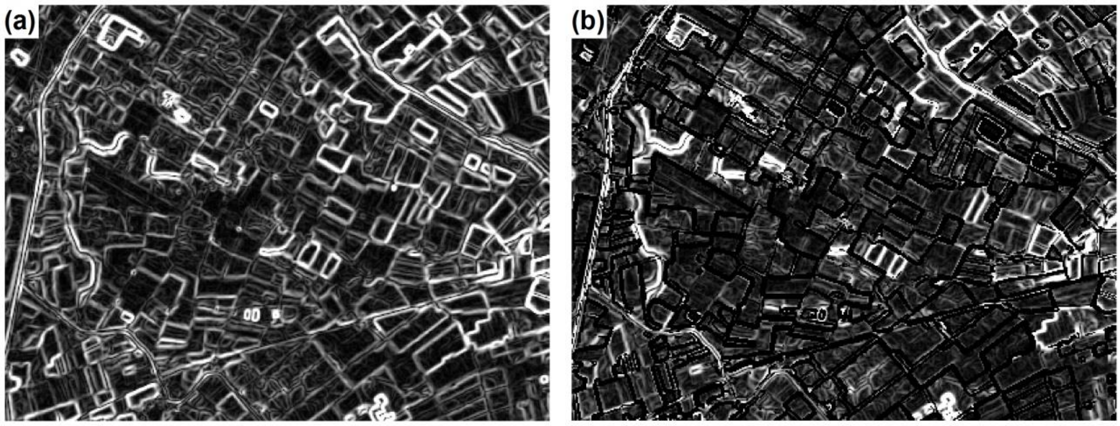

Figure 3-6 Mask application for 3rd June 2013image. (a) SBI before mask application, (b) SBI after mask application.

The mask proves to be successful in removing many of the field boundary. Although noise reduction is significant the image cleaning process is imperfect as some of the noise elements are still present as well as some of the field edges boundaries. In particular, it may be difficult to recognise soil feature boundaries from one date imagery as shown in Figure 3-7.

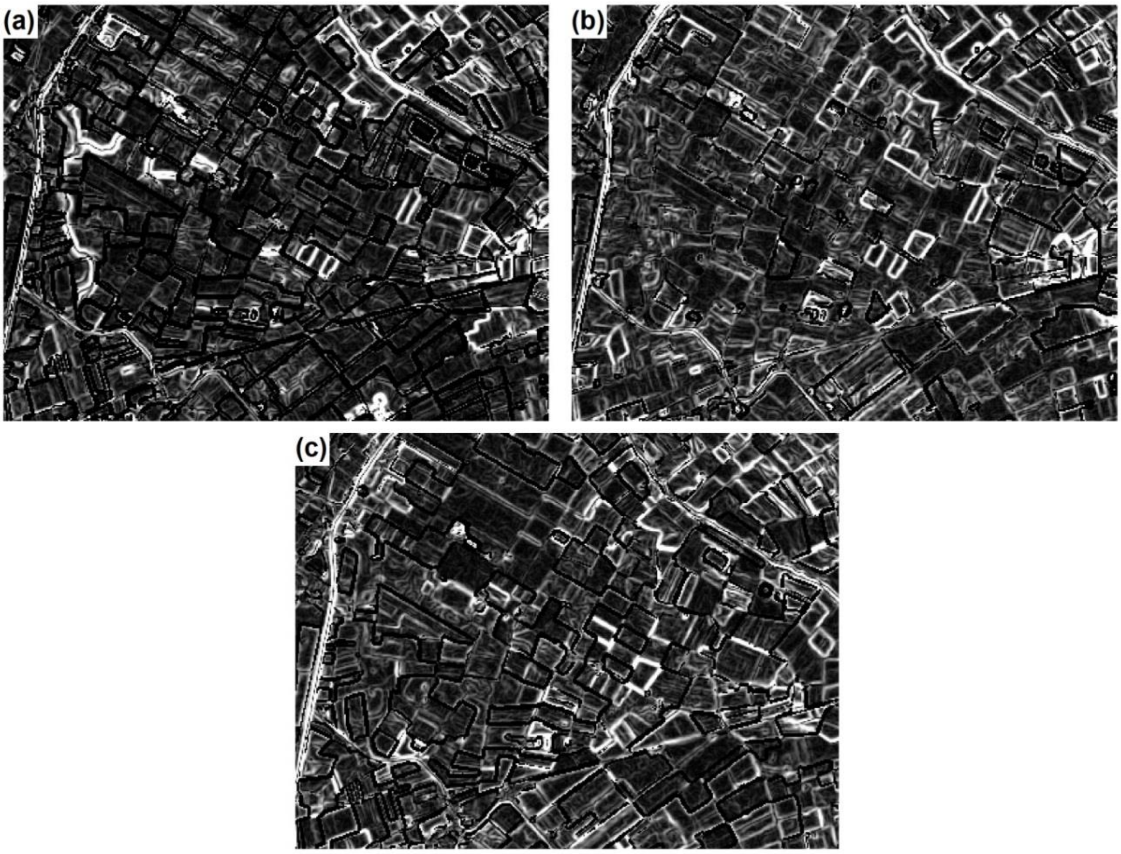

Figure 3-7 The edge features detection over 3 images showing mask application for 3 different days in 2013. (a) 3rd June, (b) 9th July, (c) 5th September.

Figure 3-7 shows that soil features are more temporally static compared to the other land cover elements such as canopy boundaries or poly tunnels, which will change more significantly over time. The fact that soil feature edges are static over different images during the growing season was used to enhance the roddons over the other features and minimise the impact of noise from other land cover features.

3.4 Enhancing the soil brightness

Although the mask procedure applied over single date image decreased noise generated by vegetation some noise features are still evident. Therefore spectral signature of roddons was enhanced by using mask procedure multiplied over satellite time series data. The resulting enhancing of soil brightness was refined by application of a simple summing up approach on seven images over growing season 2013 on which the mask approach was applied (as described in Section 3.3). The sum is computed as follows:

$$I_e\,(i,j) = \Sigma(I_M(i,j)) \qquad (3\text{-}5)$$

where $I_e\,(i,j)$ is a sum of the SBI edge images over one growing season in 2013 after mask application, $I_M(i,j)$ is SBI image after mask application and (i,j) are vertical and horizontal coordinates for pixels. The sum process enhanced the spectral response of roddons due to their static time dependant variation and other time dependent elements such as vegetation boundaries or poly-tunnels with more time variation in spectral response were enhanced less. The result of the final image processing is illustrated in Figure 3-8 (b). Similar technique has been used to enhance agricultural field boundaries (Yan & Roy, 2014) or to enhance change detection (Im & Jensen, 2005).

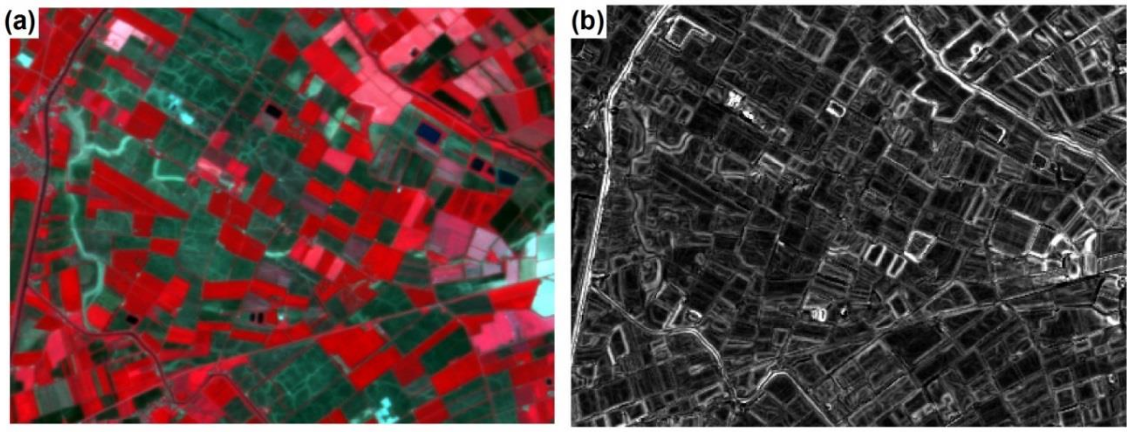

Figure 3-8 Final result after sum approach application. (a) The original UK-DMC2 for 3rd June 2013, (b) final result.

When the result is compared to the original UK-DMC2 date base image (Figure 3-8 (a)) it demonstrates that the applied methodology works successfully. Both roddons features edges (small and large) are relatively well identified and spatial distribution of roddons over test area is presented. However noise elements are still present and may be misinterpreted with roddon features.

4 DISCUSSION AND FUTURE APPLICATIONS

Discussion is divided into four paragraphs each of them dealing with different section of methodology development (section 3) with description of potential improvements. Brief overview of Methodology development is described in section 4.1 followed by SBI application (section 4.2), reduction of non-soil feature generation (section 4.3) and enhancing the soil features over surrounding land cover (section 4.4). Fifth paragraph (section 4.5) shortly describes the potential future direction of the work.

4.1 Methodology development overview

A semi-automated methodology of Roddon soil features detection was developed. The methodology is applied on three bands (green, red and NIR) images of UK-DMC2 data product over growing season 2013. The SBI was applied using three bands from the imagery to enhance the spectral difference of bright soil feature so-called roddons to darker surrounding peat soil (Section 3.2.). Detection of roddon boundaries is presented by non-directional edge detection based on enhancing feature boundaries where large spectral contrast exists (Section 3.2). To reduce noise elements generated through the procedure of soil feature detection a mask based on the NDVI was created (Section 3.3). By mask application the noise reduction (mainly noise generated by enhancing the vegetation boundaries that have large spectral difference) was significant. Reduction of remaining noise elements was achieved by enhancing the soil response i.e. application of procedure over multiple imagery and subsequently summing up the results (Section 3.4.).

Presented methodology was successful and the detection of large and small roddon features was achieved. However, noise elements are still present as shown in Figure 3-8. Future enhancing of the soil features to increase their visibility over the noise elements could be accomplished by repeating the procedure over multiple imagery with specific three bands composition. Future work to deliver complex map of roddons spatial location is required and potential future steps are outlined below.

4.2 Application of SBI

By application of the SBI soil features were enhanced together with some other types of land cover. This is due to similar response of different land cover type to application of the SBI, thus their spectral signature is close to soil line and therefore enhanced object such as poly tunnels, drainage channels, communication networks could be similar to soil features (Kauth, et al., 1979; Kauth & Thomas, 1976). Figure 3-1 (c) and Figure 3-2 (c) shows application of the SBI over two different images over one growing season in 2013. The change of vegetation canopy is significant as the crop cover matures and with increasing phenology state and as a result the underlying soil features are less visible. Obtaining the soil information from these images (mostly from July to October) is difficult and therefore their future application in described methodology uncertain. Future application of the SBI over cloud free images without vegetation cover or cover crop should bring positive results in enhancing the bright roddon features over darker surrounding peat soil.

Boundaries of roddon soil features were enhanced by application of the non-directional edge filter. This is due to large adjusted spectral contrast between bright roddons and surrounding soil features. Although boundaries of these features were detected some other noise elements (vegetation boundaries, water bodies, communication networks) as a result of similar respond to application of the SBI (mentioned above) due to similar respond of different land cover type were detected as well. This is the major contribution of noise generated during the process and therefore reduction of noise generation on initial step in methodology is essential. Thus by application of the SBI in various modifications (Jensen, 2005) for data with different band composition the reduction of noise generation can be achieved (section 4.5.).

4.3 Further removal of non-soil features

The mask created as a binary layer designed to clip out some of the noise elements from vegetation boundaries (field edges) was computed from the NDVI edge image (Figure 3-5 (b)). However some pixels carrying the soil information on the SBI edge image were also clipped out where soil boundary features based on the NDVI edge filter underlay the vegetation boundaries. Similar information loss was found when some non-vegetation boundaries such as water bodies or communication network with pixel value between 0.1 - 0.5779 were clipped out due to mask application. This may not lead to loss of soil information directly but it could be problematic with future applications due to fragmentation of soil features as shown in Figure 3-7. To avoid loss of soil information due to mask creation a new model (mask) identifying if the pixel is non-soil related should be created. Thus pixels originally clipped out by mask application based on NDVI can retain in image with their original value of the pixel (value before mask application i.e. value of SBI edge image) if the threshold is met and pixel represents the soil features pixels. Future removal of other non-vegetation features enhanced during the process is described in Section 4.5 To find a connection between separate soil features fragment would be difficult due to high frequency of agricultural fields plots and their time variability over the growing season and therefore appropriate technique of fragment identification and connection have to be delivered and this is further discussed in Section 4.5. As mentioned above the mask application clipped out some of the boundaries of non-vegetation features as their pixel values after edge filter application lay between the defying intervals. This is relatively good news however on less vegetated images where other noise elements overlying the soil features such could be vegetation residues may be detected and pixel value carrying the soil information could be lost.

4.4 Enhancing the soil response

Loss of pixels carrying the soil information due to mask application was partly reduced by final enhancing of soil brightness i.e. summing the images of one growing season after mask application. Similar technique was used by Yan & Roy (2014) where spatial location of plots of agricultural fields was enhanced by summing up weekly data products over five years. Unlike Yan & Roy (2014) the vegetation boundaries in the test area changes over the season due to different management practise required for various crops and over years due to crop rotation. Technique using multiple imagery from different data sources for example various Landsat data (Zhu & Woodcock, 2014) could increase the difference of time static soil features to more time variable vegetation boundaries and therefore enhance the boundaries of roddons. However problem with different spatial resolution of input data may result in errors connected with extraction of relatively small and spatially fragmented features (Duveiller & Defourny, 2010). Also other static features would be enhanced as well and their future removal would be required (Section 4.5). The spatial location of pixel used by mask approach to be clipped out depends on change in vegetation cover as shown in Figure 3-7. Therefore loss of pixels carrying the soil information wouldn't be large as each image use different mask with different spatial location.

Although methodology of roddons detection is presented some noise elements are still visible. The visibility of noise features generated by vegetation boundaries will slightly increase at the beginning of the enhancing of soil brightness process as presented in Figure 3-8. However with increasing number of repetitive operations of the enhancing approach over multiple imagery the visibility of time-variable feature boundaries will decrease with comparison to time-static features (such as th soil boundaries). Other static features in the landscape are also enhanced during the process such as water bodies, urban areas or communication networks and can be clipped out by application of a simple GIS approach as described in section 4.5.

4.5 Future recommendations

To enhance the difference between soil features boundaries and vegetation boundaries application of described methodology over multiple imagery can be used (Zhu & Woodcock, 2014). The application is possible for all data available with 3 bands (green, red, NIR) composition. Therefore for example a variety of Landsat data can be used.

The reduction of noise generated by other static features of landscape (water bodies, urban areas or drainage channels) can be achieved by the application of simple GIS approach based or known geospatial data layers. Known geospatial data available on on-line (http://digimap.edina.ac.uk/ or http://ordnancesurvey.co.uk/) can be used as a base layer (mask) to clip out non-soil related static elements enhanced during the process of boundary detection.

Identification of enhanced pixel to ensure that each pixel belong to one selected segment can be achieved by application of watershed approach (Bleau & Leon, 2000). This was used by Yan & Roy (2014) to separate circular agricultural field belonging to multiple segments into isolated ones. Future extraction of isolated segment can be achieved by the application of object-based analysis or unsupervised image classification (Akcay & Aksoy, 2008). Unfortunately complexity and time requirements of appropriate method of segment extraction is beyond scope and time scale of this study.

Future map defining the spatial location of roddon soil features can be modified for GPS technology on agricultural machinery and utilized to optimising the current management practice to increase yields and benefit the environment.

5 CONCLUSION

The roddons detection techniques are important steps to gather further knowledge about variations in soils and present a simple model to determinate spatial location of roddon soil features. Yet methodology presented in this study need an extensive further work to be applicable on site and for benefit through soil and crop management through its application.

This paper has attempted to deliver a methodology for roddon soil feature extraction. The scheme below shows a simple step-wise approach of the methodology application. The main steps are:

- Application of the SBI on any data composed of 3 spectral bands (green, red and NIR)
- Application of non-directional edge filter to enhance areas where there is large spectral contrast
- Creation of binary mask based on the edge NDVI approach to clip out some of the noise elements especially features with more time variation
- Enhancing the spectral difference of static features where there is large spectral contrast by repeating the procedure over multiple imagery and sum the result together

Detection of soil features such as roddon should provide us with better knowledge about soils and their spatial context and therefore help to improve current management practise to benefit both environment and product yields.

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