CRANFIELD UNIVERSITY

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REMOTE SENSING OF OPIUM POPPY CULTIVATION IN AFGHANISTAN

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Supervised
by

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Abstract

This work investigates differences in the survey methodologies of the monitoring programmes of the United Nations Office on Drugs and Crime (UNODC) and the US Government that lead to discrepancies in quantitative information about poppy cultivation. The aim of the research is to improve annual estimates of opium production.

Scientific trials conducted for the UK Government (2006–2009) revealed differences between the two surveys that could account for the inconsistency in results. These related to the image interpretation of poppy from very high resolution satellite imagery, the mapping of the total area of agriculture and stratification using full coverage medium resolution imagery. MODIS time-series profiles of Normalised Difference Vegetation Index (NDVI), used to monitor Afghanistan's agricultural system, revealed significant variation in the agriculture area between years caused by land management practices and expansion into new areas.

Image interpretation of crops was investigated as a source of bias within the sample using increasing levels of generalisation in sample interpretations. Automatic segmentation and object-based classification were tested as methods to improve consistency. Generalisation was found to bias final estimates of poppy up to 14%. Segments were consistent with manual field delineations but object-based classification caused a systematic labelling error. The findings show differences in survey estimates based on interpretation keys and the resolution of imagery, which is compounded in areas of marginal agriculture or years with poor crop establishment.

Stratified and unstratified poppy cultivation estimates were made using buffered and unbuffered agricultural masks at resolutions of 20, 30 and 60 m, resampled from SPOT-5 10 m data. The number of strata (1, 4, 8, 13, 23, 40) and sample fraction (0.2 to 2%) used in the estimate were also investigated. Decreasing the resolution of the imagery and buffering increased unstratified estimates. Stratified estimates were more robust to changes in sample size and distribution. The mapping of the agricultural area explained differences in cultivation figures of the opium monitoring programmes in Afghanistan.

Supporting methods for yield estimation for opium poppy were investigated at field sites in the UK in 2004, 2005 and 2010. Good empirical relationships were found between NDVI and the yield indicators of mature capsule volume and dry capsule yield. The results suggested a generalised relationship across all sampled fields and years (R^2>0.70) during the 3–4 week period including poppy flowering. The application of this approach in Afghanistan was investigated using VHR satellite imagery and yield data from the UNODC's annual survey. Initial results indicated the potential of improved yield estimates using a smaller and targeted collection of ground observations as an alternative to random sampling.

The recommendations for poppy cultivation surveys are: the use of image-based stratification for improved precision and reducing differences in the agricultural mask, and use of automatic segmentation for improved consistency in field delineation of poppy crops. The findings have wider implications for improved confidence in statistical estimates from remote sensing methodologies.

Acknowledgements

I would like to express my thanks to my supervisor Toby Waine for his encouragement and sacrificing his spare time, and to my co-supervisor John Taylor for his sound advice and giving me the opportunity to work in the field of remote sensing. I would also like to thank Graham Juniper for help with fieldwork and the preparation of datasets, and Murray Cheetham for volunteering his time and aircraft for ADP collection in 2010.

This research would not have been possible without the numerous discussions and the sharing of data with the staff of the UNODC and the US survey. Finally, I would like to thank my family and friends for their patience and encouragement during the weekends and holidays I spent at the computer.

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Chapter 1
Introduction

1.1 Background

Opium poppy (*Papaver somniferum*) is cultivated throughout Afghanistan with annual variation in the total cropped area and its spatial distribution. In 2014 poppy was concentrated in the provinces of Helmand, Kandahar, Nimroz, Farah and Nangarhar (see figure 1.1). The majority of poppy crops are irrigated with some rainfed cultivation in northern provinces when there is sufficient rainfall. Opium is the milky sap harvested by hand from the seed capsules as opium gum in a process known as lancing, it is then dried and sold or processed into morphine.

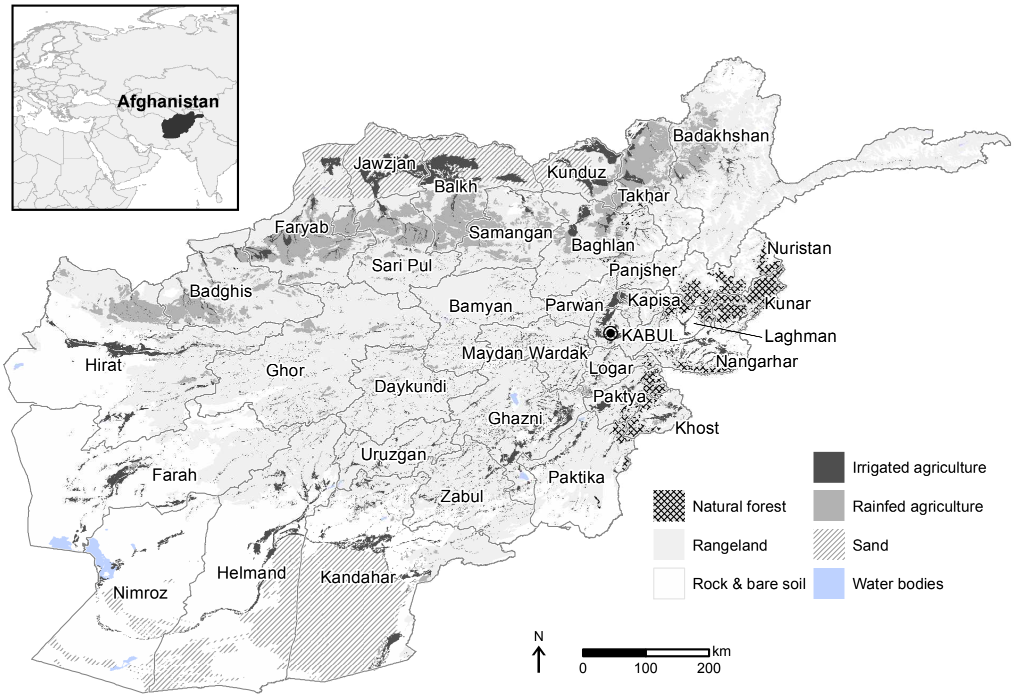

Figure 1.1. Afghanistan provinces and major land cover types.

Afghanistan produces 85% of the World's illicit opium and morphine, which is trafficked through neighbouring countries into the world market (UNODC, 2015b). Illicit drug use has serious health consequences that puts strain on public health systems for the prevention, treatment and care of drug use disorders (UNODC, 2015b). Information on the production of illicit opium in Afghanistan is essential for medium to long term planning of counter narcotics activities and monitoring trends (UNODC, 2014).

As such the United Nations Office on Drugs and Crime (UNODC) and US Government run monitoring programmes to estimate the yearly production of opium in Afghanistan. Both surveys rely heavily on remote sensing because poor security and a lack of infrastructure make visiting ground locations difficult. Their estimates do not always agree. Figure 1.2 shows US estimates of poppy cultivation from 1994 were systematically lower than the UNODC until a large reversal in 2004. Differences in estimates hamper the development of counter narcotics strategy and undermine compensation schemes linked to cultivation figures.

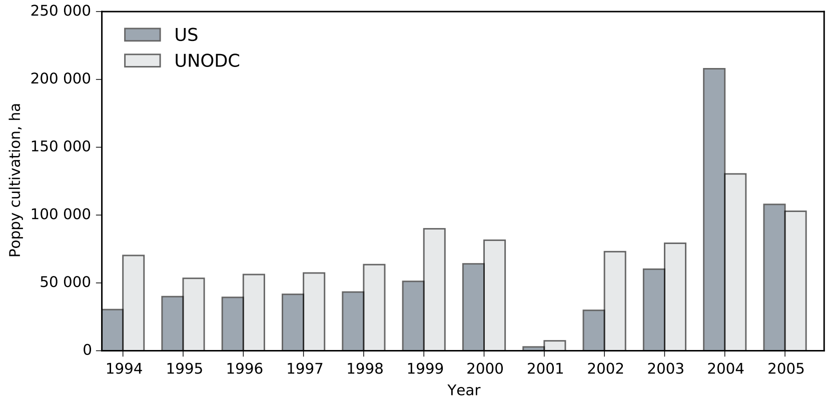

Figure 1.2. UNODC and US Government poppy cultivation estimates for years with published data. Adapted from Bennington (2008).

1.2 Thesis statement

This work investigates differences in the survey methodologies of the monitoring programmes of the UNODC and the US Government that lead to discrepancies in quantitative information of poppy cultivation. The aim of the research is improved annual estimates of opium production. The objectives are:

1. To compare the remote sensing surveys of Afghanistan's opium monitoring programmes.

2. To critically evaluate how differences in survey methodologies impact opium estimates.

3. To identify improvements to current methodologies for reducing error and bias in opium production estimates.

The thesis is made up of 5 journal articles arranged as individual chapters followed by a summary of the findings and conclusions. To avoid repetition, literature relating to the specific topics is reviewed within the introduction sections of the chapters. This introduction contains the background to remote sensing of opium and a description of the UNODC and US opium survey methodologies.

Chapter 2 is an overview of the use of integrated remote sensing technologies for opium monitoring in Afghanistan conducted for the UK Government between 2005 and 2010. This research highlighted differences in survey methodologies that could lead to disagreement in cultivation estimates between the UNODC and US Government opium surveys, relating to objective 1.

Chapter 3 presents the use of MODIS Normalised Difference Vegetation Index (NDVI) profiles for wide-area monitoring of the agricultural system in Afghanistan.

This application is novel as poppy is cultivated in field parcels much smaller than the spatial resolution of MODIS. Profiles provide accurate timing for imagery collections and highlighted the yearly variation in the extent of the cultivated area.

The effect of differences in visual-interpretation of opium poppy crops, the mapping of the total agricultural area, and the use of image based stratification are presented in chapter 4 and chapter 5 (objectives 1 & 2).

Chapter 6 details three years of field experiments conducted on UK poppy crops on the relationship between yield indicators and image derived NDVI. A bias correction methodology for the non-random yield observations collected as part of the UNODC's annual survey is presented and discussed in relation to very high resolution (VHR) imagery collections in Afghanistan.

Based on these investigations, improvements to current methodologies for reducing error and bias in opium production estimates (objective 3) are:

Wide area crop monitoring – use of time series NDVI to inform decisions on image timing in relation to crop phenology and annual changes in cultivation practices.

Image segmentation – use of automatic methods for image segmentation to improve consistency in poppy field delineation.

Image-based stratification – use of stratification to improve the precision of the UNODC's survey, leading to robust estimates with lower confidence intervals, less affected by annual differences in the area of agricultural production.

Bias correction of yield estimate – bias correction of field measurements of poppy yield indicators using NDVI from satellite imagery as an alternative to random sampling.

1.3 Remote sensing of opium poppy

The science of remote sensing is used to measure and monitor the earth's surface by exploiting differences in the reflected or emitted electromagnetic radiation of surface objects. The reflectance of green vegetation is characterised by strong chemical absorption by chlorophyll *a* and chlorophyll *b* in the visible spectrum (400–700 nm) with a small peak in green reflectance around 550 nm (Curran, 1989). In the near-infrared (700–1300 nm) incident energy is transmitted and scattered by the air-cell interface of individual leaves within the plant canopy, resulting in a strong reflected signal (Woolley, 1971). Short wave infrared (1900–2450 nm) is absorbed by water and the dry matter within the leaf structure (Faurtyot, 1997).

The detection of individual plant species from their spectral signal depends on measurable differences in reflectance between vegetation types. For opium poppy, Jia et al. (2011b) investigated spectral separability at field sites in north western China using field spectrometry to demonstrate the feasibility of poppy detection using optical remote sensing. They compared spectral profiles of opium poppy, wheat and alfalfa before, during and after poppy flowering and found a distinct spectral signature for opium poppy at all three growth stages.

Figure 1.3 shows the reflectance profiles of poppy, wheat and alfalfa at the growth stage showing maximum spectral separation (flowering & heading) from Jia et al.

(2011b). The major atmospheric water vapour bands centered at approximately 1380 nm and 1880 nm were excluded from the analysis. Before flowering the crop types were separable in the visible spectrum because of differences in chlorophyll absorption (most significantly at 438 and 528 nm). Structural differences of the poppy canopy caused by the higher leaf area and water content (1207 nm) could be measured in the near-infrared and short wave infrared. The contribution of poppy flowers to the reflected signal during flowering increased the spectral separation in the visible spectrum. After flowering visible differences were reduced because of chlorophyll breakdown during senescence. Decreased water content at harvest revealed spectral differences at 1220 nm associated with absorption by starch and cellulose (Curran, 1989). The optimal wavebands for opium poppy detection varied between growth stages because of chemical and structural changes within the crop canopies over their growing cycles.

The spectral signatures were extracted from a homogenous or 'pure' signal normalised for incident radiation from well managed and uniform crops of opium, wheat and alfalfa. The structural variation in the canopy from changes in crop management across the landscape, changes in soil background and the highly anisotropic reflectance of vegetation (Asner, 1998) were not investigated.

For airborne and satellite spectroradiometers the signal is attenuated by absorption (longer wavelengths) and scattering (shorter wavelengths) within the column of air between the surface and the sensor. The signal integration time is also reduced by the shorter dwell-time over the target compared to field methods. As a result, these sensors have broader spectral bands to achieve a high enough signal-to-noise ratio, which masks fine resolution absorption features of crop canopies (Curran, 1989). Townshend et al. (1991) summarises the factors affecting remote sensing of landcover as: 1) imaging areas of homogenous land cover is dependant on the spatial resolution of the remote sensing system as the mixing of signatures within pixels and at cover types boundaries may mask spectral differences, 2) band

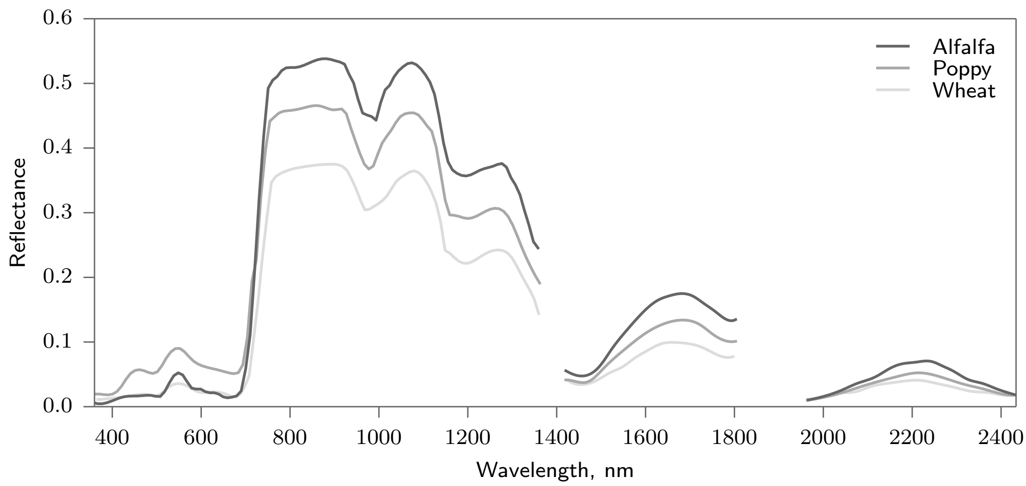

Figure 1.3. Spectral profiles for opium poppy (at flowering), wheat (at heading) and alfalfa (at flowering) modified from Jia et al. (2011b)

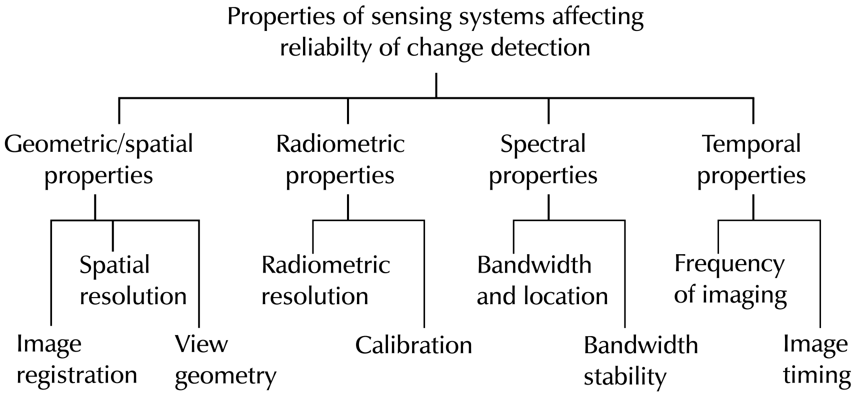

Figure 1.4. Factors affecting ability of remote sensing systems to detect change, modified from Townshend et al. (1991)

widths and locations are chosen to minimise atmospheric effects resulting in the loss of fine spectral resolution that might be necessary for accurate crop detection, 3) multi-temporal observations rely on the frequency of acquiring cloud free imagery and the accurate co-registration of images for extracting spectral data at the same locations over time, 4) the sun-sensor geometry can cause spectral changes in signature related to the bidirectional reflectance of vegetation and not changes in land cover, and 5) measurements of reflectance are dependant of radiometric calibration to reduce the effects of the atmosphere and account for changes in illumination (figure 1.4). These factors limit the detection of cover types directly from their spectral response.

Instead, statistical models are used for classification to account for the spectral variation in cover-types across an image. Supervised methods use a sample of representative pixels with known cover-type to train a classifier, which is then used to predict classes for unknown pixels. Unsupervised methods can be used to classify image data based on clustering of the pixel values into separable groups, representing spectral classes, without training data. Class labels (information classes) are then assigned using ancillary information. Unsupervised methods are often combined with, or used in place of supervised methods when there is a insufficient number of training pixels.

Early investigation of remote sensing methods for detection of opium and other narcotics were driven by the difficulty of collecting ground data in areas of illicit crop production. Sader (1990) reported on unpublished studies conducted in Thailand and India (table 1.1) on the detection of opium poppy. The results of surveys conducted with airborne multispectral sensors were reported to be successful, although no supporting evidence is presented. Poppy detection was carried out through visual interpretation and digital classification of multispectral satellite imagery.

This early work encouraged the formation of an Expert Group on remote sensing of illicit narcotics by the United Nations (1989) and further investigations into the utility of remote sensing of opium poppy and coca (Sader, 1990). Optimal conditions for remote sensing (digital classification and photo-interpretation) of poppy in

Table 1.1. Summary of unpublished opium poppy detection projects using remote sensing, after Sader (1990)(MS = multispectral)

Study area	Sensor	Date	Analysis method
India	IRS LISS-1	1988 (Dec.) & 1989 (Feb., Mar.)	Visual
India	Landsat TM	1986 & 1989 (Mar.)	Digital
Thailand	SPOT	Various	Visual & digital
Turkey	Airborne MS	Unknown	Unknown
Mexico	Airborne MS	Unknown	Unknown

Afghanistan were defined as well timed imagery, appropriate resolution and minimal intercropping, and ground data for training and evaluation (Sader, 1992).

In Northern Thailand Prapinmong et al. (1980) investigated digital classification using maximum likelihood (ML) of opium poppy, dense forest open forest, plantations, rice and shadow. Classification accuracies were reported as lower for poppy than the other classes. The authors proposed an improved methodology to incorporate elevation and slope together with imagery timed at poppy flowering in January/February or immediately after forest clearing/harvesting of the previous crop in November.

Chuinsiri et al. (1997) investigated poppy detection in Chang Mai Province of northern Thailand with opium cultivation in remote large fields, small fields on steep slopes and fields close to settlements (0.25 ha). They achieved classification accuracies of 67% and 70% for two dates of Landsat TM using ML at test sites compared with image interpretation of poppy from aerial photography. Spectral confusion with other crops was attributed to the mixed signal from sub-pixel fields at the resolution of the imagery (30m) and the variation in the growth stage of the poppy crops across the image scenes.

Land cover maps derived from image classification cannot be used to directly calculate area unless classification accuracies are >90% (Gallego, 2004). The systematic error in the classifier can be corrected by regression with an unbiased sample of higher accuracy (Cochran, 1977). Tian et al. (2011) used this approach to measure poppy cultivation in North Myanmar using unsupervised classification and manual editing of multiple image sources (SPOT-5, ALOS and ASTER), bias corrected with visual interpretation of very high resolution (VHR) QuickBird and IKONOS imagery. Although ground data was collected for verification, no accuracy figures were presented to support the claim that their information was more reliable than the UNODC's figures, which differed by up to 146.5%.

In these studies, and other work summarised in Chuinsiri et al. (1997), digital methods are reported to be inferior to photo-interpretation because image resolution is less than the field size. Interpreters can also incorporate features such as texture, size and distance to villages into poppy detection and are able to compensate for the effects of shadow on the appearance of crops.

In 2002 the UNODC adopted remote sensing methods along side its annual socio-economic opium survey of Afghanistan (UNODC, 2005) to minimise the threat to survey staff. By 2005 remote sensing was used in 15 of the 32 provinces surveyed, involving the collection and processing of 190 VHR scenes. Poppy cultivation was measured using supervised digital classification of pre-harvest and post-harvest

VHR images at random sample locations. Sample data was bias corrected using 250 × 250 m segments from ground survey or visual interpretation. Final estimates of poppy were produced by direct expansion of the sample ratio and confidence intervals calculated using bootstrapping (Efron, 1979), although these were not published.

The VHR imagery used by the UNODC has a spatial resolution smaller than individual field parcels and closer to the resolution of aerial photography used for visual interpretation of opium poppy from earlier studies. In 2005, the UNODC trialled the use of classification of full-coverage SPOT5 imagery to replace the sample approach. This was motivated by the lower cost of imagery and the potential to map the distribution of poppy for improved local estimates (UNODC, 2005). They collected and processed 70 SPOT-5 scenes over 5 provinces and measured poppy cultivation using supervised classification. The approach was found to be impractical because of the difficulty in targeting imagery (10–15 day revisit) to coincide with crop phenology.

The key factors in accurate classification of poppy summarised from the above studies are: the timing of imagery, the resolution and revisit time of the sensor, and the use of supporting ancillary data. However, there is a lack of accuracy assessment to support their conclusions. The UNODC only began releasing confidence intervals for their annual survey in Afghanistan from 2009. This lack of rigorous validation of the remote sensing of illicit poppy crops undermines its use in improving cultivation estimates (Kelly and Kelly, 2014) and could explain the preference of photo-interpretation over digital techniques.

Bennington (2008) investigated the temporal and spatial variation in spectral properties of opium poppy in VHR IKONOS imagery affecting classification accuracies. She found that at the flowering growth stage, the spectral signature of opium is separable from the surrounding crop types (mainly wheat and alfalfa) and classification accuracies over 75% are possible. The research also showed use of multi-temporal images did not improve classification if single dated images were collected around the time of poppy flowering.

More recently, hyperspectral methods were investigation by Wang et al. (2014) using satellite data from EO-1 Hyperion. Although the study was limited in scope, they reported classification accuracies of about 75% using unsupervised endmember-selection.

Classification on its own cannot be used to accurately measure the area of poppy cultivation in Afghanistan. Estimates still require the collection of sample data, either from ground survey in dangerous environments or from image-interpretation of expensive VHR imagery.

In 2006 the UNODC moved to visual interpretation of poppy at sample locations to improve the accuracy of sample data. This was facilitated by technical training in interpretation principles and image enhancement (pan-sharpening) for increasing the spatial resolution of multispectral VHR imagery to <1 m (UNODC, 2007). Their current methodology is detailed below (section 1.4).

1.4 Opium monitoring programmes in Afghanistan

The current methodology of the UNODC's annual opium sample survey, based on UNODC (2014) and UNODC (2015a), is summaried below. A overview of the survey is show in figure 1.5.

Risk areas and agricultural mask The area of potential agriculture (risk area) is a mask of the agricultural land where poppy cultivation is likely, including fallow areas where cultivation took place previously. The mask is updated yearly using visual interpretation of Landsat-8 medium resolution imagery (30 m), timed to coincide with the period of agricultural activity.

Sampling frame A 10 × 10 km sample grid is overlaid on the agricultural mask [1]. Sample squares that fall in multiple provinces are clipped to the boundary and any samples with an area <1 km^2 are excluded. Samples are selected using either a one-stage systematic random sample of the province grid squares or by random sampling within sub-regions to ensure samples are distributed equally across the sample frame. Sub-regions are defined by geographic clusters of agriculture or by prior information on poppy distribution. In 2014, the average sample fraction of the 11 provinces sampled was 13%.

Image interpretation at sample sites Pan-sharpened IKONOS, Quickbird, WorldView2 or Geo-Eye images are used to measure the cultivation of poppy at sample locations. A pre-harvest (flowering and capsule growth stages) and post-harvest VHR image is acquired for each selected sample square and ortho-rectified using a 30 m digital elevation model (DEM) and the vendor supplied rational polynomial coefficients (RPCs).

Poppy fields are manually digitised by image interpretation of false/true-colour composites of the pre-harvest images using interpretation keys of the main crops. Patterns in post-harvest images are used to confirm or edit the earlier interpretations, with each sample cross-checked by experienced interpreters to maintain consistency. Geo-referenced ground photography and aerial photographs from helicopter flights is used where available to aid in interpretation of poppy crops.

Cultivation estimate The unbiased estimate of the area of poppy cultivation, A_k, within province k, with samples of unequal selection probability is:

$$A_k = \frac{R_k}{n_k} \sum_{i=1}^{n_k} P_i \Big/ R_i \tag{1.1}$$

where P_i is the area of measured poppy in sample i, R_i is the total area of sample i, R_k is the total area of the agricultural mask and n_k is the number of samples. For estimates of provinces with equal sample selection probability,

$$A_k = \sum_{i=1}^{n_k} P_i \frac{R_i}{\sum_{i=1}^{n_k} R_i} \tag{1.2}$$

[1]Smaller sample grid of 5 × 5 km used in 2015 (personal communication, UNODC).

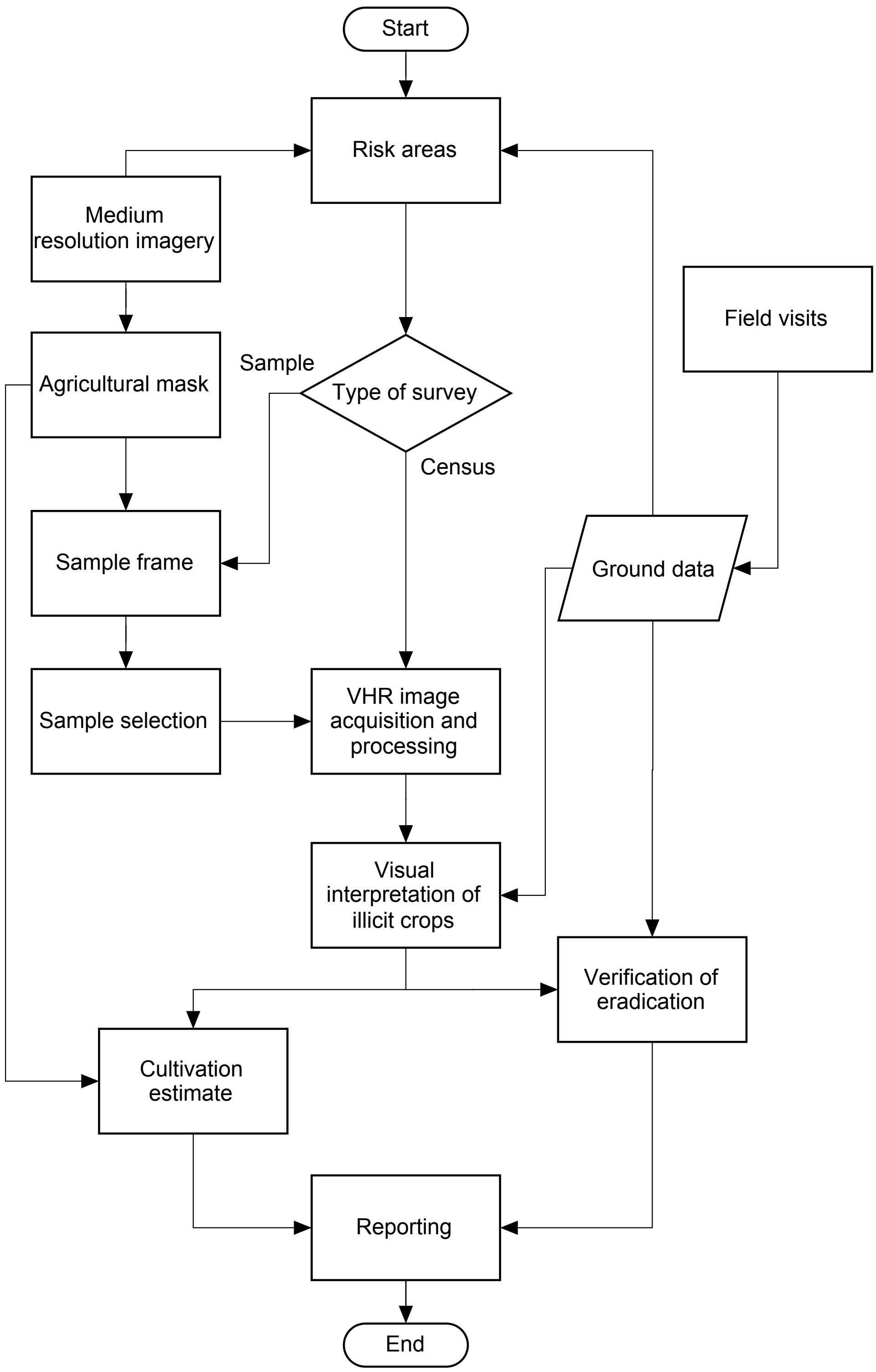

Figure 1.5. UNODC survey methodology flowchart, from (UNODC, 2015a)

The national estimate is the sum of K province estimates,

$$A = \sum_{k=1}^{K} A_k \tag{1.3}$$

adjusted for any eradicated poppy. A census approach is used for provinces with low levels of poppy cultivation, or where cultivation is highly concentrated. VHR images are targeted to cover the total extent of poppy cultivation and the total area of all digitised fields is used as the estimate.

The US Government use a stratified area frame sampling approach in their annual poppy cultivation survey, referred to as GeoTools. The methodology is not published but is based on work conducted by Luders et al. (2004) and uses the image interpretation of classified sub-metre imagery (Bennington, 2008), collected at sample sites (approximately 250 × 250 m). The sample fraction is around 4%. The methodology is explained in more detail in section 5.2.

1.5 Disclosure

The publications in this thesis follow a UK Government funded project into understanding the differences in cultivation figures from Afghanistan's opium monitoring programmes, summarised in Taylor et al. (2010). I was a research officer in the survey team, along with my supervisor Dr Toby Waine, led by my co-supervisor Prof. John Taylor. I was party to all discussions with the US and UNODC survey teams in Vienna and Kabul and implemented many of the technical developments of the parellel surveys. I prepared and analysed data and contributed to the production of project reports for the UK Government on poppy cultivation.

Between 2006 and 2009 I managed the scheduling of IKONOS and Quickbird collections and developed the preprocessing steps for both VHR and medium resolution imagery, the 2008 and 2009 collections are presented in appendix A. I also planned the Aerial Digital Photography collection in 2007 and developed a processing chain for the ortho-rectification of the imagery.

I delivered parts of the capacity building programme to the staff of the UNODC and Afghanistan's Ministry of Counter Narcotics on remote sensing techniques for monitoring poppy cultivation. In 2015, I was a major contributor to the UNODC guidelines on illicit crop monitoring using remote sensing, with Dr Waine and colleague Tim Brewer.

In Simms et al. (2014) I developed the processing chain and software tools for the MODIS profiles from work started by my colleague Graham Juniper. This included the testing of a MODIS satellite receiving station in the UK, followed by deployment to Kabul as part of the capacity building of Afghanistan's Ministry of Couter Narcotics. The paper was structured and written by myself from analysis and observations made by the team during the project period.

In Waine et al. (2014) I am responsible for the design, planning and data collection for the 2010 UK experiment and part of the data collection and analysis in 2005. I conducted the analysis of the data from the UNODC's 2011 and 2012 yield surveys and completed the manuscript in close co-operation with Dr Waine, who designed the UK yield experiments in 2004 and 2005. I presented the findings at the UNODC's tri-party conference on opium monitoring in Vienna and have worked closely with UNODC staff to develop the methodology for operational use in Afghanistan.

The paper that forms chapter 4 was written and structured by myself, from data produced by the survey team. Prof. Taylor generated the segmented field parcels and classifications, Tim Brewer is acknowledged for his work in generalising the sample interpretations.

I designed and conducted the analysis and produced the paper on the effect of the agricultural mask and image based stratification in chapter 5. I processed the DMC and SPOT imagery and wrote code for implementing the stratified area frame sampling analysis. The agricultural masks used in the study were produced by Graham Juniper, all sample interpretations were produced by the survey team during the project period.

Chapter 2
Survey and monitoring of opium poppy and wheat in Afghanistan: 2003 to 2009

This chapter presents the wider project work within which the differences in survey methodology were identified (objective 1) and the majority of the data used in the research was collected. Maps of the data collections for 2008 and 2009 are included in appendix A to demonstrate the scale of the project, a list of reports produced during 2009 are included in appendix D as examples of the wider project outputs.

Abstract

An integrated application of remote sensing technology was devised and applied in Afghanistan during 2003–2009 providing critical information on cereal and poppy cultivation, and poppy eradication. The results influenced UK and international policy and counter narcotics actions in Afghanistan.

Published as: Taylor, J. C., T. W. Waine, G. R. Juniper, D. M. Simms, and T. R. Brewer. 2010. Survey and monitoring of opium poppy and wheat in Afghanistan: 2003-2009. *Remote Sensing Letters* 1.3, pp. 179–185. URL: http://www.informaworld.com/10.1080/01431161003713028

2.1 Introduction

The annual production of opium in Afghanistan is said to exceed 90% of world production (UNODC, 2009) and to supply almost all of heroin consumption in the UK. The UK Government has a particular interest in counter narcotics (CN) and is a lead nation on policy formulation and action providing support and assistance to the Government of Afghanistan (GoA).

In 2003, there were serious deficiencies in the quantitative information on opium cultivation in Afghanistan which impeded both policy formulation and CN action. The key sources of estimates of quantity and trends in poppy cultivation were the independent annual opium surveys conducted by the US Government and, in collaboration with the GoA, the United Nations Office on Drugs and Crime (UNODC). The Surveys were providing different and often conflicting information late in the year severely limiting options for influencing the following season's crop. The information was also deficient in providing sufficient detail on the whereabouts of local concentrations of poppy cultivation and trends.

Part of the GoA's National Drug Control Strategy (NDCS) has included action to physically destroy the opium crop in the fields, by hand and/or mechanised means. The process included a scheme for compensating provincial governors for cost of eradication based on the area of crop eradicated. Thus there was also a requirement for verification of the eradicated area to assess the success of eradication and determine the size of the payments. This has had to take place against a background of insecurity, coercion and corruption rendering in-field verification unreliable.

Volatility of cereal prices in recent years and local shortages for food supply increased interest in the interaction between cereal and poppy cultivation in Afghanistan to see if encouraging farmers to grow cereals in designated Food Zones would reduce the cultivation of poppy. Current official cereal cultivation figures do not include objective field measurements instead they rely on farmer questionnaire surveys of unknown reliability, especially in the current circumstances.

2.2 Evolution of project work

Our initial role was to work with the US and UNODC Annual Opium Surveys to understand differences in survey figures and to recommend ways to improve consistency without prejudicing the independence of the Surveys' estimates. Both Surveys are science-based using remote sensing methods and detailed study of both revealed differences that could account for the inconsistency in results. Scientific trials were conducted to demonstrate benefits of recommended changes to Survey methodology; to encourage uptake and promote technical discussions between Survey teams. The trials evolved in 2006 into independent remote sensing crop surveys in selected parts of Afghanistan conducted by us for the UK Government to provide poppy information and improved local detail earlier in the growing season than the US and UNODC Surveys. Cereal cultivation surveys were added from 2007 to investigate the interaction between cereal and poppy growing.

In 2003, there were gaps in generic knowledge concerning remote sensing of poppy, poppy yield and poppy eradication so in 2004 and 2005, because security issues prevented us from doing so in Afghanistan, we conducted field trials on crop grown commercially in the UK for the pharmaceutical industry.

By 2006, it was apparent that there was serious over claiming of poppy eradication and unclassified evidence for this was required. In 2007 we conducted aerial surveys using a commercial service with an Ultracam D Digital survey camera to facilitate photogrammetric measurement of eradicated poppy fields. The on-going security problems prevented the aircraft overflying important areas of claimed eradication so we successfully evolved an alternative methodology using IKONOS satellite imagery and this was implemented through 2008 and 2009.

Afghanistan suffers a serious lack of trained technical personnel because of the persistent disruption of education during recent decades of war. The UNODC Survey team has set up a program of technical capacity-building for Afghan nationals and we have contributed key remote sensing training and mentoring to that program.

2.3 Overview of scientific trials and UK independent crop surveys

2.3.1 *UK field studies on poppy identification, eradication and yield estimation*

In 2004 we conducted multitemporal imagery trials. The optimum timing of imagery for discrimination of poppy from a range of other field crops was investigated and found to be around the flowering stage.

The UNODC estimates opium yield from capsule measurements within 1m square quadrats and then estimates average yield from a sample of locations (UNDCP, 2001). Security constraints limit access for sampling and so prejudice accurate yield estimation. We adapted a methodology developed for precision farming of cereals using minimal ground sampling (Taylor et al., 1997b; Wood et al., 2003) to investigate improvement of poppy yield estimation. There was a high correlation between NDVI and opium yield estimated by the UNODC method. This points to a role for remote sensing in improvement of opium yield surveys with reduced reliance on ground sampling but lack of resources prevented us taking it further.

In 2005 a randomised block field trial was conducted to investigate the efficacy of hand and mechanised poppy eradication and its interpretation on imagery. Mechanised methods of poppy eradication created distinctive patterns in the eradicated crop that could be recognised on imagery. Eradication at early growth stages allowed time for significant crop recovery that could also be recognised on later images. Later eradication was more efficient.

2.3.2 *Application of MODIS imagery for wide area crop information*

Afghanistan is a large, sparsely populated country famously inaccessible because of extreme terrain and poor infrastructure. Much of the country is characterised by small-scale irrigated cropping along high narrow valleys emanating from the Hindu Kush but the main irrigated agriculture is along the larger river systems such as in Helmand, Kandahar and Nangarhar provinces.

A time-series of 250 m resolution MODIS imagery from February 2000 was downloaded from the NASA archive and used to generate NDVI profiles at any location in Afghanistan. As illustrated in figure 2.1, the large range in altitude plus differences in latitude creates big variations in the timing of crop cycles depicted by the NDVI profiles. Also large areas, particularly in the north, are prone to drought which creates large annual variations in the productivity of dryland agriculture and the associated NDVI responses.

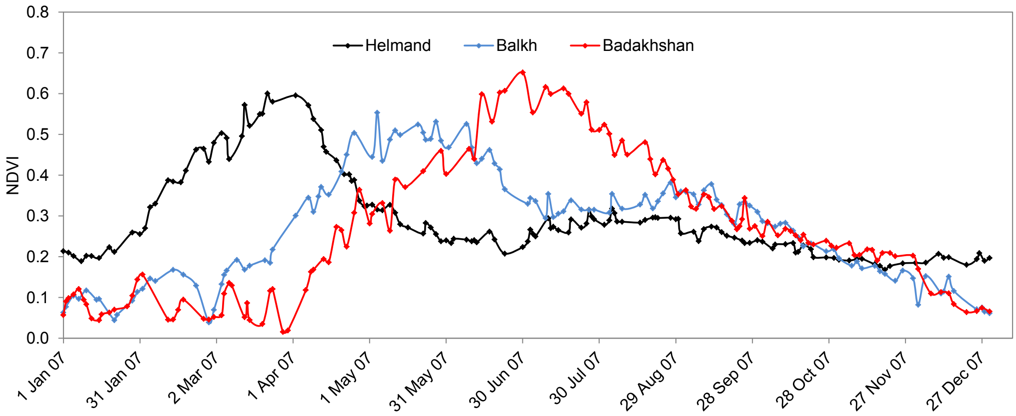

Figure 2.1. NDVI profiles from MODIS imagery at agricultural locations in Helmand (altitude 741 m, latitude 31.43° N), Balkh (altitude 1463 m. latitude 35.80° N) and Badakhshan (altitude 2502 m, latitude 36.31° N).

NDVI profiles were calibrated for crop growth stages at a sample of locations using ground photography taken by the UNODC. Profiles were then used to guide the acquisition timing of high and intermediate resolution imagery across the country for optimal discrimination of poppy around the flowering stage. In cases where weather conditions prevented optimal imagery acquisition, the timing on the MODIS profiles assisted interpretation of the high resolution imagery by informing the interpreters as to the likely crop types and growth stages present.

The NDVI profiles revealed a wide range of timings and growing patterns that, tempered with scientific judgement regarding MODIS pixel size and its orthorectification accuracy, were relatable on high resolution imagery to: identifiable crop mixes; agricultural practices such as crop rotations; and, evolution of new agricultural areas.

The time series of NDVI profiles also revealed the year-on-year variations in cropping patterns that were used to map reliability of cropping and to monitor drought onset and map affected areas.

2.3.3 *Poppy and cereal cultivation surveys*

Several alternative approaches to estimation of crop area using remote sensing were investigated. These were: the regression estimator as implemented by the EU MARS Project, described by Taylor et al. (1997a); object-oriented image analysis as implemented through eCognition (Definiens, 2003); sub-pixel analysis as developed by Applied Analysis Inc. (AAI, 2003; Huguenin et al., 1997); and Frame Sampling Analysis as implemented in ERDAS Imagine™.

We based our cultivation surveys on the Frame Sampling Analysis because it could be adapted for use alongside the UNODC Survey and there was already US experience in its application in Afghanistan reported by Luders et al. (2004). Our survey methodology was streamlined to bring forward the delivery of results to earlier in the crop season. This was achieved by the following: 1) syncronising imagery acquisition around poppy flowering; 2) reducing the sample size; and 3) reducing the size of the sampling frame by mapping only the area actively growing crops during the poppy season. The last was achieved by timing the acquisition of DMC imagery at poppy flowering which as greatly facilitated by the frequent coverage by the DMC constellation of satellites.

High resolution satellite (IKONOS) or aerial (Ultracam D) imagery was visually interpreted to map poppy and cereal fields by photogrammetry at the sample locations. Reliable interpretation keys for this were developed by cross referencing imagery with ground observations including ground photography and GPS coordinates for individual fields. The sample information was then combined with full coverage intermediate resolution DMC satellite imagery to make the poppy and cereal cultivation area estimates and to create map products of poppy and cereal distribution. All imagery preparation such as orthorectification and pan sharpening was carried out in-house to speed up delivery of imagery from suppliers and to facilitate quality control alongside speed of processing. Images were orthorectified using a high resolution controlled image base. Comparisons showed that the bulk processed products from suppliers were not consistently accurate.

Surveys of poppy cultivation area were carried out in up to nine selected provinces each year from 2005 through 2009. Surveys of cereal cultivation in Helmand and Nangarhar provinces were added from 2007. The results included: 1) the cultivated areas and annual trends for the provinces, districts and the Helmand Food Zone (as designated by the provincial governor in 2008); 2) maps indicating the probable crop distributions and changes in the area of agriculture actively growing crops during the poppy season; and, 3) details of natural events such as drought or flooding that could have influenced crop production. Figure 2.2, for example, shows the dramatic reduction of poppy cultivation in Nangarhar between 2007 and 2008 depicted in the probability distribution maps. The accuracy of our provincial area estimates for poppy and cereals was measured by the 90% confidence interval determined by using the bootstrap method. Confidence intervals were generally between $\pm$ 6 and $\pm$ 15 % for province estimates.

2.3.4 *Verification of poppy eradication*

Eradication verification was carried out in support of the UNODC and included training their staff in the verification methodology and in the systematic presentation of results for use as evidence.

Claimed areas of eradicated poppy fields were independently verified on orthorectified aerial photography from an Ultracam D camera and IKONOS imagery.

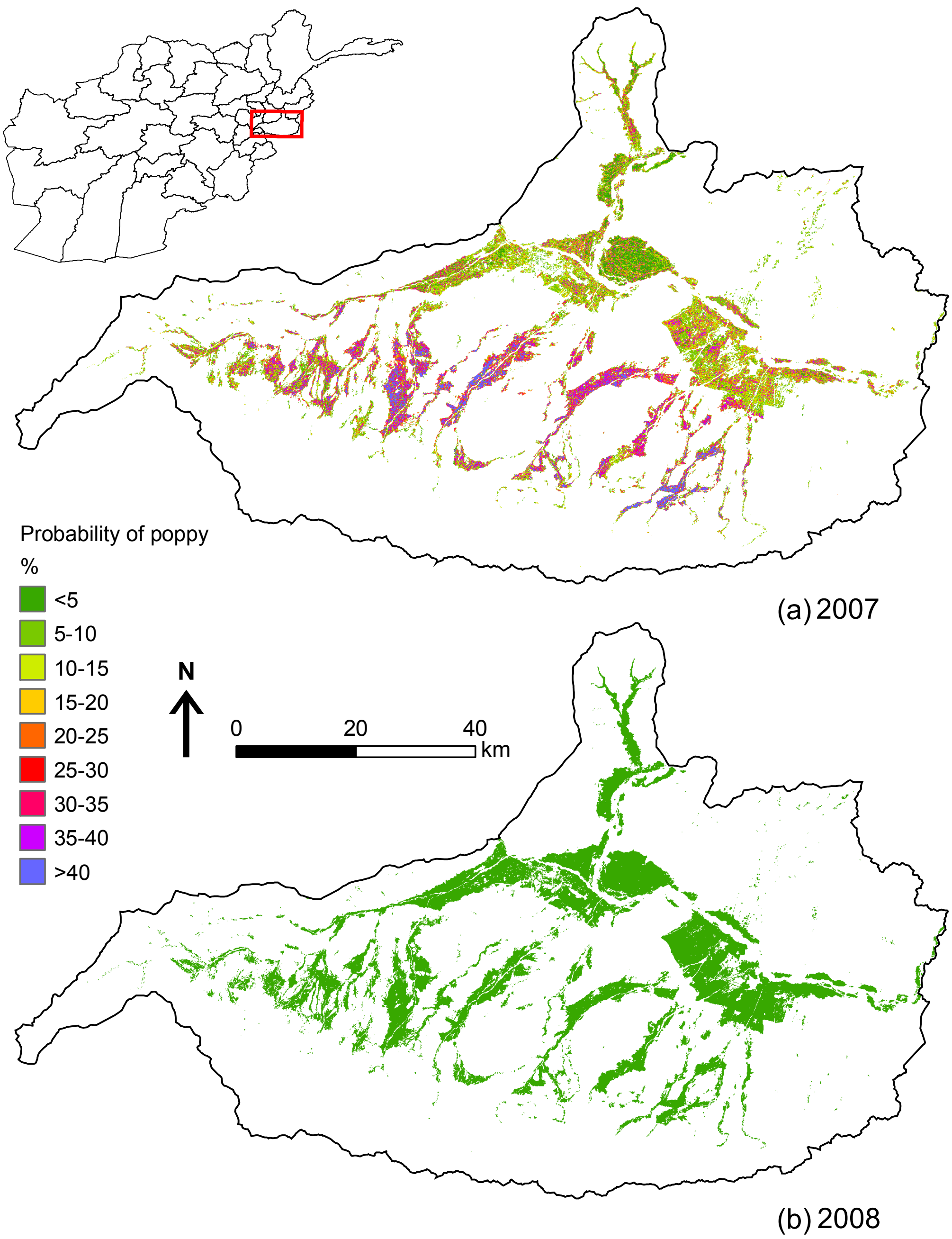

Figure 2.2. Probability of finding poppy in Nangarhar in *(a)* 2007 and *(b)* 2008.

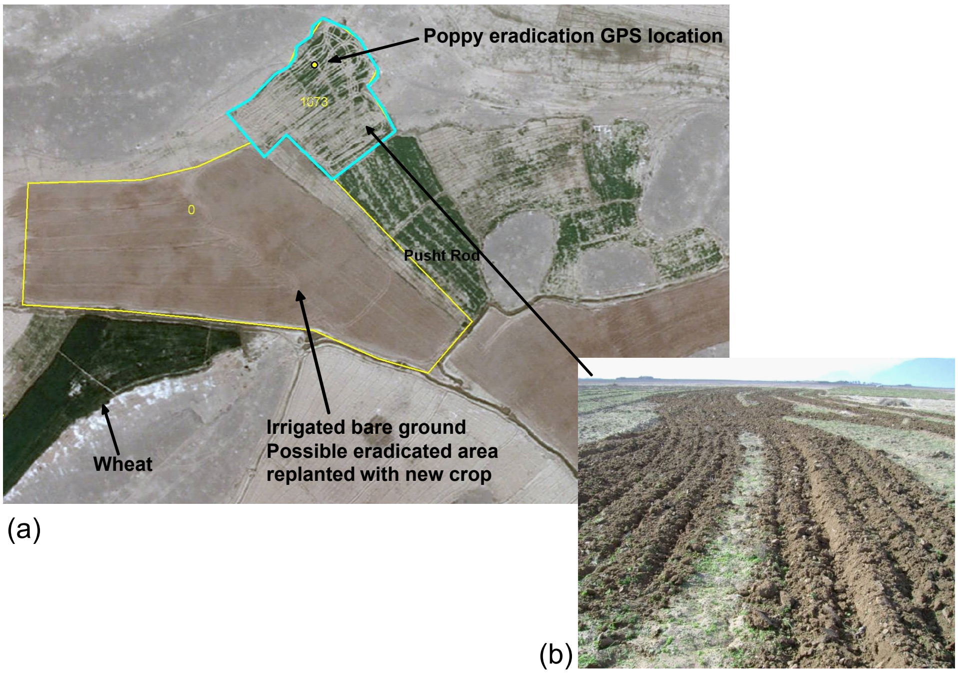

Figure 2.3. Natural colour Ultracam D imagery *(a)*, acquired 1 March 2007, showing poppy field No.1073 in Farah, which was incompletely eradicated on 17 December 2006 at very early growth stage, as seen in UNODC ground photograph *(b)*, and re-grown at the time of imagery. Ultracam Imagery ©BRITSH CROWN COPYRIGHT.

High accuracy orthorectification was critical to ensure correct identification of eradicated fields when cross referenced with the GPS coordinates and ground photography provided by eradication teams otherwise the combination of small field sizes and the GPS error could lead to inconclusive or incorrect field identification. Comparisons between our bespoke process and commercially supplied products again showed the latter as not having consistently high enough accuracy for verification of eradication. Eradicated poppy fields were revisited on later imagery to assess poppy recovery or replanting into other crops. The example Ultracam photography in figure 2.3 shows eradication patterns in partially recovered poppy fields following eradication at very early growth stages.

2.4 Commentary

An integrated application of remote sensing technology using high, medium and coarse spatial resolution imagery was devised and applied to provide critical information on cereal and poppy cultivation in Afghanistan.

Photointerpretation of sample sites, stimulated by this work, became a common feature of US, UNODC and our surveys and was frequently shared and compared by the Survey teams at overlapping sample locations generally confirming and promoting remarkable consistency in the identification of poppy fields. There were systematic differences between teams in the level of detail carried forward in the mapping of field boundaries. This systematic removal or inclusion of bare patches and field level infrastructure accounted for some differences between figures produced by the different Surveys, however, in general there was improved consistency between the main poppy cultivation estimates and trends from 2005.

The streamlined survey methodology, enabled us to provide cultivation figures several months earlier and with better detail at district level than the US and UNODC Surveys; as early as mid-May in Helmand; by mid-June in other Southern and Eastern provinces and by mid-July in the North.

At times, the results of this project have been highly controversial and unwelcome news but the science-based approach has created confidence in them and ensured they have been taken seriously. The work has influenced actions on CN in Afghanistan, and national and international policies. Results have been used and quoted by both the British Prime Minister and the Executive Director of the UNODC.

Acknowledgements

The UNODC for providing ground photography and the UK government for sponsoring the work.

Chapter 3

The application of MODIS time-series NDVI for the acquisition of crop information across Afghanistan

This chapter presents the wide area monitoring system developed to investigate temporal and spatial variations in poppy cultivation that influence survey estimates (objective 1).

Abstract

We investigated and developed a prototype crop information system integrating 250 m MODIS Normalised Difference Vegetation Index (NDVI) data with other available remotely sensed imagery, field data and knowledge as part of a wider project monitoring opium and cereal crops. NDVI profiles exhibited large geographical variations in timing, height, shape and number of peaks with characteristics determined by underlying crop mixes, growth cycles and agricultural practices. MODIS pixels were typically bigger than the field sizes but profiles were indicators of crop phenology as the growth stages of the main first-cycle crops (opium poppy and cereals) were in phase. Profiles were used to investigate crop rotations, areas of newly exploited agriculture, localised variation in land management and environmental factors such as water availability and disease. Near-real time tracking of the current year's profile provided forecasts of crop growth stages, early warning of drought and mapping of affected areas. Derived data-products and bulletins provided timely crop information to the UK Government and other international stakeholders to assist the development of counter-narcotic policy, plan activity and measure progress. Results show the potential for transferring these techniques to other agricultural systems.

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3.1 Introduction

This work investigates the use of MODIS data as part of a prototype information system to improve understanding of Afghan agriculture and crop production. The approach was to integrate 250 m Normalised Difference Vegetation Index (NDVI) data from MODIS with other available sources of remotely sensed imagery, field data and knowledge to investigate the contribution it could make to timely generation of crop information and if appropriate to make operational use of it. Of particular interest was: increased and more spatially complete understanding of the agricultural systems in Afghanistan; determination and forecast of crop development cycles for crop surveys and poppy eradication activities; and investigation of water availability and disease influences on crop production.

The work was motivated by the need for improved information on opium poppy and cereal cultivation in Afghanistan and was part of a major project sponsored by the UK government. This wider investigation, explained in Taylor et al. (2010), evolved from methodology trials in 2003 into an independent survey for the main opium cultivating provinces from 2005. At its peak in 2007 the survey covered 1.2 million ha of agricultural land and 90% of the total opium cultivation in Afghanistan, the World's major producer of illicit opium. The results were used by the US, UK and the UN to inform international counter-narcotic policy, plan actions and measure progress against the policy objectives.

In Afghanistan, there is great variation in timing and productivity of crops and a lack of reliable crop information, due in part to the country's size, varied topography, poor infrastructure and the loss of institutional knowledge after years of political instability. It is also difficult to collect field information on crops through the growing season because of poor security in the opium producing provinces, therefore such information is sparse and often non-existent, particularly in remote areas.

Remote sensing of annual and inter-annual vegetation development requires high frequency collections to allow enough cloud-free images to reconstruct the diagnostic shape of the growth curve. Wide-area coverage is also required for capturing large geographical areas in single dated scenes with minimal atmospheric and land surface differences. In time-series analysis, this maximises data available for each date and reduces further processing due to image mosaicking of smaller individual scenes. Remote sensing imagery that satisfies these requirements has a coarse spatial resolution, where pixels may contain sub-pixel mixtures of the crop types under investigation. Because of this, coarse level data are often used for monitoring natural systems or generic land-cover classes rather than spatially complex agricultural systems (Wardlow and Egbert, 2008).

Numerous previous studies have shown the advantages of using coarse resolution (1 km) satellite imagery from the Advanced Very High Resolution Radiometer (AVHRR), with its large area coverage and high collection frequency, for vegetation monitoring and agricultural information. Examples are for the study of the phenology of global vegetation (Justice et al., 1985), wildlife management and food security assessment in Southern Africa (Sannier et al., 1998), and monitoring vegetation biomass for fire risk assessment in Nambia (Sannier et al., 2002). These use NDVI described by Tucker (1979), which provides a measure of photosynthetically active vegetation. NDVI is calculated from the near-infrared and red image bands using the equation

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{3.1}$$

where ρ_{nir} and ρ_{red} are the near-infrared and red reflectance respectively. The success of research into the relationship between spectral index measurements, such as NDVI, and vegetation biophysical properties has encouraged the use of satellite observations for measuring changes in vegetation production (Goward et al., 1991).

Since 2000, the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's Terra and Aqua satellites has been used for vegetation studies over wide areas with improved spatial resolution. MODIS is ideally suited to monitoring temporal changes in NDVI, collecting daily global imagery in the red (620–670 nm) and near-infrared (841–876 nm) wave bands at a resolution of 250 m. Time-series MODIS has been used for calculation of vegetation green-up date (Wardlow et al., 2006) and profiling in the central US (Wardlow and Egbert, 2008), and the classification of agricultural areas from surrounding forest and savannah in Brazil (Victoria et al., 2012). These studies investigated agricultural systems where the field sizes are much larger than the 250 m nominal pixel size of MODIS, allowing growth cycles to be extracted for individual crops. Unlike these previous studies, the common field sizes in Afghanistan are much smaller (<1 ha), with single MODIS pixels containing the integrated response from multiple fields. The sensitivity of MODIS NDVI time-series to phenological changes for complex agricultural systems at this scale is currently unexplored.

The aim was to investigate MODIS NDVI profiles for extracting timely and practical crop information in the Afghan context. The research approach was the systematic detailed comparison of NDVI profiles with reference information to identify and understand the crop information contained in profile features. The research questions were: (1) do variations in the NDVI profile reflect distinct crop growth stages of individual crops at the 250 m resolution of MODIS; (2) can variations in crop phenology across the growing areas be identified; (3) are patterns such as multiple yearly cycles, crop rotations and fallow periods discernible from the profiles; and (4) what level of spatial detail can be detected?

3.2 MODIS NDVI profiles

MODIS Terra MOD02QKM image products were downloaded for Afghanistan from NASA's Distributed Active Archive Center (DAAC) via the Level 1 and Atmosphere Archive and Distribution System (LAADS) website starting from February 2000. The criteria for image selection were: near nadir images; predominantly cloud free; and whole country coverage in a single image. Nadir images have minimum distortion resulting from the viewing angle of the sensor. Because of problems in obtaining cloud free images across the whole country some partially cloudy (up to 25% cloud), off-nadir and partial country coverage scenes were included. Cloud cover was of greater concern during the November–April periods, especially in the mountainous areas of Afghanistan. Selected images were processed using the NASA sup-

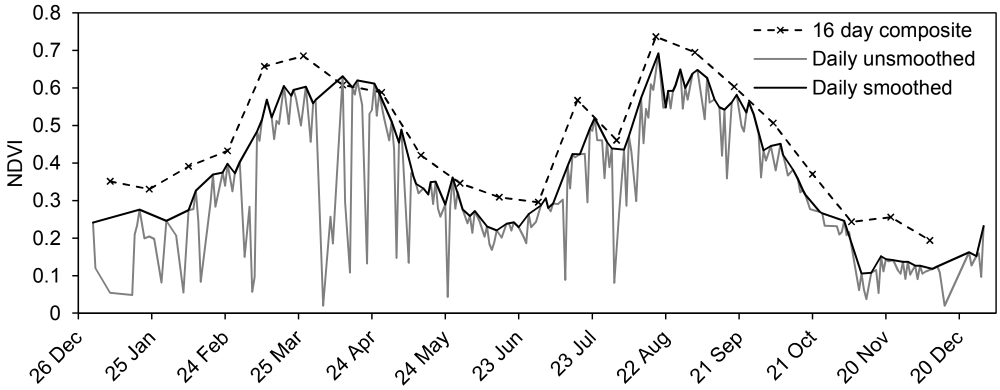


Figure 3.1. Comparison of MODIS NDVI 16-day composite (MOD13Q1) with smoothed and unsmoothed NDVI calculated from MODIS daily reflectance (MOD02QKM).

plied MODIS Swath Reprojection Tool (MRT Swath) and MOD03 geolocation product to achieve the sub-pixel accuracy necessary for time-series monitoring (Wolfe et al., 2002). An NDVI image was produced for each reflectance calibrated MODIS image and added in chronological order into a yearly stack. The date of image acquisition was linked to the stack-image band index using a separate database table. An automatic processing chain was developed for updating the NDVI stacks from downloaded MODIS images to provide profiles in near-real time.

Factors unrelated to the vegetation response can account for significant noise in the extracted profile. These variations can be attributed to sensor calibration, atmospheric conditions and the viewing angle (Goward et al., 1991). To improve profile interpretability, a smoothing algorithm was applied to the extracted data to remove changes in NDVI that are not related to the growth of the crop. The approach was modified from Viovy et al. (1992) and uses a moving, forward looking time window to remove high frequency variation and random changes caused by data errors such as saturated pixels.

Another approach to removing noise in NDVI profiles is to use composite data. MODIS 16-day composite products (MOD13Q1) are available for download that contain a representative NDVI value for the composite period; selected by filtering the data based on the quality, presence of cloud and viewing angle of the sensor (Huete et al., 2002). Figure 3.1 shows a comparison of the 16-day composite product (MOD13Q1) with daily smoothed and unsmoothed NDVI calculated from MOD02QKM daily reflectance. The composite data show a similar shape to the smoothed daily values with greater temporal stability. The systematic offset in the composite values is attributed to the preferential selection of the highest NDVI values within the compositing period (Hmimina et al., 2013) and the increase in NDVI values due to the atmospheric correction applied during generation of the MOD13Q1 product (Leeuwen et al., 2006).

The generalisation of the NDVI values for the composite profile masks some of the variation that could be related to phenological changes. Plotting values at the median date of the compositing period will also lead to a shift from the actual collection date of the NDVI value. With the flowering period of poppy lasting only two weeks, the timing shift in the profile could have a significant effect on the sensitivity and operational use of the profile information. Since the research was focused on detailed analysis at the limit of MODIS resolution, the use of daily NDVI values were preferred to composite data because of the potential loss of diagnostic detail in the profile shape and timing. The time delay between imagery collection and availability of 16-day composite products (3–4 days after the compositing period) also limited their use for near-real time monitoring.

To aid the analysis, an interactive tool was developed within a GIS for generating profiles by querying locations in the context of the reference spatial datasets. The tool was designed to display profiles for any location in Afghanistan with users able to modify the date range of extracted profiles and control the amount of smoothing. Profiles were extracted for single pixels and 3x3 pixel averages to assess the effect of local smoothing on profile interpretation.

3.3 Availability and preparation of reference data

Direct access to the field for the collection of ground data for cross-referencing with MODIS NDVI profiles was not possible because of security threats. In the early stages of the research, crop data were made available by the United Nations Office on Drugs and Crime (UNODC) through our role as formal advisors on the development of survey design, survey methodology and image analysis. For its yearly cultivation survey the UNODC collects a sample of very high resolution (VHR) satellite images (sample blocks) distributed across Afghanistan, and ground data (250 × 250 m segments) within the imaged area. Segments are visited by UNODC trained surveyors and the crop types within individual fields are identified and photographed (UNODC, 2005). Ground observations of crop types and geo-referenced photography is also collected during field visits by UNODC surveyors at locations away from the image blocks.

As the project evolved into an independent survey, further VHR (IKONOS and Quickbird) images were added to the database each year together with full coverage multispectral medium-resolution imagery (32 and 22 m) from the Disaster Monitoring Constellation (DMC) satellites. In 2007, aerial digital photography (ADP) was collected in 21 provinces at multiple dates for image-interpretation of poppy at sample locations and verification of claimed eradication. Geo-referenced ground photography from multiple sources, including the UNODC cultivation and eradication verification surveys, for each year were also added to the database.

Meticulous orthorectification of all imagery datasets was undertaken to ensure the accurate co-registration with extracted MODIS NDVI profiles. This was carried out by the project team as the geometric accuracy of the products from imagery suppliers were not sufficiently accurate. Processing in-house also reduced image delivery time and allowed full quality control of the image correction process. All datasets were ortho-rectified using a country-wide 30 m digital elevation model (DEM) and a controlled image base (CIB) for control. Quickbird and IKONOS scenes were ortho-resampled using a version of the vendor supplied Rational Polynomial Camera model refined using ground control (Grodecki and Dial, 2001). ADP was orthorectified using standard photogrammetric techniques to refine the initial stereo model derived from the aircraft's inertial measurement unit (IMU). Each block of overlapping frames was triangulated by bundle adjustment of automatically generated tie points. The resulting models were improved and quality checked using horizontal ground control from the CIB. Frames were then ortho-resampled using a DEM extracted from the stereo model of the block. Check point residuals of <5 m were achieved for VHR image and ADP ortho-rectification. Sub-pixel rectification of the DMC imagery was achieved using ground control and a rigorous sensor model developed by Spacemetric AB, available within Keystone Workstation software.

Field observations and photography were quality checked by plotting their coordinates on the ortho-rectified VHR imagery. By identifying features visible in the photographs on the VHR imagery it was possible to detect, and is some cases correct, errors in the geolocation of photos and shifts in the location of field observations.

Between 2005–2009 over 300 VHR scenes, 33 DMC images (full-country coverage between 2007–2009) and 12,500 frames of ADP were collected across the major poppy cultivating provinces. Figure 3.2 shows the spatial distribution of the imagery datasets together with the UNODC field segments and photography locations for 2005. This large reference database allowed for extensive cross-referencing to analyse and verify the consistency of MODIS NDVI profile interpretation.

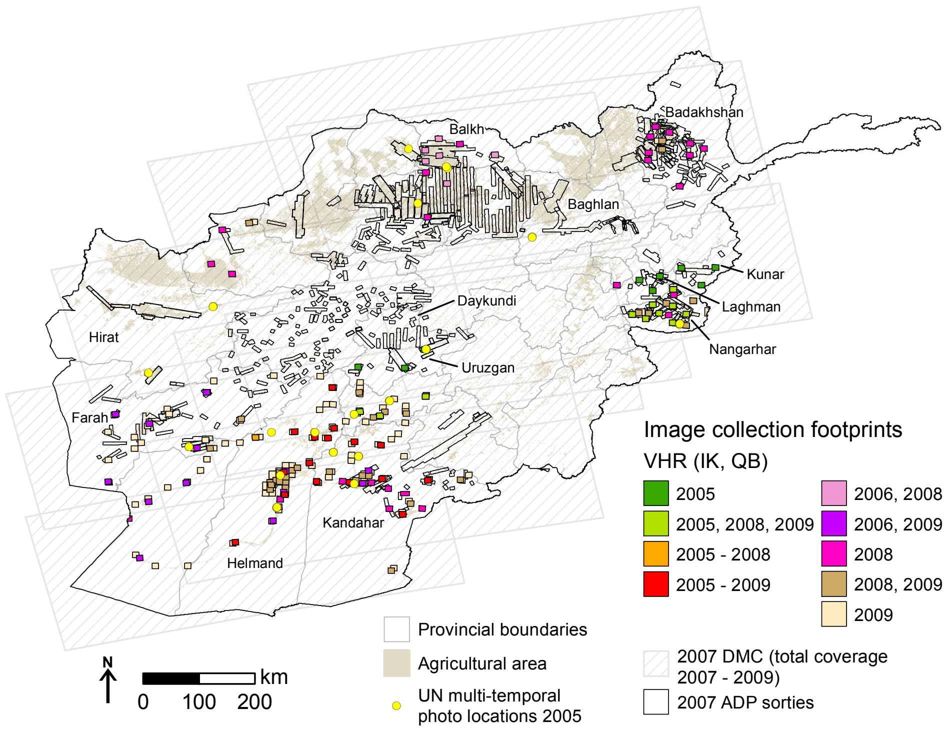


Figure 3.2. Distribution of very high resolution (VHR), medium resolution DMC and aerial digital photography (ADP) collections between 2005–2009 in the main opium producing provinces of Afghanistan.

3.4 Profile interpretation

3.4.1 *Temporal cropping patterns*

The seasonal development of profiles was compared at numerous locations identified from the reference datasets in areas of opium production. These included rain-fed (dry-land) and irrigated sites in the main agricultural areas and upland valleys.

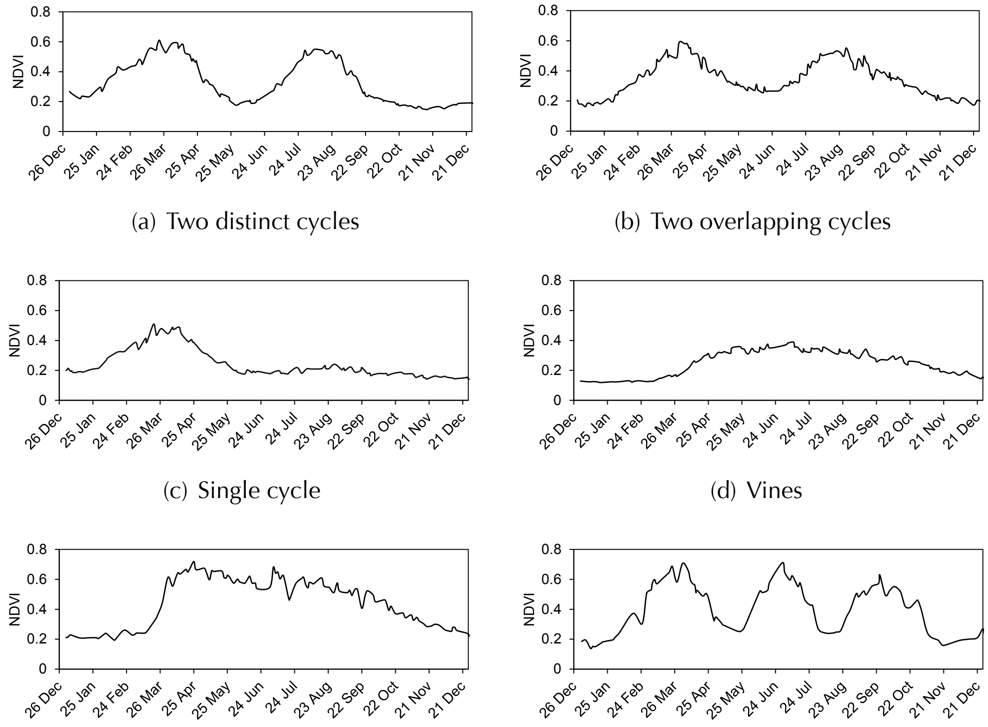
Figure 3.3 shows examples of distinct temporal cropping patterns identified from analysis of the profile shapes. Figure 3.3(a) shows double peaks representing separate crop cycles, where the NDVI value returns to the baseline between peaks. Double peaked profiles were also identified containing overlapping first and second cycle crops planted in the same crop-mix (figure 3.3(b)). Opium poppy and cereal crops such as wheat, barley and oats are typical first cycle crops. Second cycle crops include vegetables and maize. Poppy is not grown in the second crop cycle as it is not suited to the heat of late summer.

Higher altitude locations (greater than 1500 m) tend to have single crop cycles (figure 3.3(c)) as there is limited growing time between snow melt in March–April and the onset of winter. Distinctive single profiles with a more gradual return to the baseline were identified in crop-mixes dominated by vines (figure 3.3(d)) and tree crops (figure 3.3(e)); with tree crops distinguished by a steeper green-up and higher peak due to their increased canopy biomass compared to vines. A small area in central Nangarhar Province was identified with three distinct peaks (figure 3.3(f)) containing short cycle crops.

3.4.2 *Crop phenology*

NDVI profiles were cross-referenced with field data collected by UNODC in 2005, consisting of multi-temporal crop photography from 47 field locations, which represented the large geographical variation of the poppy growing areas (figure 3.2). Field data included the main crops grown in the first cycle with opium poppy, namely cereals and the forage crops clover (*Trifolium*) and alfalfa (*Medicago sativa* L.).

Figure 3.4 shows an example of the profile extracted for the site in Musa Quala, Helmand Province with the dates of the photographs showing the growth stages of the crops. Before February the profile is relatively stable with a low NDVI value of around 0.15, indicating the presence of limited amounts of photosynthetically active vegetation. The poppy and cereal crops at this location were either autumn sown and remained largely dormant during the winter, or spring sown and emerged late January or early February. Leaf production increases the plants' biomass and starts the upward trend in the profile at (a). By March the biomass has increased (b) as the poppy moves into stem elongation and the wheat into tillering followed by stem elongation. A few weeks later the poppy plants develop buds in a distinctive hook shape and flowering starts in early April at the same time as cereal crop anthesis (flowering) (c). The peak in NDVI indicates the peak green vegetation activity around the end of poppy flowering (d) and the start of seed-capsule development. Reflectance changes in sub-pixel poppy fields due to colour differences at flowering



(a) Two distinct cycles

(b) Two overlapping cycles

(c) Single cycle

(d) Vines

(e) Tree crops

(f) Three distinct cycles

Figure 3.3. Examples of multi-temporal cropping patterns identified from MODIS NDVI profiles across the opium producing provinces of Afghanistan.

are a small part of the reflected signal at the scale of MODIS and flowering poppy itself was not observed in the profiles. The opium harvest starts once the green poppy capsules have developed, and lasts while the scored capsules still provide opium gum. Once the opium harvest is finished the poppy plants are no longer irrigated and quickly dry and senesce (die back) (e). There is a rapid decline in photosynthetic activity, showing as a decrease in the NDVI profile back to the baseline. The cereal crops are ripening at the same time, in phase with the poppy and are harvested later in June. The dead poppy plants and capsules often remain in the ground (f) and are then cleared (g) in preparation for the next crop.

Alfalfa and other vegetable crops occupied only a small proportion of the cropped area. Alfalfa is typically cut for feeding as green plant material or made into hay, and generally produces multiple cuts each year. Vegetables usually had short growth cycles and were progressively harvested green. This means that the peak vegetation activity of these crops is often out of phase with the predominant cereal and poppy crops. However, at current Afghan production levels the effect was not visible in the overall profile trends.

The peak vegetation activity, corresponding to the first cycle peak of the NDVI profile, was at the flowering stages of both poppy and wheat. The timing of the flowering period is critical information for planning of counter-narcotic and cultivation survey activities and also coincides with the optimum time for image-interpretation

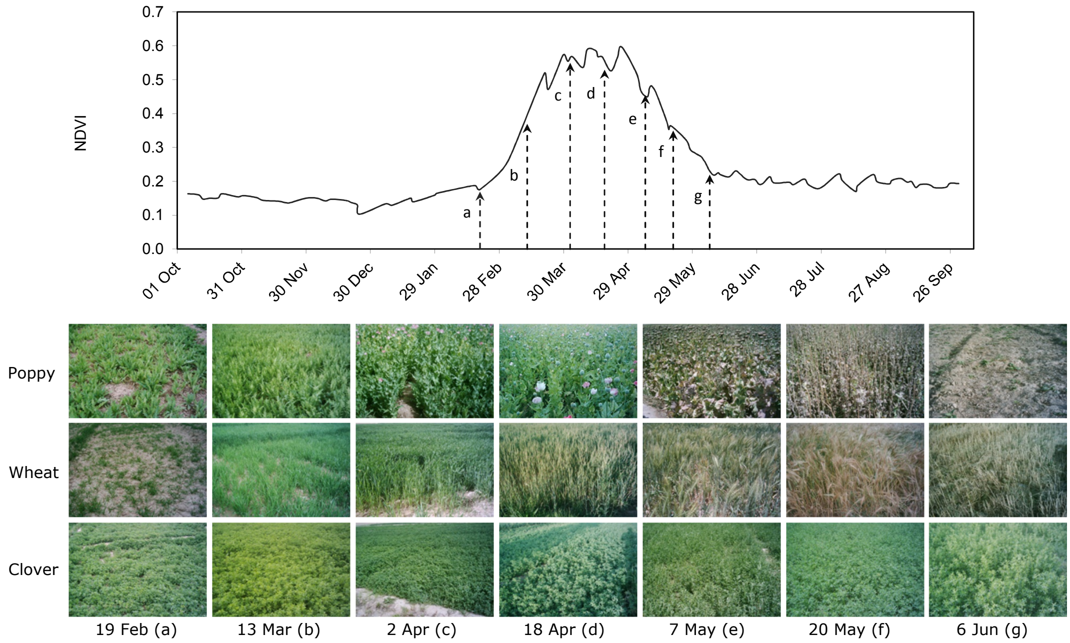


Figure 3.4. MODIS NDVI profile development in 2005 evidenced by UNODC ground photography for opium poppy, wheat and clover in Musa Qala, Helmand Province. Photography ©UNODC/Ministry of Counter Narcotics, Government of Afghanistan.

of poppy crops in VHR images. The growth stages of the main crops were found to be in phase and profiles were indicative of the phenology of the sub-pixel crop mix. A mixed profile from staggered planting and development dates in multiple sub-pixel crop cycles would limit the use of coarse resolution MODIS. However, this was not observed in the reference data for the main opium producing provinces, where the crop mix is dominated by cereals and poppy.

3.4.3 *Interpretation of peak NDVI*

The photosynthetic response between years measured by the difference in peak NDVI can be related to changes in productivity where a MODIS pixel is dominated by a single crop (Becker-Reshef et al., 2010). At the field scale in Afghanistan, the peak NDVI is the combined response from sub-pixel field parcels and will vary according to the composition and vigour of the individual crops. The effect of crop mix on profile height was investigated to assess if peak NDVI could be used as an indirect measure of productivity at the resolution of MODIS. All available ground segments and visual interpretations from the reference VHR imagery were compared with NDVI profiles for each year of available data. Profiles were compared at the same locations between years so NDVI measurements were independent of the difference in background soil. Figure 3.5 shows an example for the growing seasons 2005–2007 in Helmand Province. High resolution (1 m natural colour pan-sharpened) VHR IKONOS image subsets of the area around the MODIS pixel (nominal 250 m pixel location indicated by red square) are shown for each year. The

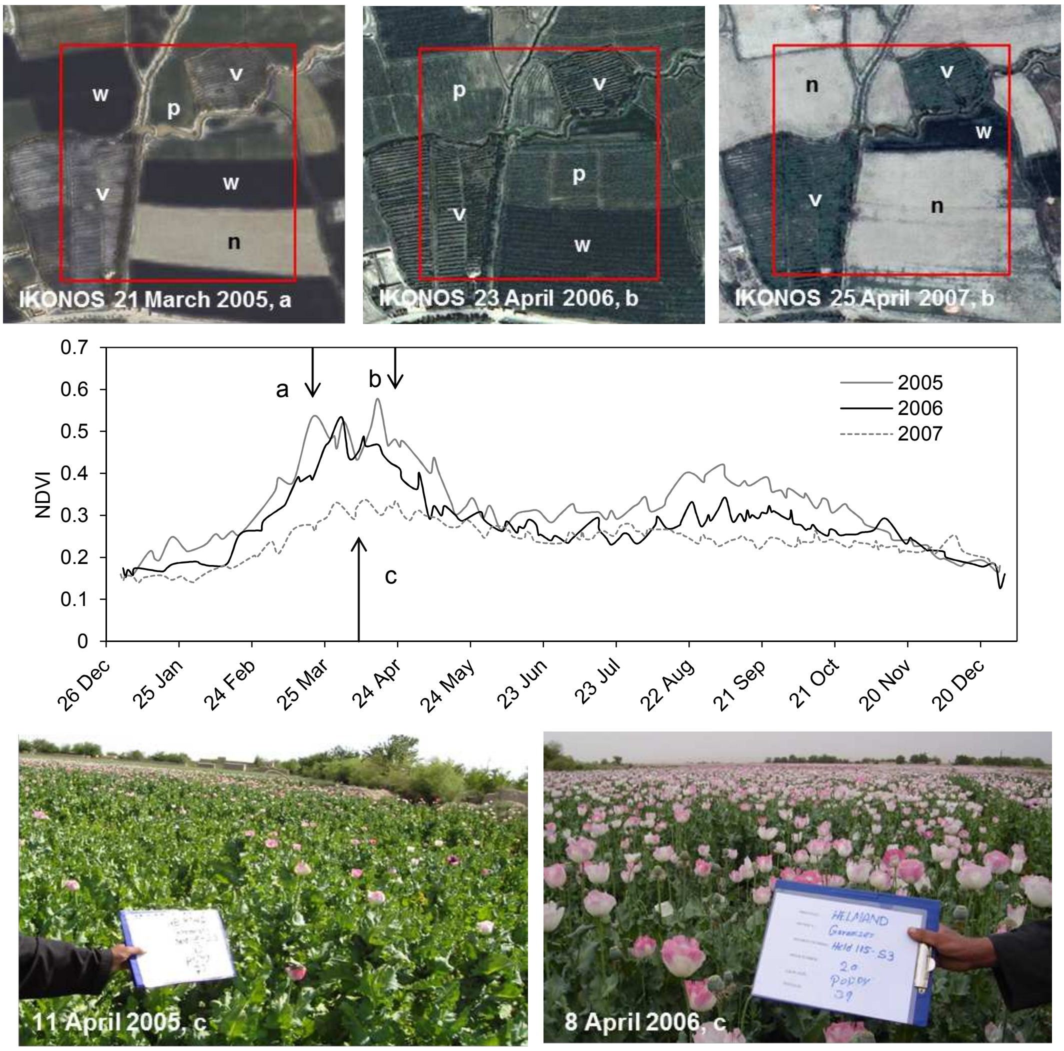


Figure 3.5. Visual comparison of crop-mix interpreted from VHR IKONOS imagery, ground photography and MODIS NDVI profiles for a location in southern Helmand. Crop types (w - wheat; p - opium poppy; n - no-crop; and v - vines) are identified on the true-colour composite IKONOS subsets within the nominal MODIS pixel (red square). The image and photography dates are marked on the profile (a - 3rd week of March; b - 2nd week of April; and c - 3rd week of April). Photography ©UNODC/Ministry of Counter Narcotics, Government of Afghanistan.

general timing of the subsets and ground photography are marked on the profile (a = 3rd week of March; b = 2nd week of April; and c = 3rd week of April). For the 2005 and 2006 season, the peak NDVI values are approximately 0.55. In 2007 the peak NDVI is reduced to 0.3. The poppy and wheat fields are in rotation between 2005 and 2006 while the vineyards are present in all three years. In 2007 a higher proportion of bare ground in the crop mix within the MODIS pixel is visible which lowers the average NDVI.

The variation in profile height reflected changes in vegetation activity relating to growing conditions and the mix of crop types. In irrigated areas with a stable crop mix, the magnitude of the profile peak was used to compare the relative productivity between years. In marginal areas, variation in profile height was indicative of a change in the number of planted fields resulting from crop rotation, crop failure or farmer decisions not to plant because of limited water availability. Profile data were used to map the spatial variability in relative productivity for investigating the quality of agricultural land and the effects of environmental factors such as cold weather on the development of crops.

3.5 Crop information system

3.5.1 *Geographical variation in crop timing and planning VHR imagery acquisition*

The survey methodology for estimating the annual area of poppy cultivation relied on image-interpretation of opium crops at sample sites. Accurate interpretation of crops from VHR imagery is affected by the growth stage of the crop at the time of image collection, which is optimal around the flowering period (Taylor et al., 2010) when poppy exhibits a contrasting colour and texture to other crop types. Interpretation becomes uncertain in images collected outside this period, either before the establishment of the crop canopy or after flowering as the crops begin to senesce.

Variations in the timing of the first cycle profile peak were compared at all ground locations in the reference database to assess differences in crop timing across the poppy growing regions. Figure 3.6 shows an example of crop cycle timing for locations in Helmand (lat. 31.55°N, alt. 758 m), Balkh (lat. 35.81°N, alt. 1405 m) and Badakhshan (lat. 36.61°N, alt. 2562 m). The first cycle peak at the Helmand location is one and three months out of phase with the Balkh and Badakhshan profiles respectively. The profiles are representative of the large variability in phenology caused by latitude and altitude found across Afghanistan.

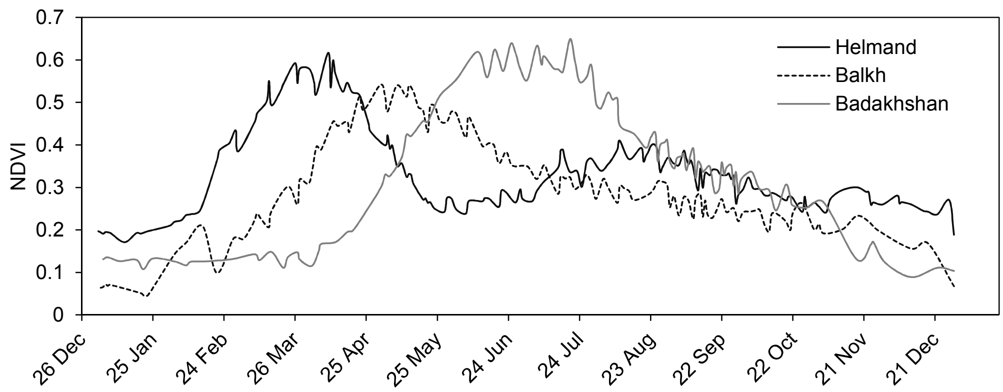


Figure 3.6. MODIS NDVI profiles at agricultural locations in Helmand (lat. 31.55°N, alt. 758 m), Balkh (lat. 35.81°N, alt. 1405 m) and Badakhshan (lat. 36.61°N, alt. 2562 m) provinces in 2007.

Figure 3.7 shows an example from Badakhshan with a two month timing difference in the first peak between adjacent valleys induced by topographic height differences. This is significant as imagery targeted to coincide with flowering in

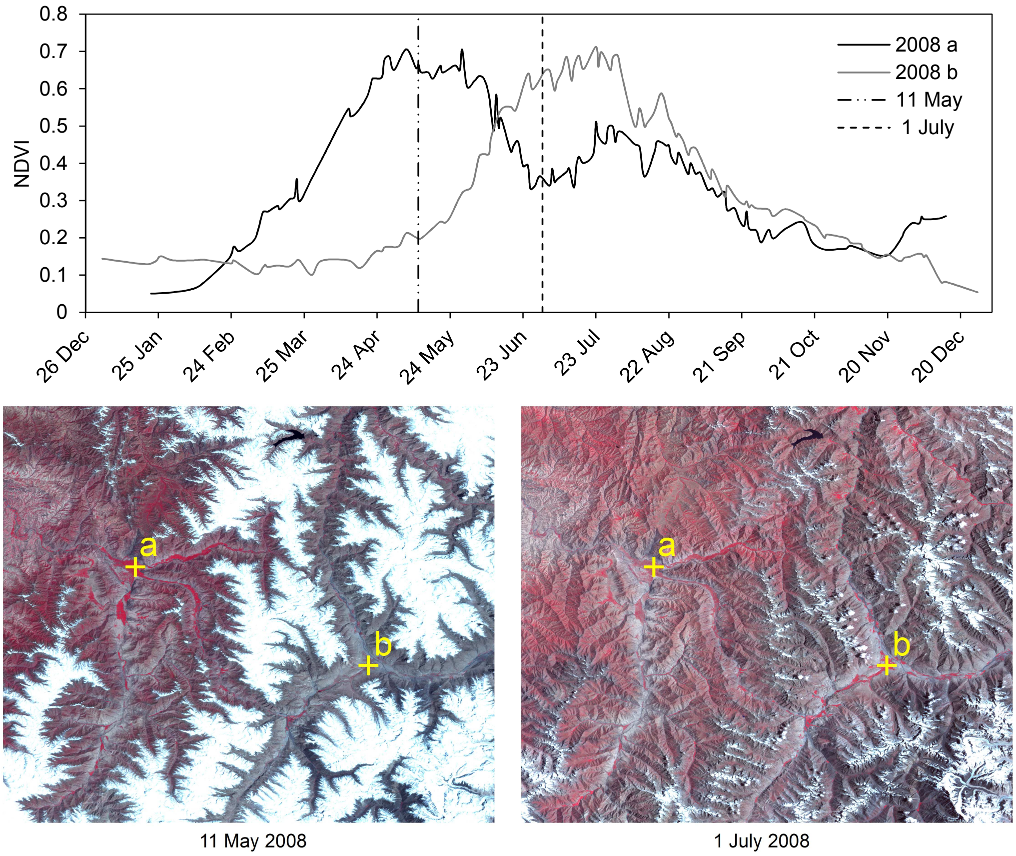


Figure 3.7. MODIS NDVI profiles extracted for points a and b (70 km apart) in Badakhshan Province shown on DMC false-colour composite image subsets (collection dates marked on the profile).

area (a) will be too early in area (b). Conversely, imagery targeted at (b) will be too late for interpretation in area (a).

By analysing the profiles at individual sample locations, two to three week collection windows were determined for VHR image collections (working back from the peak) and could be adjusted by monitoring the development of the profile in relation to the historical trends. Profiles were also used to define timing zones for poppy flowering over the wider coverage area of the medium resolution (22–30m) DMC imagery.

Establishing the crop development stages and tracking the evolution of the NDVI profiles for the current season in near real time enabled us to create and disseminate forecasts of poppy crop development throughout Afghanistan. In addition, profiles extracted at sample locations after VHR image collection were used to assess the growth stage of crops being interpreted; particularly in cases where images were collected outside of optimum timing windows because of cloud. This enabled analysts to select the appropriate interpretation key for discrimination of the main crops to increase interpretation accuracy, leading to improved area estimates for opium poppy cultivation.

3.5.2 *Land-use changes and rotations*

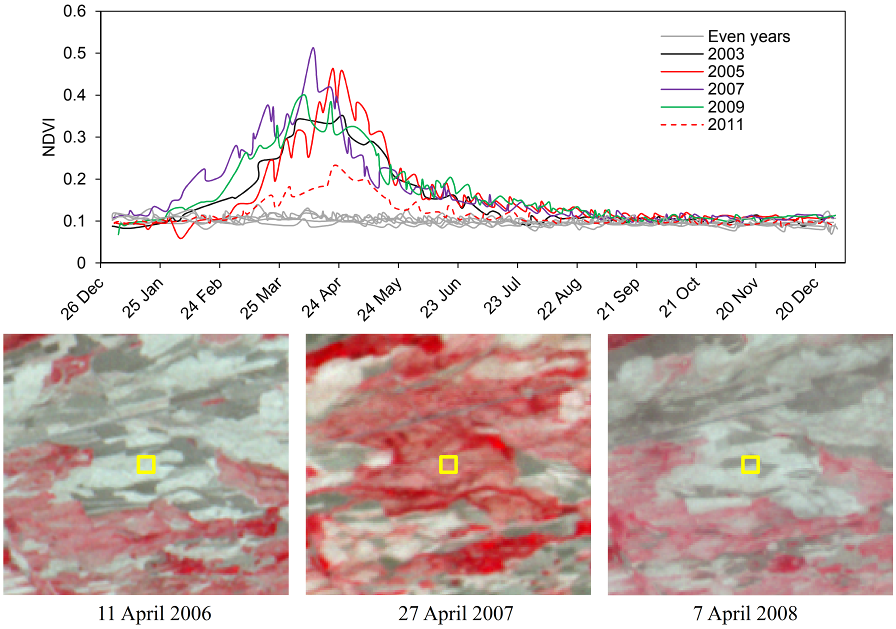
The significant yearly variations in the area of agricultural production, mapped by classification of DMC imagery, were identified as potential sources of error in the cultivation estimates of opium poppy. These were investigated using profile data to establish if differences were the result of agricultural expansion or part of a system of land rotation. Figure 3.8 shows two profiles extracted from areas of change in the yearly classification of agricultural land together with near-infrared false-colour multitemporal DMC images, where red indicates the presence of green vegetation. The profile in figure 3.8(a), extracted from the area of Daman, Kandarhar, shows vegetation activity in alternate years. At this location the imagery clearly shows blocks of agricultural land moving from bare ground into production and back again between 2006–2008. These areas, away from the main irrigated valleys, were part of a managed rotation of agricultural land. Changes in management practices were detectable for areas greater than a MODIS pixel (~2×2 pixels) where groups of fields were under similar management. Changes at a finer resolution were not detectable in complex areas as the reflected energy received at the sensor for each MODIS pixel is known to contain a significant amount of signal from the surrounding area (Huang et al., 2002). This increases the NDVI values of non-vegetated areas above the baseline if adjacent pixels contain vegetation.

The profile in figure 3.8(b) is typical of a newly exploited area with no historical vegetation activity prior to 2007, followed by steadily increasing production. The DMC imagery shows the evolution of the area from desert in 2006 to an established agricultural area with identifiable field structures in 2010. These areas are created to extend the overall cultivated area or to move production of illicit crops away from zones under pressure from counter-narcotic activities. New areas of cultivation could be interpreted at a higher resolution (single MODIS pixels) than areas of rotation because of the contrast between new vegetation and the previously bare desert. Profiles were used to verify reports that poppy cultivation had been displaced from the main cultivated area in Helmand Province to the north of the Boghra Irrigation Canal.

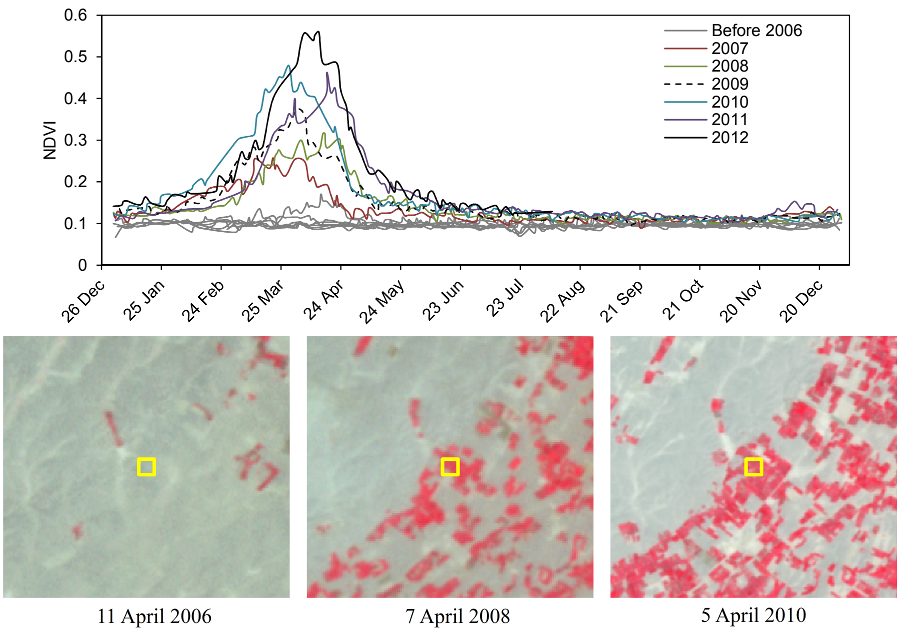
Temporal changes in the distribution of agricultural land are significant for assessing the development of newly exploited areas and the year-on-year changes due to environmental factors affecting land management.

3.5.3 *Verifying field reports of disease*

Figure 3.9(a) shows a profile for the Kajaki District of northern Helmand for the 2008–2010 growing seasons. The 2010 profile shows an early die-back compared to 2009 data consistent with field reports that fungal disease had resulted in rapid senescence after flowering (D), lowering the yield potential by shortening the harvest period. The 2008 profile shows a delayed green-up in the crops (F) and a reduced peak response caused by the cold spring weather. Fields have reduced biomass due to the restricted growing season and poor crop establishment leading to bare patches within fields.

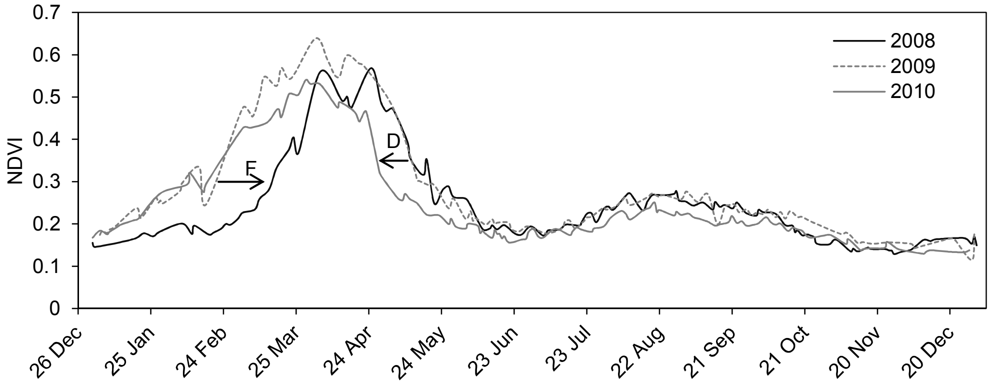


(a)

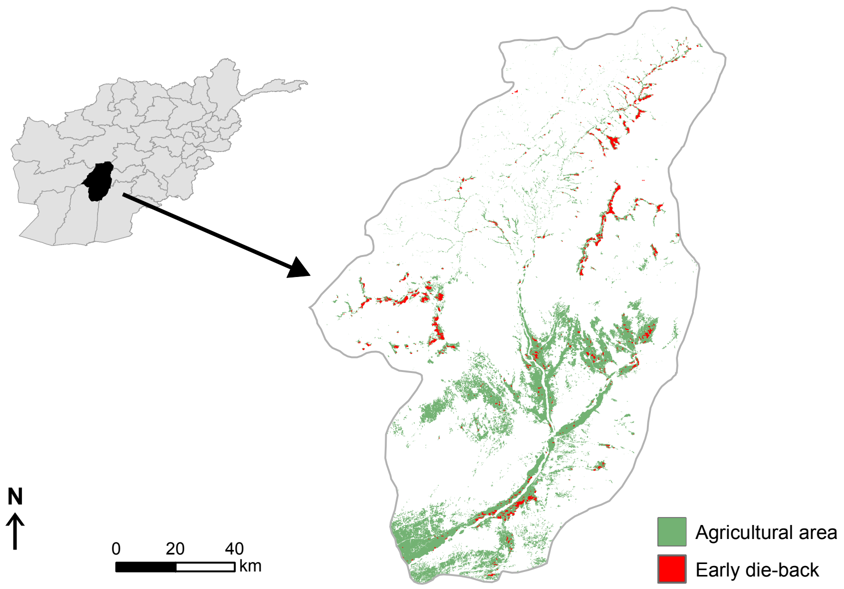


(b)

Figure 3.8. MODIS NDVI profiles and multitemporal DMC image subsets (near-infrared false colour composite) for areas of crop rotation (a) in Kandahar province and newly exploited agriculture (b) in Helmand Province. Extraction locations shown by yellow square representing a nominal MODIS pixel (250m × 250m).



(a)



(b)

Figure 3.9. MODIS NDVI profiles (a) and map of early die-back associated with fungal disease (b) for the north of Helmand Province. Profiles show late green-up in 2008 (F) and early crop senescence in 2010 (D) compared to a typical year (2009).

Diagnostic features of the 2010 profile in figure 3.9(a) were mapped by identifying the early die-back associated with the disease. The date difference between the end of the 2010 profile and the average yearly profile in the MODIS time-series database for each pixel was calculated; with the end of the first peak defined as the minimum peak height between the first two cycles or the return to baseline for single cycles. Potential die-back pixels were then classified by thresholding the date difference. The map product in figure 3.9(b) shows the distribution of potential disease areas in northern Helmand Province. Map products derived from the profile database can be used to estimate the spatial extent of environmental phenomena, identifiable in individual profiles, to target the limited ground resources for measuring their effect on opium production.

3.5.4 *Local changes in land management*

Figure 3.10 shows three distinct management zones within a small area of Baghlan Province. Profile (a) shows an area with two crop cycles with a generally higher second cycle. Profile (b) has two cycles of approximately equal height and a shape characteristic of a crop mix containing vines or other permanent crops. Profile (c) characterises a zone with less reliable agriculture, with a single cycle and a large variation in the height of the peak between years with no cultivation in 2008, a drought year. Cross referencing the coarse resolution profile data with VHR imagery showed changes in cultivation practices were detectable between adjacent groups of MODIS pixels. This level of spatial sensitivity in the profile data allowed it to be used in conjunction with other, accurately geo-referenced datasets within the GIS for investigating localised variation in cultivation practices and land management. This enabled analysts to assess the multi-temporal variation observed in single dated observations from VHR interpretations and ground data, going back to the start of the MODIS archive in 2000.

3.5.5 *Reliability of cropping*

The relative inter-annual productivity is an important metric for assessing the quality of agricultural land. Identifying the areas of high double crop reliability allows policy makers to determine where higher production agricultural areas are located, hence where farmers have the best agricultural potential for alternatives to opium poppy cultivation.

Figure 3.11 shows a typical double cropping profile from the main irrigated area of Helmand Province. The profile shows two distinct peaks, the first around the end of March and the second at the end of August, for each year of profile data. Typically such double cropped areas have reliable water supply and operational irrigation systems. At some locations the second crop cycle only occurs in years with sufficient rainfall or snow melt for irrigation.

Map products produced from the geo-database of MODIS NDVI imagery show the historical spatial distribution and reliability of double cropping areas across the whole of Afghanistan. The number of yearly crop cycles was calculated for each MODIS pixel by first splitting each years' profile in two at Julian day 161, which

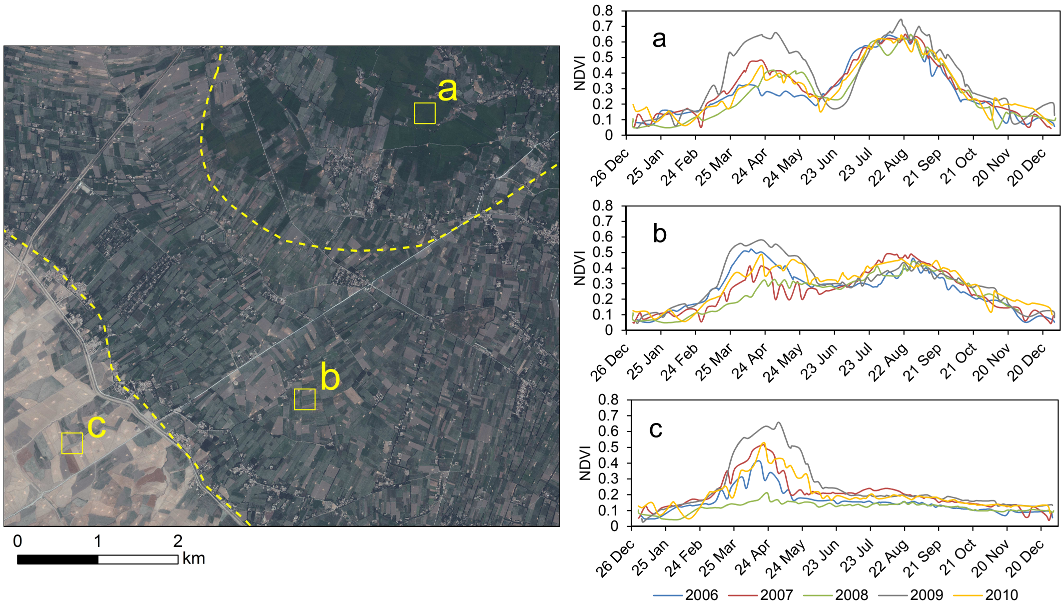


Figure 3.10. MODIS NDVI profiles for three distinct agricultural zones in Baghlan Province. Zones (separated by dotted yellow lines) and profile extraction locations (nominal 250 m yellow squares) shown on VHR imagery (GeoEye 13 September 2009).

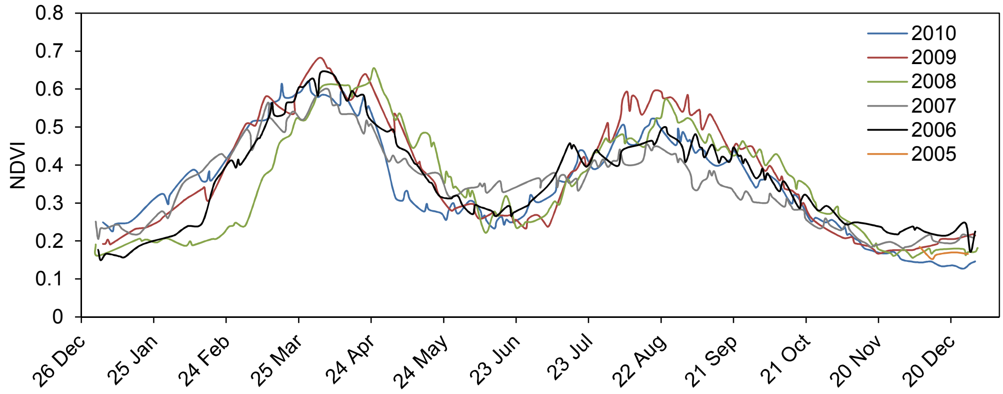


Figure 3.11. MODIS NDVI profiles for a location in Nad Ali, Helmand Province with reliable double cropping.

represents the point of maximum separation between the first and second cycles. The date of maximum NDVI for both halves of the profile was then calculated and thresholded to remove low values. Single, double or no crop cycles were classified for each year of profile data according to the occurrence of peaks in each half of the split. Misclassifications caused by peaks occurring around the split date and at the start of the following years' cycle were filtered by setting a minimum distance between peak dates of 90 days.

Figure 3.12 shows the reliability of double cropping between 2000 and 2006 for the Eastern Afghanistan province of Nangarhar within the area of agricultural production. The colours show the occurrence (or reliability) of two crop cycles in seven

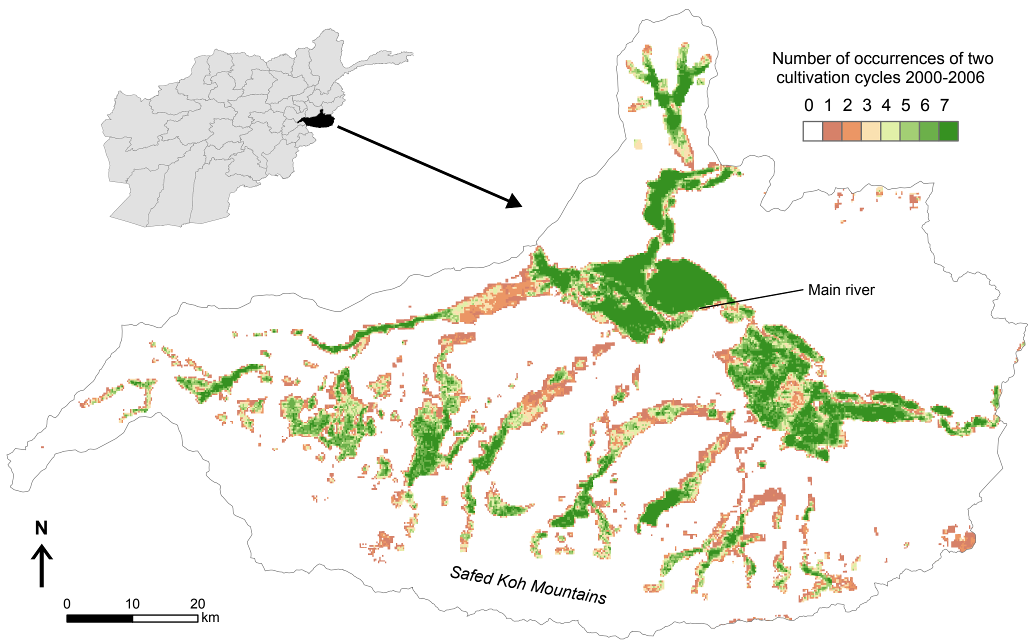


Figure 3.12. Reliability of double cropping in Nangarhar Province.

years of data. Brown areas have double cropping for 1 year in 7 through to green, where double crop cycles occur in all seven years. In Nangarhar there are broadly two types of agricultural land: the flat irrigated area around the central Kabul River and the snow and rain fed valleys extending northeast from the Safed Koh mountain range that runs along the southern border. The irrigated central valley around the river is highly reliable for double cropping (shown in green). The higher valleys extending from the Safed Koh are also in green indicating good water supply from reliable snow melt each year. Moving northeast towards the central valley, the reliability of double cropping reduces (shown by the colour change from green, progressing to brown). Visual interpretation of the winter snow pack showed a link between snow extent and variability in downstream crop reliability. Time-series MODIS (near-infrared false-colour images) and NDVI profiles were used to assess changes in snow accumulation between years for identifying potential water availability issues early in the growing season. The link between the extent and condition of the snow pack, and net primary production for irrigated agriculture is an area of ongoing research.

3.5.6 *Near-real time monitoring*

As well as identifying historical trends in cropping, profiles were used in near-real time for monitoring the vegetation development in the current season. Climatic conditions in Afghanistan are highly variable across the country and from year-to-year. Irrigated areas can suffer shortages of water due to a lack of snowmelt.

Drought affected areas are mainly identified anecdotally from field reports and are poorly mapped, with no early warning of water shortages that may impact on the production of both illicit and licit crops. Profiles and their derived mapping products were used to assess the reliability of agricultural production as an indicator of drought by plotting the current year's vegetation development in relation to historical profiles using a method adapted from Sannier et al. (1998). Figure 3.13 shows the drought status in Nangarhar Province for week 15 in 2009. The drought status in the map is calculated by comparing the NDVI in week 15 to the profile history at each pixel location. The profile at location (a) shows the 2009 profile tracking higher than the historical mean and the maximum observed NDVI at this location (green on the map). Conversely, profile b shows a lower than average NDVI with little or no vegetation activity (red on the map). This near-real time information on the current growing season was provided to policy makers in bulletins focused on the early warning of drought and the spatial extent of the affected areas across Afghanistan.

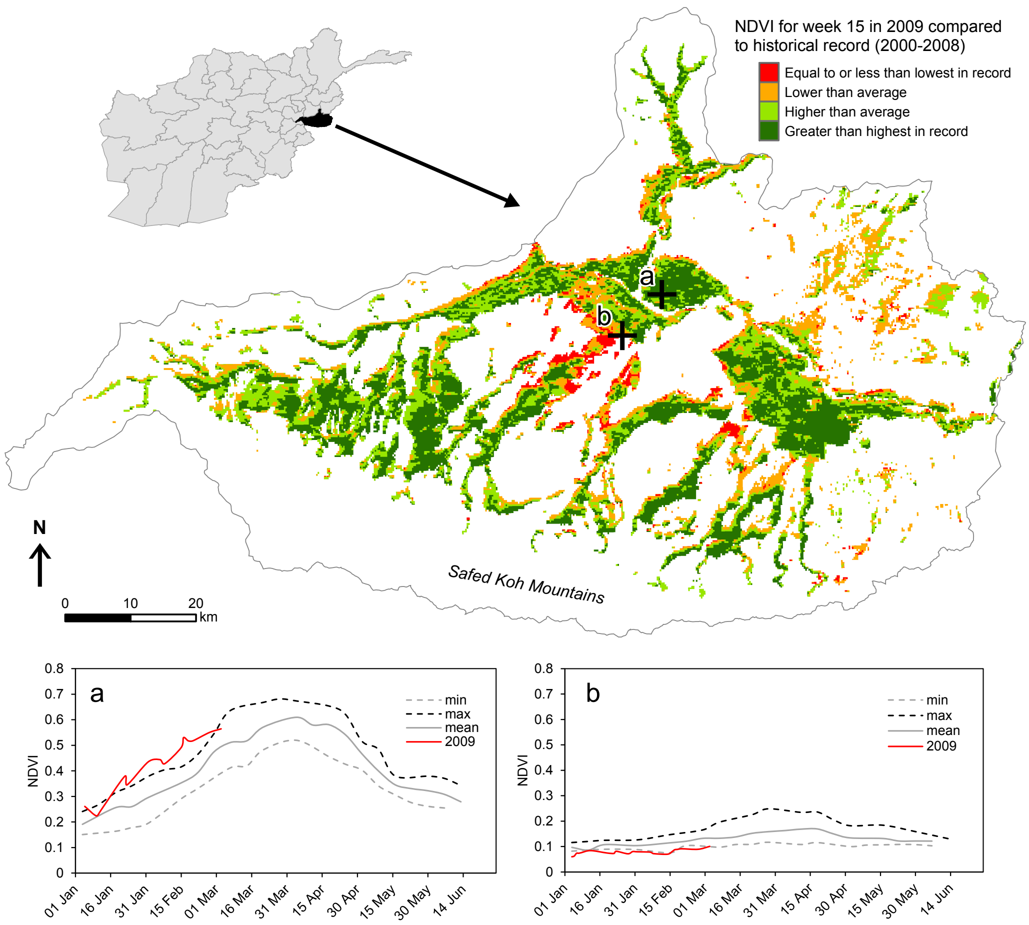


Figure 3.13. Drought status map for week 15 (2009) in Nangarhar Province and profiles showing the 2009 vegetation development in relation to the historical minimum, maximum and mean NDVI for the period 2000–2008 at locations a and b.

Areas of dry-land agriculture show significant yearly variations in productivity due to fluctuating water availability from unreliable rainfall. Figure 3.14(a) shows a typical dry-land vegetation profile from the Sholgara District of Balkh Province. There is a single vegetation cycle in 2007 with a peak NDVI of 0.5, while in 2008 there is no vegetation activity. Figure 3.14(b) shows the spatial distribution of active agricultural land in 2007 and 2008 associated with the fall in vegetation activity for the province. The rain-fed southern half has 46% more active land in 2007 compared to 2008. Yearly variations can account for significant differences in cultivation estimates; as the area under cultivation is used to extrapolate sample estimates of opium cultivation to provincial and national levels. Profiles were used to monitor these areas to capture trends in the development of vegetation for the season. Early information on dry-land drought conditions was used to reduce VHR image collections over non-productive areas, increasing resources available for other areas.

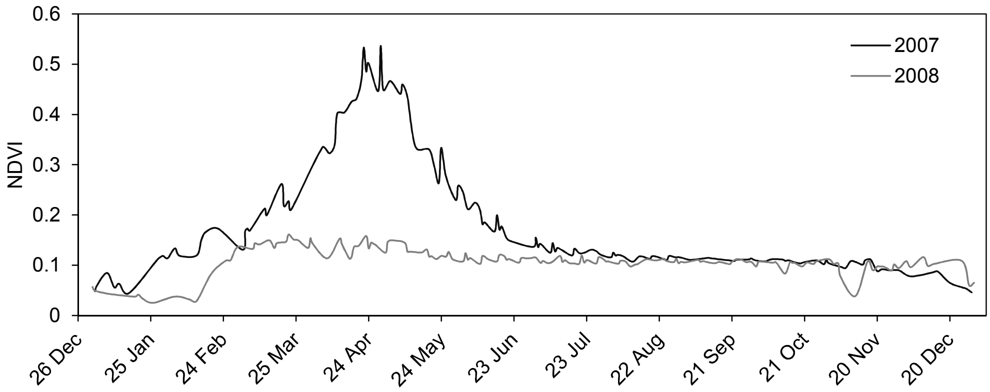
3.6 Conclusions

MODIS NDVI profiles were part of an operational system supporting cultivation surveys between 2005–2009 for the main opium producing provinces in Afghanistan. Despite the coarse spatial resolution of MODIS relative to the field sizes in Afghanistan, profiles are sensitive to phenological changes as the growth cycles of the main first cycle crops are in phase. The peak of the first growth cycle was found to be coincident with the flowering period for poppy crops and was used to assess the variation in timing induced by latitude and topography across Afghanistan. Profiles improved the accuracy of cultivation estimates by optimising the collection of VHR imagery for maximum interpretability of opium poppy from surrounding crops at sample locations. They also informed the selection of interpretation keys for crop growth stage within VHR images acquired outside of their planned collection windows because of cloud, improving interpretation.

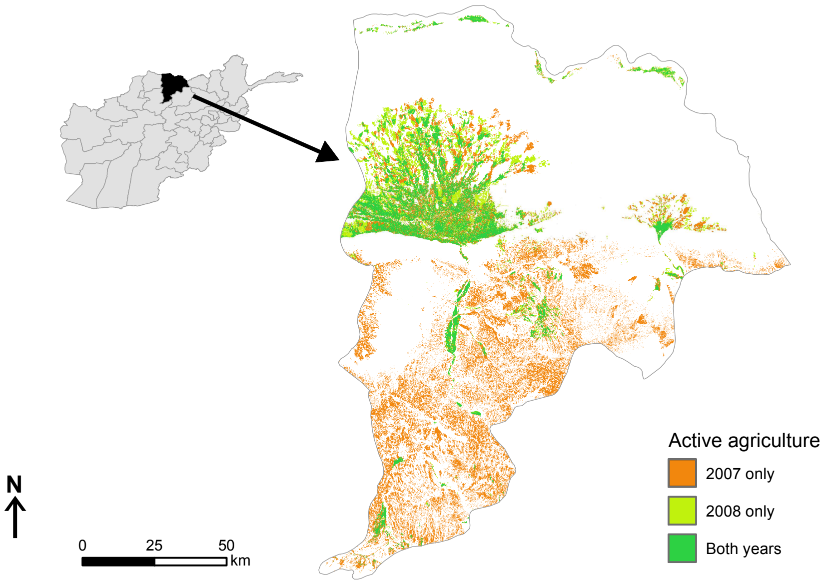
The variation in height and number of peaks in the NDVI profile reflects the change in the productivity at any location between years. Historical data provided information on the reliability of cropping cycles and were used to investigate anecdotal claims of environmental impacts on the development of crops. Reports of crop damage caused by frost and disease were investigated and, once verified, used to estimate the spatial extent of the phenomenon.

Profiles are sensitive to localised variation caused by changes in land management and environmental factors such as water availability. Management zones were identified between adjacent groups of fields by their distinct profile shapes. Profiles were used to investigate the rotation of agricultural land and the development of newly exploited agricultural areas.

Visual interpretation of profiles found diagnostic features that correspond to certain crop mixes, especially those containing tree crops and vines. Further investigation is needed into the potential for automatic extraction of sub-pixel crop types using the shape characteristics of the profiles. Characterising the sub-pixel crop mix would improve the monitoring of phenology for specific crops and has potential for investigating yield variation over wide areas.



(a)



(b)

Figure 3.14. Typical MODIS NDVI vegetation profile from dry-land area in Sholgara District, Balkh Province (a), and area of agricultural land under production for Balkh Province in 2007 and 2008 (b).

Mapping generated from the complete coverage MODIS NDVI database provided policy makers with detailed information on the quality and distribution of agricultural land. Specialised map products were produced for characterising the reliability of double cropping as an indicator of agricultural production levels on a country-wide basis. They were used for the targeting of counter-narcotics activities, such as crop eradication, and for evaluating the suitability of areas for providing farmers with alternatives to opium poppy cultivation.

MODIS imagery was processed in near-real time – images normally available for download from the NASA LAADS within 2 days of collection – allowing the geodatabase of NDVI images to be kept up-to-date during the growing season. This enabled monitoring of vegetation green-up following snowmelt early in the crop growth cycle. The evolution of the current year's profile in relation to historical profile data provided: early warning of changes in the timing of opium crops compared with previous years; potential drought in irrigated areas; and the presence of vegetation in highly variable dry-land areas. Further investigation into the variation in production using a Vegetation Productivity Indicator (VPI), used by Sannier et al. (1998), is now possible given the length of the historical MODIS record.

Time-series NDVI profiles are a powerful tool for detailed vegetation monitoring. MODIS provides low cost, near real-time data over large geographical areas at the frequency required for capturing changes in crop development and land-use. This work demonstrates that MODIS 250 m NDVI profiles are sensitive to changes in crop phenology and management at the scale of the agricultural systems in Afghanistan. They are not limited to regional studies of natural systems or large-scale agriculture – where the field sizes are greater than the sensor resolution – and can be used operationally in near-real time for monitoring localised variations in agricultural systems over large areas. This work also suggests different sub-pixel crop mixes could exhibit distinct NDVI profiles, enabling the approach to be used in other agricultural systems. There is great potential for applying these techniques in other geographical regions as MODIS data is provided free at the point of delivery, is global in coverage and has well-developed software tools. Profiles provide a low cost method for monitoring the variation in annual and inter-annual vegetation development for investigating changes in agricultural practices and land use, especially in fragile agricultural systems.

Acknowledgements

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Chapter 4
Image segmentation for improved consistency in image-interpretation of opium poppy

This chapter presents an investigation into the effects of sample bias on final estimates of poppy cultivation (objective 2), and image segmentation for improved consistency in field delineations (objective 3).

Abstract

The image-interpretation of opium poppy crops from very high resolution satellite imagery forms part of the annual Afghanistan opium surveys conducted by the United Nations Office on Drugs and Crime and the US Government. We tested the effect of generalisation of field delineations on the final estimates of poppy cultivation using survey data from Helmand province in 2009 and an area frame sampling approach. The sample data was reinterpreted from pan-sharpened IKONOS scenes using two increasing levels of generalisation consistent with observed practice. Samples were also generated from manual labelling of image segmentation and from a digital object classification. Generalisation was found to bias the cultivation estimate between 6.6% and 13.9%, which is greater than the sample error for the highest level. Object classification of image-segmented samples increased the cultivation estimate by 30.2% because of systematic labelling error. Manual labelling of image-segmented samples gave a similar estimate to the original interpretation. The research demonstrates that small changes in poppy interpretation can result in systematic differences in final estimates that are not included within confidence intervals. Segmented parcels were similar to manually digitised fields and could provide increased consistency in field delineation at a reduced cost. The results are significant for Afghanistan's opium monitoring programmes and other surveys where sample data are collected by remote sensing.

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4.1 Introduction

Annual Statistics on opium cultivation are produced by the United Nations Office on Drugs and Crime/Afghanistan's Ministry of Counter Narcotics (UNODC) and the US Government to monitor the annual production of illicit opium and evaluate the success of counter narcotics (CN) programmes. They conduct independent surveys based on the extrapolation of area measurements collected at sample locations. The total agricultural area is split into primary sampling units (PSU), from which a statistically representative selection is taken. The cropped area of poppy within each PSU is calculated and the total area of poppy is estimated by multiplying the mean proportion of crop from the sample by the area of agriculture. The surveys differ in their sample proportion, size of PSU and use of stratification.

In both surveys, the area of opium poppy at sample locations is measured by directly digitising crop parcel boundaries from very high resolution (VHR) satellite imagery. Crops are identified by trained interpreters using the standard image-interpretation elements of size, shape, shadow, colour, texture, pattern and association. To maintain consistency, an interpretation key is developed from prior knowledge of the appearance of opium crops in VHR imagery. Keys contain examples of the different crop types and any variation in their appearance with growth stage or management practices.

For accurate area estimates the digitised sample should be a true representation of reality at the sample site. Sources of bias in image interpretation are incorrectly labelled parcels (labelling error) (Gallego, 2006) and imprecision of class definitions relating to what is seen on the imagery e.g. where to place a boundary on a continuum (Foody, 2002). Mapping the true location of parcel boundaries requires a resolution high enough to visualise distinct boundaries between features in the imagery (Goodchild and Hunter, 1997). Other potential sources of bias are the scale of digitisation and the inclusion of features within crop polygons due to image resolution or the minimum mapping unit (Carfagna and Gallego, 2005).

The effect of differences in interpretation is the subject of debate between the UNODC and US survey teams as it is difficult to measure and not accounted for in the confidence interval of the final estimate. This article presents the results of research into interpretation bias caused by systematic differences in image-interpretation of poppy. The research questions were: is generalisation in field delineation a significant source of bias in the survey estimate; and can image processing methods improve the consistency of interpretation. This work was part of a wider project for improving cultivation estimates in Afghanistan that took place between 2003–2009, described in Taylor et al. (2010).

4.2 Data and methods

4.2.1 *Stratified area frame sampling*

A stratified area frame sampling methodology was used as part of the wider investigation into the differences between the UNODC and US surveys. The approach, referred to as GeoTools in some literature, is designed to improve the accuracy of a ratio sample estimate by stratification of the sample frame using satellite imagery (Koeln and Kollasch, 2000). The area of poppy within each stratum s is calculated from n number of samples by

$$m_s = \frac{\sum_{i=1}^{n} m_i}{\sum_{i=1}^{n} a_i} A_s \tag{4.1}$$

where m_i is the area of the poppy within stratum s in sample i, a_i is the total area of sample i in stratum s and A_s is the total area of the stratum in the study area. The total area estimate for poppy (M) is the combined estimates for all strata,

$$M = \sum_{s=1}^{x} m_s \tag{4.2}$$

The purpose of stratification is to minimise the within-stratum variance compared to the variance between strata by grouping areas that are homogenous, with low variation in the occurrence of poppy (Cochran, 1977).

The confidence interval of the estimate is calculated by bootstrapping, which uses Monte Carlo simulation to approximate the distribution of M from N repetitions of equation (4.1) using a random draw of the sample,

$$M^* = M(X_1^*, \ldots, X_n^*) \tag{4.3}$$

where $X_1^*, \ldots, X_n^*$ is an independant random selection of the original samples with replacement. This results in N calculations of M^*. The upper and lower confidence intervals are found by ordering the values of M^* and taking the value corresponding to the percentile required. For example, M_{500}^* and M_{9500}^* for the 90% confidence level for $N = 10,000$.

The samples were selected by first defining a 10 km × 10 km grid coincident with the UNODC's image collection areas, known as blocks, which was sub-divided into 1 km × 1 km PSUs. Random 1 km squares were selected within each block until a 2% sample was obtained. A map of agricultural production was used to mask out PSUs with less than 20% of their area in agriculture.

The research was carried out using a subset of the 2009 Helmand Province area frame sampling dataset, comprising 61 samples interpreted from 14 IKONOS pan-sharpened VHR images (figure 4.1). The spectral strata were created from a 32 m resolution multi-spectral image (red, green, near-infrared wavebands) from the Disaster Monitoring Constellation (DMC).

4.2.2 *Image data and processing*

Image acquisition for DMC and IKONOS imagery was timed to coincide with poppy flowering, the optimum growth stage for image-interpretation, using an information system based on time series NDVI from the Moderate Resolution Spectroradiometer, described in Simms et al. (2014).

Figure 4.1. Sample distribution and extent of stratified agricultural area for the central part of Helmand Province, Afghanistan 2009.

The DMC level L1R image, acquired on 25 March 2009 was orthorectified using the bespoke sensor model in Keystone Workstation® software with a controlled image base (CIB) and a 30 m digital elevation model (DEM), to achieve sub-pixel geometric accuracy. The Iterative Self-Organising Data Analysis Technique (ISODATA) was used to cluster the image pixels into 90 spectral signatures and the image classified using a maximum likelihood discriminant function. The resulting classified pixels were grouped into agriculture and non-agriculture information classes by visual image-interpretation. The non-agricultural classes were then removed and the agricultural mask was manually edited in areas of spectral confusion between natural vegetation and agriculture. The original image was then subset to the area within the agricultural mask and the classification procedure repeated with 30 classes to produce the spectral strata.

The IKONOS geo-bundle images were pan-sharpened using a modified IHS approach to 1 m resolution (Siddiqui, 2003). The greater spectral range of the IKONOS panchromatic band compared to the combined multispectral bands was found to increase brightness in the blue band of the pan-sharpened image. This effect was reduced by modifying the panchromatic band to remove part of the near-infrared signal,

$$\rho_p^* = \left(1 - \frac{\rho_4}{\rho_1 + \rho_2 + \rho_3 + \rho_4}\right)\rho_p \tag{4.4}$$

where ρ_p is the radiance of the panchromatic band and ρ_n is the radiance of multi-spectral band n, before applying the modified IHS algorithm. Each image was then ortho-resampled using the vendor supplied Rational Polynomial Camera model refined using control points from the CIB and 30 m DEM (Grodecki and Dial, 2001).

4.2.3 *Image interpretation and segmentation*

The frame sampling analysis was conducted for a series of sample sets, each comprising 61 samples, created using 5 different interpretation methods. They were: the original 2009 image interpretations; two levels of increasing generalisation in field boundaries; automatic segmentation with manual classification; and automatic segmentation with object classification.

The original 1 km samples were image-interpreted from 14 pan-sharpened IKONOS images (table 4.1). Each image was assessed for crop growth stage and then contrast stretched to optimise the display of the 16 bit data and reduce any distortion during visual display (8 bit) in the software. Sample sites were assigned to trained interpreters who digitised poppy and cereal field parcels using the standard image interpretation method. Poppy crops are distinguished from crops of wheat and alfalfa by visual differences in colour and texture in true-colour and false-colour (near-infrared) VHR composite images. Bare areas of fields and within-field features visible in the imagery were not included within the cropped poppy area.

Table 4.1. IKONOS image acquisition dates (2009) and poppy growth stage.

Date	No. of images	Growth stage
25 March	7	Stem elongation
3 April	1	Flowering
8 April	1	Flowering
11 April	2	Flowering
25 April	3	Capsule

Interpretation consistency was cross-checked by assigning 5% of the samples to multiple interpreters. Systematic differences in interpretation were identified in the overlapping samples and corrected. Consistency in colour representation of crops in false-colour and true-colour composites (stretching) was maintained through supervision and use of auxiliary information on timing from the crop information system. Every sample was cross checked by an experienced interpreter before analysis.

Copies of the original 2009 image-interpreted samples were edited to create two sample sets with increasing levels of generalisation. Samples were first vectorised and polygon boundaries smoothed to improve the cartographic quality. Each sample was then manually re-interpreted using the original VHR imagery. For level 1, paths and single-vehicle width gaps between cropped areas with little or no field margin vegetation were manually removed. Single lines of trees and narrow irrigation channels between polygons were removed by digitising a new boundary along the centre line of the linear feature. Un-cropped areas less than approximately 50 m^2 within parcels were merged with the surrounding polygon. Poor quality crops not previously delineated were added to the mapped area. Convoluted field boundaries found in polygons where crop density reduced gradually to bare soil were simplified manually.

Level 2 was a further generalisation of the level 1 interpretation. Edits were made to remove paths and single vehicle-width tracks with vegetated margins. Single lines of trees and tracks associated with irrigation channels were removed by digitising a centre line along features. Un-cropped areas greater than 50 m^2 within parcels that were interpreted as cultivated were merged with the surrounding polygon. Finally, partial fields with areas of poor or damaged crops were extended to the whole field parcel where there was evidence of an intention to cultivate.

Figure 4.2 shows examples of level 1 and 2 edits made to sample 39 and sample 36 overlaid on IKONOS near-infrared false colour imagery. At level 1, field polygons for sample 39 include linear features between parcels such as trees, tracks and drainage ditches. Within-field areas of bare soil or poor crop are removed at level 2 and field parcels are extended to boundary edges. In sample 36, patchy areas are extended at level 1 to incorporate more of the poor quality crop and the drainage features that separate parcels. At level 2 the whole block of variable crop becomes a single polygon representing the farmers intention to cultivate.

A third sample set was created to simulate a methodology where images are automatically segmented and the resulting parcels classified manually by image-interpretation. Automated segmentation was performed for each IKONOS image used for interpretation using eCognition® software. The software uses a bottom-up region merging technique to group homogeneous pixels into objects of similar size and scale based on a scaling factor (Benz et al., 2004). A scaling factor of 80 was determined by systematic testing and found to be suitable for the segmentation of opium and cereal parcels from the 1 m resolution IKONOS images. A single level segmentation was then run on each image using the same scaling factor and homogeneity criteria of 0.1 for shape factor and 0.5 for compactness (Baatz et al., 2004). Segmented polygons were then intersected with the original 2009 samples and their classes assigned by selecting the majority class from the original interpretation for each polygon.

The final sample set was created by conducting an object based nearest neighbour classification within the software for the segmented polygons in each IKONOS scene. The classifier was trained using fields of poppy and cereal selected in areas away from the sample squares. Classified samples were then extracted at coincident locations to the 2009 sample. A small number of anomalies were found in the samples caused by unclassified areas in the object classification. These areas were masked out of all 5 sample sets.

Each of the 61 samples in each set were rasterised at a grid resolution of 1 m to match the format of the original 2009 samples. The different levels of generalisation and automatic methods were then compared by running 5 separate stratified area frame sampling analyses to estimate the total area of poppy using the same 30 spectral strata.

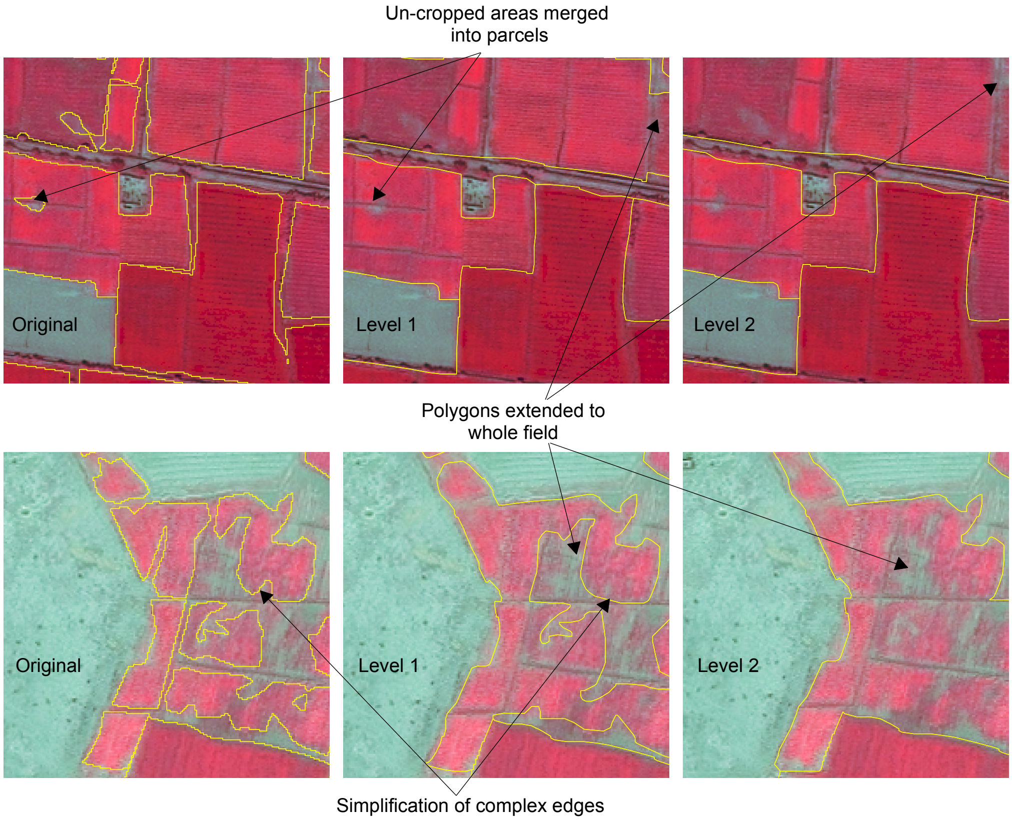


Figure 4.2. Example of level 1 and 2 edits to sample 39 (top) and 36 (bottom). Boundary delineations overlaid on IKONOS (near-infrared false-colour) imagery

4.3 Results

Table 4.2 shows the poppy area estimates for the 5 interpretation methods. The estimates range from 39 534 to 51 463 ha and have a similar lower (~8%) and upper (~10%) confidence interval (90%). Generalisation of interpretation increases the poppy estimate by 6.6% for level 1 and by 13.9% for level 2. The increase in the poppy estimate for the level 2 interpretations is greater than the upper confidence interval using the original sample (10.4%). Automatic segmentation of the field parcels with manual class assignment increased the estimate by 2.4%, the smallest difference of all methods from the original sample estimate. The object classification increases the estimate by 30.2% from the original estimate.

Figure 4.3 shows the individual poppy proportions for each interpretation method plotted against the original samples. For the level 1 and level 2 (figure 4.3(a) and figure 4.3(b)) the generalisation in the interpretation creates a positive bias in sample proportion that increases with the proportion of poppy in the sample. In figure 4.3(c), the proportion of poppy in automatically segmented samples is similar to the original interpretation proportions. The object based classification of the samples (figure 4.3(d)) shows a positive bias towards poppy and a reduction in the coefficient of determination (R^2) to 0.84 from >0.99 for the other methods.

Table 4.2. Poppy area estimates and 90% confidence intervals for different levels of generalisation and automatic segmentation using 61 samples in the Helmand trial area, with percentage difference from the original (* outside confidence interval).

Method	Area (ha)	Upper (%)	Lower (%)	Diff. (%)
Original	39 534	8.5	10.4	
Level1	42 145	8.1	10.5	6.6
Level2	45 031	8.3	10.6	*13.9
Segmentation manual	40 488	8.4	11.0	2.4
Segmentation trained	51 463	7.4	9.0	*30.2

Figure 4.4 shows a visual comparison of part of sample 67 for the different automatic methods with manual interpretation. The results of the segmentation overlaid on the IKONOS image (figure 4.4(a)) show accurate delineation of field parcels, within-field bare patches and tree-lined boundaries between parcels. These objects match the general shape of manually interpreted field parcels (figure 4.4(b)) and the manual classification of the objects (figure 4.4(c)) shows good agreement with the original interpretation. However, differences can be seen in the complexity of the parcel edges and in cases where single objects from the segmentation are split in the image-interpretation. Heterogeneous areas in the imagery, where multiple linear features intersect with small parcels, are incorrectly labelled as the segmented objects cover multiple classes.

Table 4.3. Confusion matrix of 61 object classified and image-interpreted samples (as proportions), rasterised to 1 m.

		Object classification				
		Poppy	Other	Cereal	Total	Producer
Original interpretation	Poppy	0.13	0.03	0.01	0.17	0.76
	Other	0.05	0.49	0.02	0.56	0.88
	Cereal	0.04	0.04	0.19	0.27	0.7
	Total	0.22	0.55	0.23	1	
	User	0.59	0.89	0.83		
				Overall agreement	0.81	

In the object-classified sample (figure 4.4(c)) there are errors in the classification of field parcels and boundary features. A confusion matrix of the classified and original image-interpreted samples is shown in table 4.3. Assuming the visual interpretation as the reference data, the user accuracy of the object classification of poppy is 59% with a higher commission error compared to the omission error. This shows a bias towards the classification of poppy that increases the overall estimate.

4.4 Discussion

We have tested the two sources of sample interpretation error that could bias the final area estimate. They are the delineation of the parcel boundaries and the misclassification of crop types within parcels (labelling error). As expected, the results show a positive bias in the sample estimate from generalising the sample interpre-

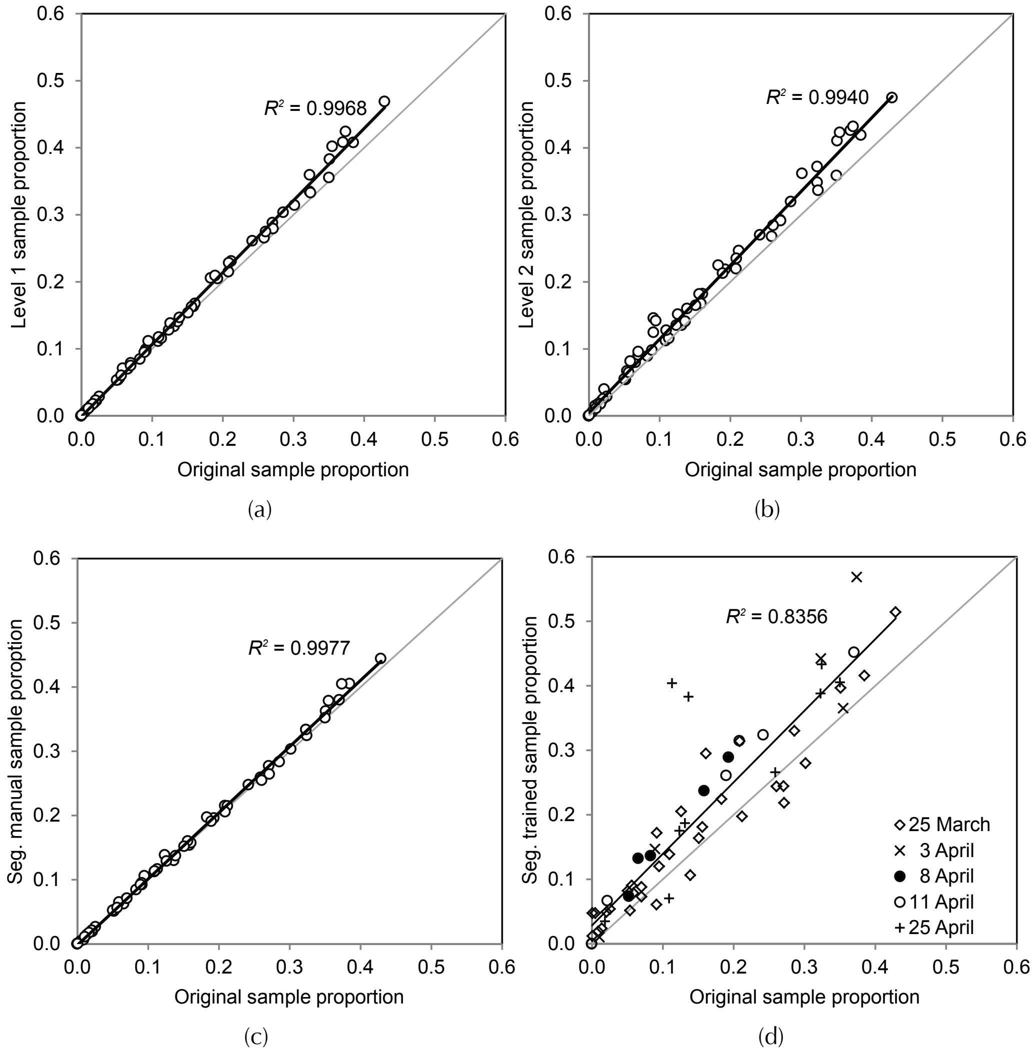


Figure 4.3. Linear regression of (a) level 1 and (b) level 2 generalisations, (c) manually assigned and (d) digitally classified segmentation (seg.) with original poppy proportions for all 61 samples.

tations. What is significant is the magnitude of the bias: for the higher level of generalisation it is greater than the sample error estimated from the bootstrap (13.9% vs 10.6%).

There are several factors in manual image-interpretation that can lead to the levels of generalisation investigated. The first is a tendency for interpreters to digitise fewer vertices in parcel boundaries to speed up the interpretation of individual samples. This is particularly the case when delineating large blocks of contiguous fields that contain the same crop type. Within-field features such as irrigation ditches and linear features between fields are more likely to be included within parcel boundaries to improve the interpreters' productivity.

The second factor is the definition of a field parcel in the interpretation key. If the interpreter is tasked with identifying the farmers' intention to cultivate a certain crop, the field delineation will include within-field bare patches and poor crops

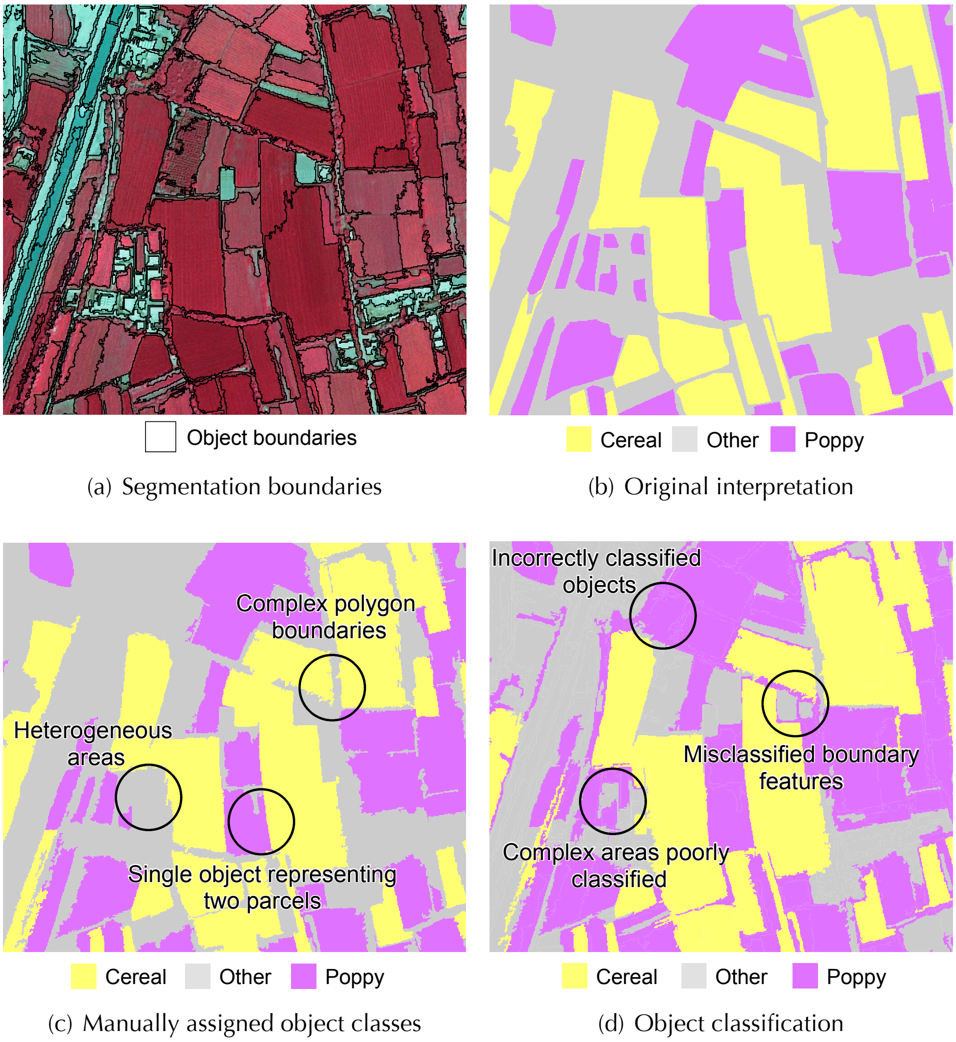


Figure 4.4. Example of manual interpretation and classification of automatically segmented field parcels from pan-sharpened IKONOS imagery.

by design. In crops with a uniform canopy this approach will produce similar results to interpretations delineating the actual visible crop area. However, in areas of marginal agriculture or in years with poor crop establishment this will greatly affect the proportions of the target crop within samples and the resulting area estimates.

The third factor is the scale of digitised crop areas and is related to the resolution of imagery. Interpreters using aerial digital photography can accurately delineate areas of thin crops and within-field features that are not visible in lower resolution satellite imagery. In marginal areas or in crops with poor establishment this will create systematic differences in interpretation related to the appearance of thin parcels of poppy and the size of within-field features in the imagery. If the area of these small features makes a significant contribution to the cropped area of poppy the sample interpretations will become unreliable.

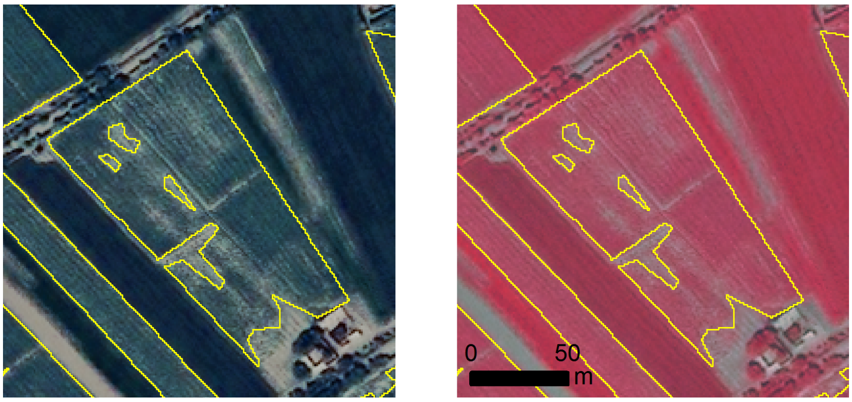
Finally appearance of crops in imagery changes according to their growth stage. Errors could be introduced by interpretation of underdeveloped crop canopies from images collected early in the growing season. In the example from 2008 shown in figure 4.5, background soil is visible through the canopy within poppy fields on 28 March (figure 4.5(a)) that is subsequently covered by the time of the second image on 27 April (figure 4.5(b)). The early interpretation (yellow lines) excludes parts of the field at the earlier date that are included in the later interpretation. In 2008, poor crop establishment due to cold spring weather caused visible differences in the crop canopy at the stem elongation growth stage. In a normal year the canopy would be expected to be fully developed at this growth stage and within canopy bare patches digitised out during interpretation as being un-cropped. Figure 4.6 shows another area from Helmand Province in 2008 where the early damage to the crop has resulted in bare patches (figure 4.6(a)) that are still visible in the later image (figure 4.6(b)). Inclusion of these areas within the samples will lead to an over estimation of the cropped area of poppy.

The effect of these factors will vary between groups of interpreters according to their specific training, the interpretation key and the imagery source; and also between interpreters within the same group. Methods to maintain accuracy and consistency across samples are standard practice for surveys that rely on image-interpretation and include comparisons of sample interpretations between individuals; review of samples by more experienced interpreters; and multiple-pairs-of-eyes, where teams of interpreters consider marginal cases together.

Controls to limit the level of generalisation require more resources as the area of the sample increases. Smaller samples allow for shorter, more focused analysis and are easier to cross reference to maintain consistency between individual interpreters. Conversely, large samples (e.g. an entire VHR image) that include hundreds of fields are more likely to contain field boundary generalisations and omissions of within-field features, especially in areas dominated by the crop of interest. They are also more difficult to quality check and cross reference. The effect of interpreter generalisation is compounded in larger samples with poor crop establishment; where accurate digitisation of complex field parcels is a significant increase in the work load of the interpreter.

Segmentation and object classification were investigated for potential improvements to the consistency and speed of sample interpretation. Image segmentation

(a) 28 March 2008



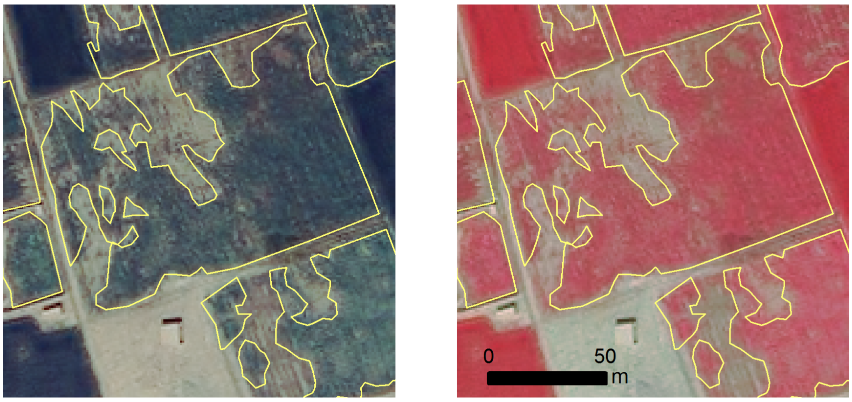
(b) 27 April 2008

Figure 4.5. True-colour and false-colour subsets of pan-sharpened IKONOS images for two dates showing area of poppy cultivation in Helmand Province with poor crop establishment. Poppy fields delineated in yellow.

produced similar results to the manual delineation of field parcels by interpreters. In the case of eCognition, the manual steps of the segmentation are limited to the selection of suitable homogeneity criteria, which were found to be constant across image scenes in this study. Once this is done whole images can be segmented in minutes and the work of the interpreter is focused on the labelling of field parcels with some minor editing of boundary errors in complex areas. This speeds up interpretation and prevents generalisation that might arise from interpretation of contiguous blocks of the same crop and complex field boundaries. Further research into optimising the segmentation of poppy crops and the effect of growth stage and image resolution on the accuracy of segmented field parcels is necessary to support its use in operational surveys.

Totally automatic methods limit the effort of image-interpretation to a subset of representative fields for training and evaluating the classifier. The object classification was found to be unsuitable for automatic interpretation as the systematic error in the classified samples biases the final cultivation figure (30.4% increase in poppy area for this study). These results highlight the importance of systematic

(a) 27 March 2008



(b) 27 April 2008

Figure 4.6. True-colour and false-colour subsets of pan-sharpened IKONOS images for two dates showing area of poppy crops damaged by cold weather that did not recover, Helmand Province. Poppy fields delineated in yellow.

bias correction for obtaining accurate area estimates from image classifications, as discussed for pixel based classifiers by Gallego (2004).

Provided the quality of interpretation can be controlled, survey interpretations can be consistent within survey teams across growing seasons for comparisons of inter-annual estimates. However, differences in interpretation keys – relating to the imagery and the definition of the interpretation classes – are likely to be a source of disagreement between estimates from independent surveys. Within the context of the annual opium surveys in Afghanistan, consistency between the UNODC and US estimates was greatly improved from 2005 through sharing of interpretations at overlapping sample sites (Taylor et al., 2010). Differences in crop classification were reconciled and systematic differences in the interpretation approach were identified, leading to harmonisation of cultivation estimates without affecting the independence of the surveys.

4.5 Conclusions

Generalisation in sample interpretation results in systematic differences in final estimates of poppy that are not accounted for in the confidence interval of the final estimate. Estimates were 6.6% and 13.9% higher for generalised samples, which is greater than the confidence interval for the higher level of generalisation. These results show that disagreement in annual estimates between Afghanistan's monitoring programmes can result from systematic differences in class definitions and interpretation keys for poppy.

Image segmentation produced similar parcel boundaries to manual digitising. The manual labelling of image segments shows potential for increasing the speed of interpretation while maintaining a consistent delineation of field parcels. Further research is required to optimise the segmentation of images collected at different crop growth stages and to investigate the effect of VHR image resolution before operational use. Object based classification of VHR imagery was found to be unsuitable for samples production because of low labelling accuracy.

This work highlights the requirement for controls to maintain the consistency of interpretation. Suitable class definitions and keys relating to the features visible in VHR imagery are essential to reduce differences between individuals and teams of interpreters. We recommended splitting larger samples to allow for shorter, more focused analysis and improved quality control.

The results are significant for surveys that use visual interpretation of remotely sensed data. Imagery must be of the appropriate resolution and class definitions applicable to observable differences in the imagery to capture a true representation of reality and avoid bias.

Acknowledgements

The authors would like to thank the UK Government for sponsoring the research.

Chapter 5
Improved estimates of opium cultivation in Afghanistan using imagery based stratification

This chapter presents an investigation into the effects of the agricultural mask and image-based stratification on final estimates of poppy cultivation (objectives 2 & 3). Supporting data on the variation in agricultural area between years is included in appendix B. Maps of poppy cultivation distributions for 2007 to 2009 are included in appendix C. The Python code written to conduct the stratified frame sampling analysis is available on request [1].

Abstract

The United Nations Office on Drugs and Crime and the US Government make extensive use of remote sensing to quantify and monitor trends in Afghanistan's illicit opium production. Cultivation figures from their independent annual surveys can vary because of systematic differences in survey methodologies relating to spectral stratification and the addition of a pixel buffer to the agricultural area. We investigated the effect of stratification and buffering on area estimates of opium poppy using SPOT5 imagery covering the main opium cultivation area of Helmand province and sample data of poppy fields interpreted from very high resolution satellite imagery. The effect of resolution was investigated by resampling the original 10 m pixels to 20, 30 and 60 m, representing a range of suitable image resolutions. The number of strata (1, 4, 8, 13, 23, 40) and sample fraction (0.2 to 2%) used in the estimate were also investigated. Stratification reduced the confidence interval by improving the precision of estimates. Cultivation estimates of poppy using 40 spectral strata and a sample fraction of 1.1% had a similar precision to direct expansion estimates using a 2% sample fraction. Stratified estimates were more robust to changes in sample size and distribution. The mapping of the agricultural area had a significant effect on poppy cultivation estimates in Afghanistan, where the area of total agricultural production can vary significantly between years. The findings of this research explain differences in cultivation figures of the opium monitoring programmes in Afghanistan and recommendations can be applied to improve resource monitoring in other geographic areas.

This chapter is prepared for submission to *International Journal of Remote Sensing* as: SIMMS, D.M., WAINE, T.W., TAYLOR, J.C.. Improved estimates of opium cultivation in Afghanistan using imagery based stratification.

[1] https://bitbucket.org/dspix/safs.git

5.1 Introduction

Afghanistan is the source of 90% of the World's opium and almost all of the heroin in the UK. The two main organisations monitoring the cultivation of illicit opium are the United Nations Office on Drugs and Crime/Afghanistan's Ministry of Counter Narcotics (UNODC), and the US Government. For both programmes the annual cultivated area is obtained by measuring poppy at random sample sites from image-interpretation of very high resolution (VHR) satellite imagery. The two surveys are independent and use different sources of VHR imagery, sample fractions, sample sizes and methodology for expanding the sample observations to provincial and national estimates.

Remote sensing can be used to define sample units and sampling frames, optimise the allocation and size of sampling units and improve sample estimates by regression or calibration (Carfagna and Gallego, 2005). In Afghanistan, the UNODC and US annual opium surveys use remote sensing as there is limited capacity to collect accurate field data because of poor security after decades of war. Imagery is used to map the area of agricultural production and for visual interpretation of crops at sample locations.

Agricultural production in Afghanistan takes place in blocks of irrigated land close to the main rivers, ribbons running along upland river valleys, and extensive rain fed areas. These areas have strong contrast with large mountainous areas and desert. In both surveys the agricultural area, known as the agricultural mask, is determined by digital classification and visual interpretation of medium resolution imagery, such as SPOT (10–20 m), DMC (32 m) and AWiFs (56 m), to exclude areas of non-agriculture from the sample frame. Images must have a wide enough swath and short enough revisit time to allow for suitably timed cloud-free collections covering the poppy producing provinces. Differences in the agricultural mask between surveys directly affect cultivation estimates as the agricultural area is a multiplier in the statistical expansion of the sample proportion of poppy to the provincial scale.

A major difference between the US and UNODC methodologies is the use of medium resolution imagery to stratify the agricultural area within the mask based on spectral response. A stratified estimate is designed to minimise the within-stratum variance compared to the variance between strata to improve the accuracy of a ratio estimate (Cochran, 1977). In Afghanistan, Luders et al. (2004) tested a stratified approach using spectral classes from Landsat 7 imagery and found that stratification lowered the variance of the overall estimate. They also suggest buffering the mask to ensure sparse fields and the edges of agricultural areas are not excluded from the analysis because of the resolution of the imagery. Their work forms the basis of the current US survey methodology.

A degree of homogeneity in poppy cultivation within the strata, referred to in statistical terms as weak or second order spatial stationarity, is required for any increase in precision (Koeln and Kollasch, 2000). At the scale of agricultural production in Afghanistan, where individual fields are typically <0.5 ha, the spectral signal from medium resolution imagery (>20 m) is a mixture of crop types, bare soil and infrastructure such as roads and compounds. Variation in crop phenology across image scenes will also affect the spectral response. The effect of stratification on area estimates of poppy was identified as a potential source of discrepancy between UNODC and US cultivation figures.

In 2003 the UK Government commissioned research into explaining conflicting information from the cultivation figures produced by the UNODC and US Government in an attempt to harmonise the results of Afghanistan's opium surveys (Taylor et al., 2010). As part of the trials conducted alongside the main surveys, we produced stratified and unstratified estimates of poppy using image data from the Disaster Monitoring Constellation (DMC). 30 spectral strata were chosen as a compromise between maximising the number of separable classes in the classification and avoiding the creation of under-sampled strata. Table 5.1 shows the differences in the most probable poppy estimates from stratified and unstratified agricultural masks for selected provinces (2006 to 2009). In Helmand and Uruzgan the stratification reduced the estimate in every year (by 12,204 ha in Helmand 2007). In the other provinces stratification increased or decreased the estimate in different years. Stratified estimates have improved confidence intervals for all provinces in all years.

Table 5.1. Opium poppy cultivation estimates and 90% confidence intervals (%) 2006 to 2009 for selected provinces. Province boundaries do not match those from other published sources and figures should not be directly compared.

		Unstratified			Stratified (30 strata)		
Province	Year	Poppy, ha	-CI90	+CI90	Poppy, ha	-CI90	+CI90
Helmand	2006	73 930	12	12	61 945	8	8
	2007	100 894	9	9	88 690	6	6
	2008	97 348	7	7	81 256	5	6
	2009	78 361	8	8	76 383	7	6
Kandahar	2006	7 777	33	46	9 244	26	30
	2007	12 140	31	38	13 634	28	32
	2008	16 851	25	26	16 658	17	14
	2009	20 372	23	24	19 198	18	17
Uruzgan	2006	-	-	-	-	-	-
	2007	10 659	32	31	8 487	23	21
	2008	10 803	26	26	7 094	16	16
	2008	8 304	21	22	6 841	17	19
Nangarhar	2006	4 067	62	76	5 182	63	72
	2007	20 349	25	25	19 222	22	20
	2008	<500	-	-	<500	-	-
	2009	<500	-	-	<500	-	-
Badakhshan	2006	3 149	62	70	3 337	67	69
	2007	2 303	36	39	2 322	37	37
	2008	659	42	46	561	41	44
	2009	-	-	-	-	-	-

These cultivation figures show how unexplained differences in estimates can undermine confidence in opium surveys and impede policy formulation on counter narcotics. This paper presents work prompted by technical discussions with the UNODC and US Government on the use of spectral stratification. It investigates the effect of buffering the agricultural area, resolution of the imagery used for stratification, the number of strata, and sample fraction on cultivation estimates of opium poppy.

5.2 Stratification, resolution and buffering

The effect of stratification, image resolution and buffering on estimates was investigated using SPOT5 10 m resolution multispectral imagery, targeted for a study area in the main production area of Helmand province in 2007 (figure 5.1). Image acquisition was timed to coincide with the cultivation of crops using an information system based on time series NDVI from the Moderate Resolution Spectroradiometer (Simms et al., 2014). The SPOT imagery was orthorectified using a controlled image base (CIB) and a 30 m digital elevation model (DEM) for control, to achieve sub-pixel geometric accuracy. The image was then resampled using bilinear interpolation to 20, 30 and 60 m pixels, representing a selection of suitable medium resolution imagery sources.

The stratified area frame sampling methodology can be split into five steps: (1) agricultural mask creation; (2) stratification; (3) sample selection; (4) image interpretation of samples; and (5) final estimate and confidence interval calculation.

An agricultural mask was created for each resolution by classification using maximum likelihood and 90 spectral signatures extracted by clustering pixel values using the Iterative Self-Organising Data Analysis Technique (ISODATA). The resulting classified pixels were grouped into agriculture and non-agriculture information classes by visual image-interpretation. The agricultural area at each resolution was buffered by one pixel and stratified by clipping the resampled multispectral imagery to the mask before clustering into 30 spectral vegetation classes using ISODATA and maximum likelihood classification, resulting in three buffered strata layers. The buffer pixels of each strata were then removed to create an additional three unbuffered strata layers.

The sample was designed within the existing UNODC sample selection to allow direct comparison and make use of their ground survey data. A sample size of 1 km × 1 km and sample fraction of 2% of the agricultural area was chosen based on experience of monitoring crop inventories in Europe assisted by remote sensing (Taylor et al., 1997a), resulting in 48 samples (figure 5.1).

A VHR image (IKONOS or Quickbird–2) was targeted to coincide with the flowering period of opium poppy for each block using the same crop information system used to target the medium resolution acquisitions. The flowering period lasts for approximately two weeks and is the optimum time in the crop cycle for discrimination of opium poppy from other crops. Each acquired VHR image was pan-sharpened to 1 m resolution and ortho-resampled using the vendor supplied Rational Polynomial Camera model refined using control points from the CIB and a 30 m DEM (Grodecki and Dial, 2001).

The cultivated area of opium poppy and wheat was delineated by visual image-interpretation at each 1 × 1 km sample location. Interpretation keys were developed for opium poppy and the main first cycle crops using ground observations and pho-

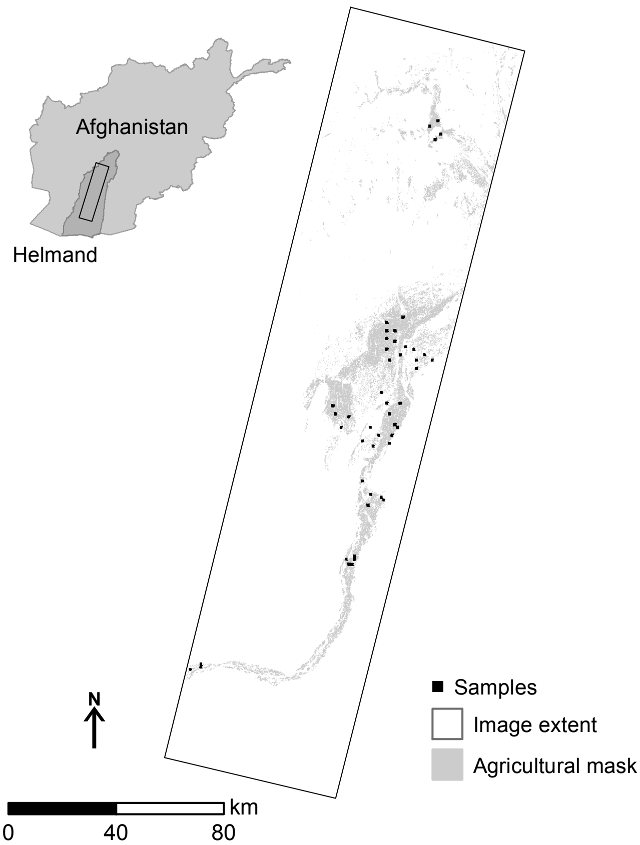


Figure 5.1. The extent of the SPOT-5 image acquired on 2 April 2007 and 48 sample locations in Helmand Province, Afghanistan.

tography from the UNODC's segment surveys. Consistency in interpretation was maintained by cross-checking a 5% overlap between individual interpreters.

The area of the poppy within each stratum is calculated from n number of samples by

$$m_s = \frac{\sum_{i=1}^{n} m_i}{\sum_{i=1}^{n} a_i} A_s \tag{5.1}$$

where m_i is the area of poppy within stratum s in sample i, a_i is the total area of sample i in stratum s and A_s is the total area of the stratum in the study area. The total area estimate for poppy is the combined estimates for x number of strata,

$$M = \sum_{s=1}^{x} m_s \tag{5.2}$$

The stratified estimate can be directly compared with an unstratified direct expansion by combining the individual strata into a single stratum representing the total agricultural area. Equation (5.2) becomes

$$M = \frac{\sum_{i=1}^{n} m_i}{\sum_{i=1}^{n} a_i} A \tag{5.3}$$

where A is the total agricultural area.

The confidence interval of the estimate is calculated by bootstrapping to approximate the distribution of M from N repetitions of equation (5.1) using a random draw of the sample,

$$M^* = M(X_1^*, \ldots, X_n^*) \tag{5.4}$$

where $X_1^*, \ldots, X_n^*$ is an independent random selection of the original samples with replacement. This results in N calculations of M^*. The upper and lower confidence intervals are found by ordering the values of M^* and taking the value corresponding to the percentile required. For example, M^*_{500} and M^*_{9500} for the 90% confidence level for $N = 10,000$.

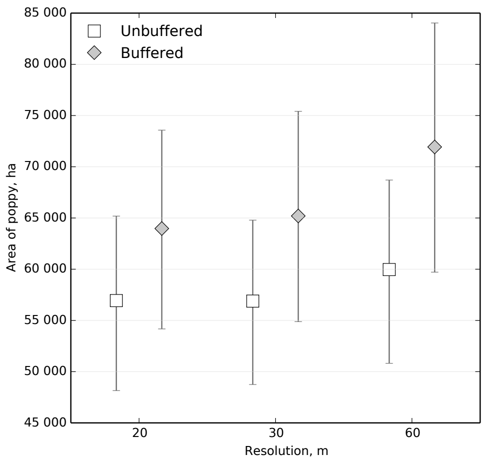
The total area of poppy was calculated for each mask resolution using buffered and unbuffered strata (equation (5.2)) and a single stratum (equation (5.3)) using the same 48 image interpreted samples.

Buffering the agricultural mask increased the stratified (30 strata) and single stratum estimates of poppy at all three spatial resolutions tested (figure 5.2). Table 5.2 shows the difference in the single stratum and stratified area estimates, the total masked area and the proportion of measured poppy in the sample after buffering. The agricultural area increases by 36, 39 and 48% after buffering for resolutions of 20, 30 and 60 m respectively, with a corresponding decrease in the proportion of poppy within the sample of about 7%. Buffering the agricultural area includes more of the measured area of poppy within the sample for all resolutions (1.4 to 2.2%). Stratification greatly reduced the positive bias caused by buffering (figure 5.2), with the differences in buffered estimates in table 5.2 within about 4% of unbuffered estimates for the three resolutions tested, compared to differences of 12, 15 and 20% for the single stratum estimates.

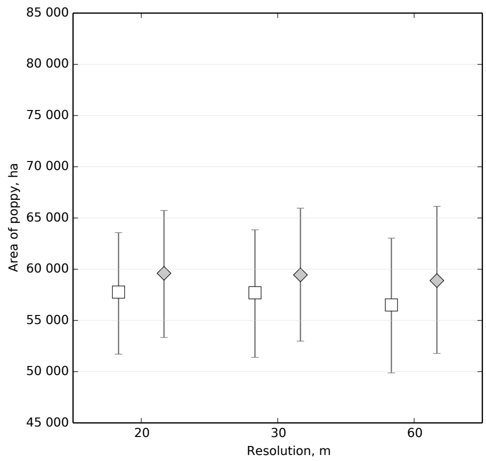
Table 5.2. Effect of buffering at 20, 30 and 60 m resolution on total area of the agricultural mask, proportion of poppy, measured area of poppy within the sample, single stratum and stratified poppy area estimates.

Resolution, m	Difference in total mask area, %	Difference in proportion of poppy, %	Difference in sampled poppy, %	Difference est. single, %	Difference est. stratified, %
20	36.0	-7.1	2.2	12.4	3.2
30	38.7	-6.7	1.4	14.6	3.0
60	47.6	-6.8	1.9	20.0	4.2

In general the agricultural mask was consistent with the extent of poppy cultivation in the samples with no noticeable alignment error between the orthorectified imagery used for stratification and image-interpretation. Figure 5.3 shows the effect



(a) Single stratum



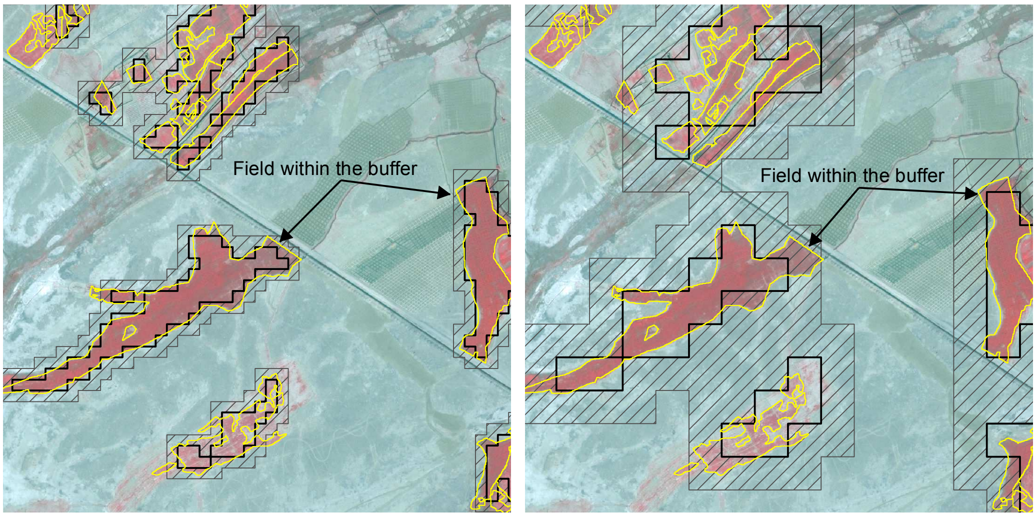
(b) Stratified

Figure 5.2. (a) Single stratum and (b) stratified area estimates for buffered and un-buffered agricultural masks created from 20, 30 and 60 m resolution imagery using a 2% sample. Error bars represent 90% CI range.

of buffering on the measured area of poppy at the sample scale. At a resolution of 20 m, some of the measured field area falls outside of the unbuffered mask because the field edge digitised from VHR imagery is more detailed than the mask boundary. At 60 m (figure 5.3(b)), the mask boundary is even more generalised, with a greater mismatch between the mask boundary and the field edges caused by the increased pixel size of the medium resolution imagery. Buffering increases the measured area of poppy included within the sample for all mask resolutions. The buffered mask at 20 m resolution includes more of the measured area of poppy than at resolution of 30 m and 60 m across all the samples despite the increasing total area of the mask (table 5.2).

The buffering of the masked area lowers the proportion of poppy in samples as the masked area increases: reducing the average proportion of poppy. However, this does not compensate for the large increase in the masked area as the effect is limited to samples at the interface between agriculture and non-agriculture. For example, the sample in figure 5.4(a) is located at the mask boundary in marginal agriculture, where the masked area makes up a greater proportion of the total area of the sample compared to the location in figure 5.4(b), which is within the main irrigated valley. This leads to the positive bias in the area estimate seen in figure 5.2.

The measured area of poppy missing from the mask was caused by small areas of poor quality crops with a weak spectral response and the detail of the agricultural boundary caused by the resolution of the mask. These effects were more evident at 60 m resolution, where the proportion of active vegetation within the pixel decreases in relation to the non-vegetated surface and there is greater mismatch between the detail of the boundary mapped from VHR and medium resolution imagery.



(a) (b)

Figure 5.3. Agricultural field boundaries in yellow, digitised from VHR imagery, overlaid with (thick line) unbuffered and (hatched area) buffered agricultural masks at resolutions of (a) 20 m and (b) 60 m. Background image false colour pan-sharpened IKONOS, acquired 17 April 2007.

The next section investigates the effect of strata number and sample fraction on estimates and the relationship between the spectral classes and poppy cultivation.

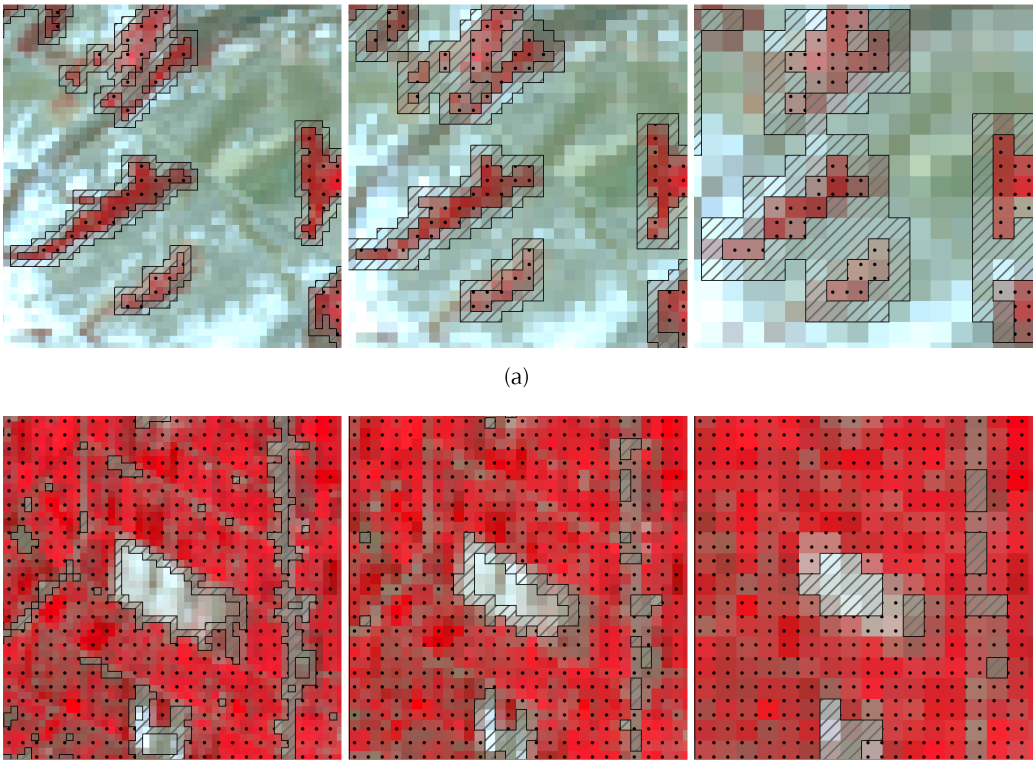
5.3 Number of strata and sample fraction

The effect of the number of spectral classes used in the stratified estimates was investigated using the resampled 20 m multi-spectral SPOT5 image, subset to the agricultural mask. An increasing number of strata were derived hierarchically from unsupervised clustering of the image pixels to allow direct comparison between the resulting poppy estimates. Firstly, a layer with 4 strata was created from the subset image using ISODATA. Each of these strata were then split into two by re-clustering the original image pixels within each stratum to produce an 8 strata layer. At this point the 8 strata were assessed for homogeneity using the relative standard error of the bootstrapped estimate,

$$RSE_s = \frac{\sigma(m_s^*)}{\bar{m}_s^*} \tag{5.5}$$

where $m_s^* = m_s(X_1^*, \ldots, X_n^*)$ for $N = 10,000$ draws of the sample. Any stratum with a RSE_s >0.1 was subdivided into two new strata, which resulted in a 13 strata layer. This splitting process was repeated twice more, resulting in layers with 23 and 40 strata. Splitting was stopped at 40 to avoid under-sampling those strata with small areas.

Estimates for the stratified layers (1–40 strata) using proportions of the original sample data at intervals of 0.2% were then calculated. Sample proportions were simulated using a random draw of the original sample squares for each iteration of the bootstrap $(X_1^*, \ldots, X_k^*)$, where k is the number of samples for the required sample



(a)

(b)

Figure 5.4. Examples of two 1 x 1 km samples in (a) marginal agriculture and (b) in the main irrigated area of Helmand Province comparing the buffered (hatched) and unbuffered (dotted) agricultural mask for image resolutions of 20, 30 and 60 m (left to right) resampled from SPOT5 image, acquired 2 April 2007.

proportion. The sample cultivation estimate was calculated from the mean of the bootstrapped estimates $\bar{M}_p^*$ and the precision of each poppy estimate as 1 - relative standard error,

$$\text{precision}_p = 1 - \frac{\sigma(M_p^*)}{\bar{M}_p^*} \tag{5.6}$$

Figure 5.5 shows the improvement in the precision of the area estimate of poppy as the sample fraction and the number of strata increase. The area estimate using 4 strata and a sample fraction of 1.6% has a similar precision to the original single stratum estimate with a 2% sample fraction. Increasing the number of strata to 8 lowers the required sample fraction to 1.4% for a single stratum estimate of similar precision. For estimates with more than 8 strata the gains in precision are less. A 40 strata estimate is close to half the sample fraction (1.1%) required for a direct expansion estimate of the same precision (2% sample).

The effect of the individual strata on the overall estimate can be seen in figure 5.6. Splitting the single stratum (agricultural mask) into 4, separated three strata with higher proportions of poppy (>0.25) and lower RSE_s (<0.11) from a stratum with a lower proportion of poppy (0.14) and a higher RSE_s (0.23). The higher RSE_s showing

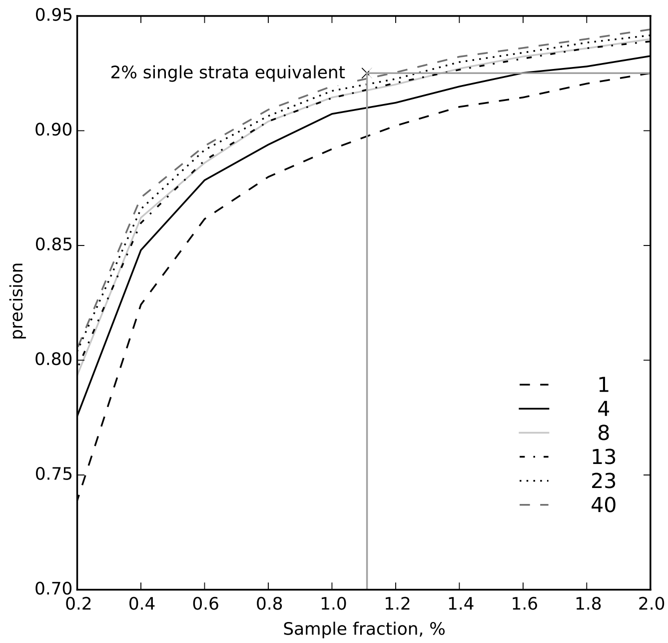


Figure 5.5. Variation in overall precision (1 - relative standard error) of bootstrapped area estimates of poppy with variation in sample fraction and the number of strata (20 m SPOT5). The 40 strata sample fraction with precision equivalent to 2% single strata is marked.

greater variation in the stratum estimate of poppy from the sample. Separating this more mixed stratum decreases the overall *RSE* from 0.080 to 0.067, improving the precision of the estimate.

Further splitting of the strata results in an increase in precision for some of the strata. The strata in the top half of the dendrogram (s01–s31) in figure 5.6 are generally more mixed with a lower proportion of poppy, where splitting does not result in a reduction in RSE_s, except in s21. In the lower half, the strata with a higher proportion of poppy have low RSE_s and, being identified as homogeneous, are not split further (s31–s34). These results show the stratification improving the estimate by separating high production areas with lower variance in poppy cultivation from lower production areas with higher variance, reducing the overall *RSE*. This lowers the overall variance compared to the sample as a whole and reduces the size of the confidence interval in line with the findings by Luders et al. (2004).

5.4 Discussion

Adding a pixel buffer to the agricultural area is a strategy to capture poppy cultivation that might be missed because of the timing or resolution of the imagery used to create the mask, or misalignment with the sample data. Buffering the mask increased the area of sampled poppy included in the analysis. However, this increased the area of the mask disproportionally across the samples relative to the

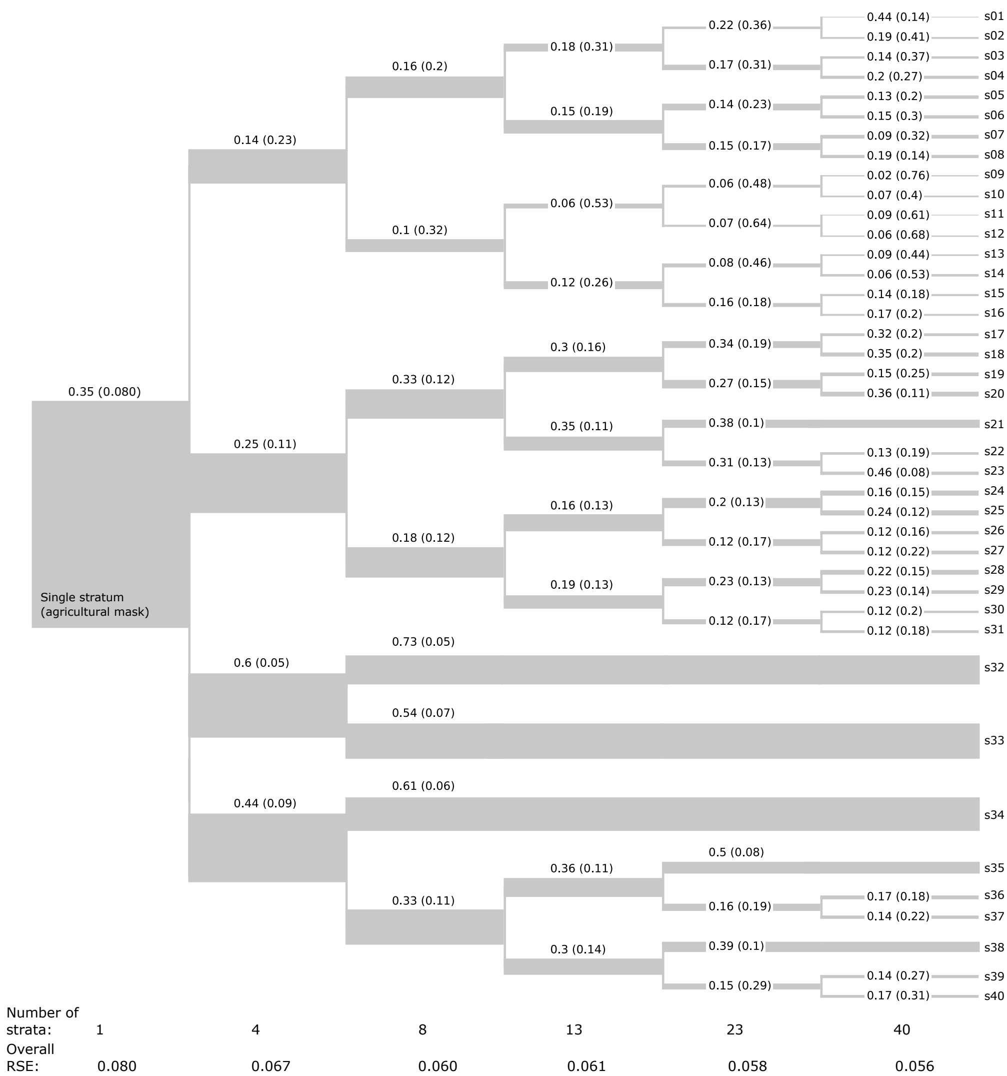


Figure 5.6. Dendrogram showing the proportion of poppy and relative standard error (in brackets) after successive splitting of heterogeneous SPOT5 20 m strata within the agricultural mask using ISODATA. The thickness of the line is proportional to the area of the stratum. Stratum labels prefixed with 's'.

detail in the mapped boundary between agriculture and non-agriculture. The effect on the single stratum area estimate was much greater than the inclusion of more of the measured poppy area. For direct expansion estimates a rigorous approach to image orthorectification to ensure sample data is coincident with the agricultural area is preferable to buffering the mask. Precise timing and appropriate resolution of medium resolution imagery will also ensure that sampled fields fall within the current active agriculture.

The agricultural mask is the multiplier in the stratified (equation (5.1)) and single strata (equation (5.3)) expansion of the sample and has the greatest effect on the overall estimate. The mask serves to improve efficiency by reducing the total area and ensures resources are not wasted sampling areas where poppy cultivation does not take place. There are two main approaches to creating a mask of the agricultural area for annual opium estimates in Afghanistan: the area of active agriculture; and the area of potential agriculture.

The active mask is created each year and only contains those areas that are currently in production. The separation of agricultural areas from the desert, natural vegetation and high mountains is achieved by unsupervised classification and visual interpretation of medium resolution imagery such as Landsat and DMC. While time consuming, this process is straightforward as there is high spectral contrast between the active vegetation and the desert when imagery is correctly timed to coincide with the presence of crops.

In contrast, the potential mask is updated yearly with areas of new agriculture, retaining the existing mapping from previous years. It is much faster to produce once a baseline has been established as only newly exploited areas require imaging and further analysis, opposed to total coverage over the target provinces for each year.

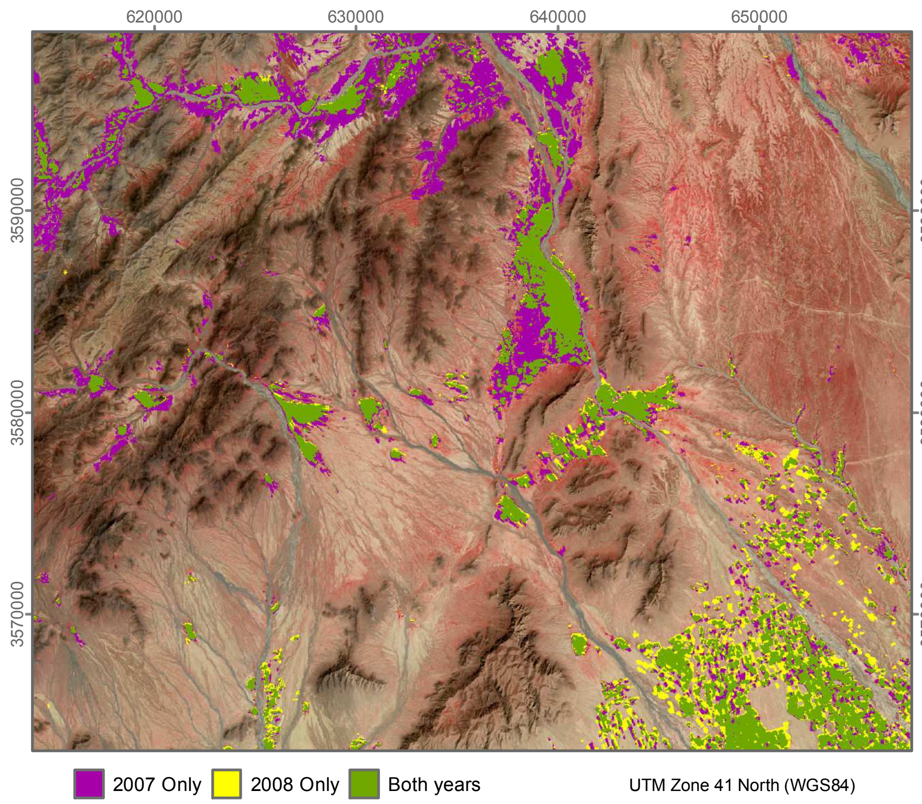


Figure 5.7. Change in active agricultural mask between 2007 and 2008, northern Helmand Province, Afghanistan. Background image SPOT-5 false-colour composite, acquired 2 April 2007.

In Afghanistan there are significant annual changes in the area of active agricultural land under cultivation caused by variation in water availability from snow melt and rainfall (Shahriar Pervez et al., 2014), crop rotations and agricultural expansion. Figure 5.7 shows an area of northern Helmand where the active area is larger in the higher valleys in 2007 (purple) compared with 2008, where there is more active area in the valley (yellow). The green area is active agriculture that was consistant over the two years. The changes in the active agricultural mask for selected provinces from the wider project work from 2006 to 2008 are shown in table 5.3. The study area is located in Helmand Province, which has the lowest annual total change. Kandahar and Balkh have differences of up to 50%, highlighting the importance of understanding the effect of the agricultural mask on opium estimates. The total change can be misleading as some areas are in rotation and there are shifts in cultivation of poppy crops from the main irrigated valley into newly exploited desert areas (irrigated from wells). These changes take place in both high production and marginal areas and contribute to the yearly change in the distribution of agricultural land, as shown in Simms et al. (2014). Amending the mask to include all potential agriculture would include areas out of rotation and large areas of rain fed agriculture, which are unable to support cultivation in years with insufficient rainfall. Using a potential agricultural mask without a significant increase in the amount of sampling would artificially inflate the area estimate of poppy.

Table 5.3. Area of agricultural mask (hectares) between 2006 and 2008 in poppy producing provinces of Afghanistan. Percentage difference with previous year in brackets.

	2006	2007		2008	
Helmand	277 416	280 228	(1)	287 859	(3)
Uruzgan	61 311	58 764	(-4)	62 307	(6)
Nimroz	32 681	35 007	(7)	26 813	(-23)
Kandahar	119 728	186 870	(56)	182 120	(-3)
Nangarhar	85 396	102 565	(20)	101 520	(-1)
Badakhshan	168 842	123 626	(-27)	-	
Farah	94 673	95 840	(1)	104 520	(9)
Balkh	-	310 425	(-)	150 234	(-52)

The decision to use an active or potential mask is influenced by the availability of suitably timed imagery and the resources within the monitoring programme. In general terms, using imagery with larger coverage improves the chances of cloud free collections during the crop growth cycle at the expense of spatial resolution. This work shows that moving to coarser image resolutions will lead to an overestimation of the agricultural area where the boundary is complex.

The stratified estimate is more robust to changes in the agricultural mask from buffering and image resolution compared with a single stratum direct expansion of the sample proportion. The homogeneity of individual strata was highly variable as the majority of pixels have a mixed spectral response because of small field sizes compared to imagery resolution. These results are consistent with findings by McRoberts et al. (2002) that mixed strata will improve estimates where they are limited to small areas, such as boundary cases, if large areas have lower variance, with either high or low proportions of the land cover of interest.

The distribution of poppy can be mapped by plotting the probability of poppy associated with each stratum for each pixel. This is useful for examining trends in cultivation, for example, figure 5.8 shows higher cultivation density in newly ex-

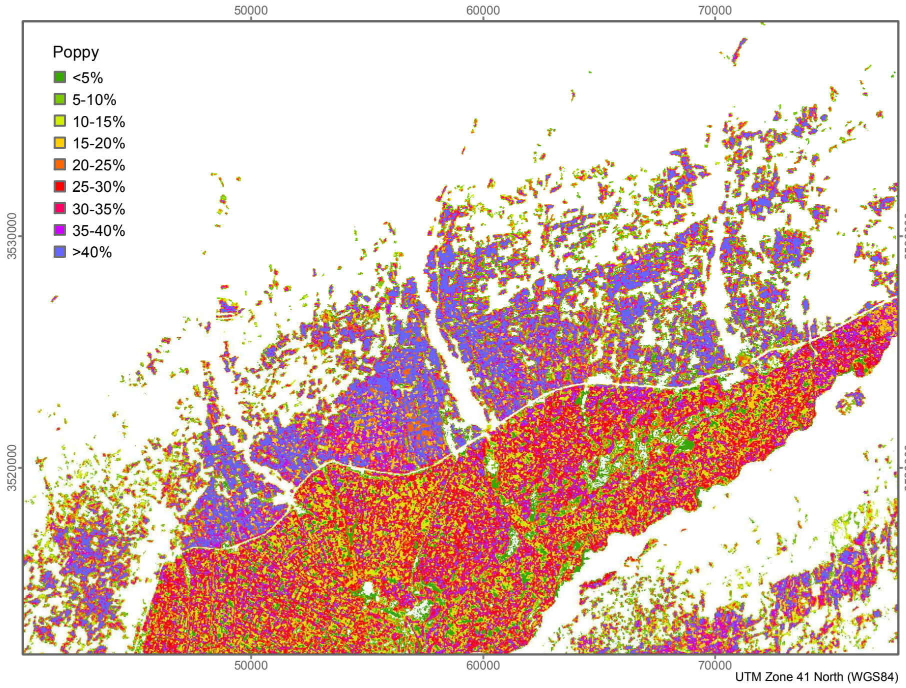


Figure 5.8. Poppy distribution map for part of Helmand Province 2009 showing a higher concentration of poppy cultivation north of the main irrigation canal.

ploited areas to the north of the main irrigated area in Nad Ali, Helmand Province in 2009. However, since the probabilities are from a global estimate, the accuracy of any estimate from a single or group of pixels is unreliable (Tomppo et al., 2008). In general the homogeneity of poppy cultivation in the strata is low and the probabilities should be used with caution when used to map spatial distribution. Areas of mixed spectral response and high variance in poppy cultivation are open to misinterpretation at the local scale. A suggested improvement to the stratification is to include a spatial component to the clustering to reduce the effect of mixed strata between areas with different cultivation practices. Use of higher frequency image collections could also provide information to stratify areas where temporal cropping patterns are associated with poppy cultivation.

Stratification was performed using ISODATA with no prior information of the relationship between the clusters and the probability of poppy cultivation. The clustering results may not be optimal as they are dependant on the pre-selection of the number of clusters and the initial cluster means (Duda and Canty, 2002). The splitting of heterogeneous clusters reduced the variance in some strata but the selection of an appropriate precision for a homogeneous cluster will vary with the underlying variance in the sample data. The total number of strata splits is also limited by the sample fraction as the estimates from under-sampled strata will become unreliable.

Optimising the stratification to maximise the precision of the estimate and a reliable measure of the spatial homogeneity of poppy within the strata requires further work. Algorithms that take spatial information into account, such as the mean-shift

(Comaniciu and Meer, 2002) and probabilistic label relaxation (Canty and Nielsen, 2006), could reduce the within strata variance by separating spectrally mixed strata.

5.5 Conclusions

The definition of the agricultural area can lead to significant differences in area estimates of poppy cultivation in Afghanistan. Buffering the agricultural mask increased the sample estimate for the study area between 3 and 4% for stratified and between 12 to 20% for unstratified estimates. The results highlight the effect of the spatial structure of the agricultural boundary on area when buffering. The source of medium resolution imagery in relation to the scale of the agriculture being sampled is an import consideration to avoid over estimation when using direct expansion.

Spectral stratification reduced the variance in the sample estimate of poppy for the areas studied. Estimates using 40 strata and a sample fraction of 1.1% had a similar precision to unstratified direct expansion estimates using a 2% sample fraction. Hence, stratified estimates can be made using a smaller sample, which lowers the survey costs relating to the purchase of VHR imagery and image interpretation. It also reduces the requirement for surveyors to visit dangerous field locations for verification when image-interpretation is uncertain.

Stratified estimates were more robust to changes in the sample distribution and sample fraction compared to unstratified estimates. The greatest effect was lowering the sample proportion for large areas of low poppy cultivation within the agricultural mask. These findings are significant for Afghanistan's opium monitoring programmes because of the large inter-annual fluctuations in the agricultural area, where the use of potential agriculture masks could lead to differences in survey estimates between the UNODC and US Government.

It is recommended to stratify agricultural masks to minimise discrepancy in estimates from independent survey teams related to differences in their agricultural mask and sample design. Stratification does not add significantly to the cost of survey as medium resolution imagery is already collected for defining the mask.

Stratification also reduced the effect of the decreased resolution on direct expansion estimates when using the 60 m mask. This is significant as the ability to use coarser resolution sensors would increase the availability of suitably timed imagery available to the surveys at low cost.

The spatial stability of poppy cultivation within individual strata was low. Further research into the spatial and temporal relationship between spectral strata and poppy cultivation is suggested to improve the homogeneity of strata, increase the efficiency of sample estimates, and maps of poppy distribution.

These results demonstrate the benefits of imagery based stratification in sample surveys and support its use in other geographic regions for improving agricultural statistics.

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Chapter 6

Towards improving opium yield estimates using remote sensing

This chapter presents the development of a bias correction methodology for the small non-random yield sample collected as part of the UNODC's annual survey (objective 3).

Abstract

Yearly estimates of illicit opium production are key metrics for assessing the effectiveness of counter narcotics policy in Afghanistan. Poor security often prevents access to sample locations and puts pressure on field surveyors, resulting in biased sampling and errors in data recording. Supportive methods using aerial digital photography for improving yield estimates were investigated in the UK in 2004, 2005 and 2010. There were good empirical relationships between NDVI and poppy yield indicators (mature capsule volume and dry capsule yield) for individual fields. The results suggested a good generalised relationship across all sampled fields and years (R^2>0.70) during the 3–4 week period including poppy flowering. Regression estimates using this relationship with the imagery counteracted bias in the sample estimate of yield, reduced sample error and enabled the production of detailed maps showing the poppy yield distribution. The application of this approach using VHR satellite imagery was investigated in the context of the annual opium survey in Afghanistan. Initial results indicated the potential for bias correction of yield estimates using a smaller and targeted collection of ground observations as an alternative to random sampling.

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6.1 Introduction

Annual estimates of illicit opium production in Afghanistan are produced by the United Nations Office on Drugs and Crime/Afghanistan Ministry of Counter Narcotics (UNODC/MCN) from the estimated cultivated area of opium poppy (*Papaver somniferum*) multiplied by the average yield per unit area of dry opium gum calculated from field survey. Even in relatively safe areas, local survey teams can be subjected to coercion or corruption and access to some of the sample locations may be impossible, especially as the key poppy growing provinces in the south are the least secure. These security constraints reduce the quality of the data and compromise the random design of the survey.

In response to questions on the veracity of the yield survey data raised by stakeholders, the UNODC/MCN developed statistical tests to assess the quality of their data (UNODC, 2012). They determined that data from surveyors correctly following the protocol would capture a wide variation in poppy capsule volumes. Field data were considered unreliable if the coefficient of variation of capsule volume was below a threshold or if the capsule measurements contained duplicates. Data failing the tests were removed and in 2012 revised estimates for the period 2006–2009 were published. Only a small number of the total surveyed fields were considered suitable for inclusion in the revised estimates (table 6.1). For 2009, the estimate is made using observations from only 16 fields (<8 ha) out of a total of 123,000 ha of poppy cultivation in Afghanistan and reduces the overall estimate of opium production by 36%.

Table 6.1. Revised opium yield estimates 2006-2009 after UNODC quality testing (UNODC, 2012)

Year	Surveyed fields	Fields passing all tests	Original yield, kg ha^{-1}	Revised yield estimate, kg ha^{-1}	Reduction in production estimate, %
2006	714	153	37.0	32.3	13
2007	531	76	42.5	38.5	6
2008	568	71	48.8	37.8	22
2009	699	16	56.1	32.2	36

Changes since 2012 in the training and supervision of surveyors and the selection of survey sites in safer working areas, have resulted in improved field data quality according to the UNDOC's test criteria. However, these changes reduce the number of surveyed fields – from 685 in 2011 to 114 fields in 2012 – and result in a non-random sample design that produces a statistically un-representative estimate of opium yield in Afghanistan (UNODC, 2012). This estimate will bias the average dry opium yield and hence the yearly estimate of opium production.

6.2 Background

6.2.1 *Opium yield estimate in Afghanistan*

Objective estimates of average yields in national crop surveys, for example in the US, are typically made by cutting and weighing from a random sample of small plots. Early yield forecasts are sometimes made from the same plots by measuring yield indicators such as plant stand density, and number and size of fruiting heads (Vogal and Bange, 1999).

In Afghanistan opium gum is harvested by hand by a process known as lancing. The mature green capsules are scored using a wooden tool with five or six small blades mounted in a row at one end. With a single stroke, multiple parallel incisions are made to the capsule surface, typically in a diagonal orientation. The opium gum 'bleeds' from the incision and is scraped from the capsule surface the following day. This process is repeated 3–7 times on new sections of the capsule surface. The fresh opium gum has variable moisture content and is dried to create a more standardised and concentrated product. Estimation of dry opium yield using direct measurements of opium gum is impractical for field survey because of the protracted multiple lancing and gum collection and the need for drying.

The UNODC/MCN make opium yield estimates indirectly using sample measurements of the volume of capsules per unit area and an empirical relationship to dry opium gum yield based on data collected in Pakistan and Thailand (UNDCP, 2001):

$$Y = \frac{(V_c + 1495) - ((V_c + 1495)^2 - 395.259V_c)^{0.5}}{1.795} \tag{6.1}$$

where Y is dry opium gum yield (kg ha^{-1}) and V_c is mature capsule volume (cm^3 m^{-2}).The volume of an individual capsule (V_{ci}) is calculated using the prolate spheroid model:

$$V_{ci} = \frac{4}{3}\pi ab^2 \tag{6.2}$$

where a is half the capsule height excluding the stigma and b is half the capsule diameter. The same authors also present an empirical equation using the weight of capsules per unit area instead of volume:

$$Y = \frac{(W + 184) - ((W + 184)^2 - 493.92W)^{0.5}}{2.94} \tag{6.3}$$

where W is mature capsule dry mass (kg ha^{-1}). The capsule volume approach is used by UNODC in Afghanistan, as it is quicker and avoids the need to remove capsules for weighing.

Measurements are taken at sample locations selected randomly from a sample frame of village locations across the poppy producing provinces. At each selected village, a surveyor subjectively chooses three fields that represent good, normal and poor crops. Within each field, three 1 m^2 quadrats are positioned randomly along a transect, as explained in UNDCP (2001). In each quadrat, the number of capsules, flowers and buds expected to contribute to yield are counted and the average volume per capsule estimated by measuring a subsample comprising all capsules on randomly selected plants until at least 10 capsules have been measured. These measurements are used to estimate the total volume of capsules per unit area and equation (6.1) is applied to estimate the dry opium yield for each quadrat. An average yield (weighted by province area) is then calculated and multiplied with the cultivated area of opium poppy to estimate the dry opium production. This methodology is very time consuming and a large number of samples are required to make credible estimates of opium yield at regional and national level.

6.2.2 *Remote sensing of yield*

Remote sensing methods have been used to assist in the estimation of crop yield by exploiting relationships between measured crop parameters and spectral properties. Linear combinations of red (R) and near-infrared (NIR) reflectance, referred to as vegetation indices (VIs), are correlated to measured crop parameters such as leaf area index, above ground biomass and plant stand density, which in turn are correlated to final yield in crops of wheat, millet, soybean, cotton, barley, tomato and maize in a range of geographical locations (Domenikiotis et al., 2004; Koller and Upadhyaya, 2005; Liu and Kogan, 2002; Prasad et al., 2006; Rasmussen, 1997; Tucker et al., 1980; Weissteiner and Kühbauch, 2005).

Taylor et al. (1997b) exploited the relationship between VIs and above ground biomass in cereal crops by extrapolating yield indicator measurements across aerial digital photography (ADP) to minimise the requirement for field observations. They modelled Normalised Difference Vegetation Index (NDVI) and yield estimates based on samples of plant population, number of viable tillers, number of ears per unit area and number of viable grains per ear at different crop growth stages. They found that the spatial pattern of crop development and yield potential in fields and field groups is established early in the crop cycle, indicating a relatively wide window of opportunity for acquisition of imagery to support yield estimation.

This methodology was developed further in the context of precision farming of wheat (*Triticum aestivum* L.) and barley (*Hordeum vulgare* L.) by Wood et al. (2003). Only eight sites were required to correlate NDVI and yield indicators for a group of similar fields, provided the selection of sites was constrained to represent the range of NDVI across the fields and samples had good geographic distribution and separation.

These studies are based on a statistical technique known as the regression estimator (Cochran, 1977), where the correlation between high accuracy sample observations and coarser data representing the population (known as an auxiliary or co-variate) are used to reduce the variance of the sample estimate. This technique has been tested operationally at the regional scale using imagery for improving crop inventories in Europe by the Monitoring Agriculture with Remote Sensing (MARS) programme (Taylor et al., 1997a) and by the USDA in the United States (Allen and Hanuscak, 1988). The population mean for individual crops was calculated from digital image classification and substituted into the linear regression of the sample observations with the coincident pixels from the digital classification. These programmes found a reduction in variance of the sample estimate and a correction for highly biased samples using imagery.

A regression based approach could provide improved precision in sample estimates from the small yield sample in Afghanistan and correct for the bias in the sample distribution if a correlation between opium yield indicators and VIs was established. Suitable very high resolution (VHR) satellite imagery is already collected by the UNODC/MCN at random locations as part of their annual opium cultivation survey. If the yield ground survey took place at these locations the VHR imagery could provide a basis for improved yield estimation.

In this paper we present research into improving yield estimation in Afghanistan with remote sensing. Firstly the relationship between poppy yield indicators and NDVI is investigated at field sites in the UK. The application of a regression estimator utilising satellite imagery collected for the UNODC/MCN's cultivation survey in Afghanistan is then discussed. The field trials were originally conducted for the UK government as part of wider project, described by Taylor et al. (2010), to investigate the uncertainty in Afghan opium production estimates. Further work was conducted of behalf of the UNODC/MCN using data from their 2011 and 2012 yield surveys and VHR imagery collections.

6.3 UK field trials

6.3.1 *Field sites*

Controlled field experiments involving opium poppy are not possible in Afghanistan as cultivation is illegal. Instead, initial field experiments were conducted in the south of England in 2004 and 2005 on opium poppy grown for the pharmaceutical industry. The fields were located within a few kilometres of each other on the same farm in Hampshire. In 2004 the field names and areas were: 'No 34' (24.8 ha) and 'Aero4' (22.9 ha). In 2005 they were 'L21' (7.62 ha) and '25–6–7' (32.45 ha). The planting dates for opium poppy in 2004 were 8 March in Aero4 and 23 April in No34, which had been replanted later because of frost damage. In 2005 both L21 and 25–6–7 were planted on 15 March. Parts of the fields L21 and 25–6–7 that were used for other experimental trials are excluded from analysis in this study. In 2010 a further two poppy fields (4.36 and 18.68 ha) near Haseley, Warwickshire were added to the trial. In all cases the fields were managed using standard agricultural practices, with uniform inputs of fertiliser and pesticide within each field.

6.3.2 *Crop growth stages and timing of aerial digital photography*

The NDVI response of crops varies with time because of the change in R and NIR spectral response through the growth stages of the crop. Poppy growth stages have not been formally defined so the following description was developed in consultation with agronomists in charge of the commercial crop.

The growth and development of the poppy crop starts with the emergence of cotyledons followed by progressive leaf production, which is often referred to as cabbage stage because of the resemblance to early growth of cabbages. Stem elongation follows which sees the emergence of downward-pointing buds forming characteristic 'hooks' at the top of the stems. As the stem lengthens the hook straightens and the bud develops into the flower. Individual flowers last about 24 hrs and are followed by development and swelling of the green capsule which can last up to two weeks as the seeds develop. Additional capsules are often produced on secondary stems emanating from the main stem in a progression so flowering of the crop as

Table 6.2. Planting dates, image acquisition dates and poppy crop growth stages at each field site.

Field site	Planting date	Image date	Growth stage
Aero4	8-Mar-04	11-Jun-04	Flower bud development/flowering
		28-Jun-04	Capsule development
		13-Jul-04	Seed development
		6-Aug-04	Senescence
No34	27-Apr-04	11-Jun-04	Leaf production/stem extension
		28-Jun-04	Flowering
		13-Jul-04	Senescence
		6-Aug-04	Seed development
L21 & 25-6-7	15-Mar-05	12-May-05	Leaf production
		7-Jun-05	Stem extension/bud development
		22-Jun-05	Flowering/capsule development
		12-Jul-05	Seed development/senescence
Haseley	15-Mar-10[a]	24-Jun-10	Capsule development

[a] Approximate date.

a whole can last several weeks with 'hooks', flowers and capsules being present at the same time. It is during this period that opium gum would be harvested in Afghanistan by lancing. The capsules then mature and dry, and the leaves drop as the plant senesces. Planting density is variable and complete canopy closure does not usually occur, especially in Afghanistan where farmers need to walk through the crop at harvest.

Ground observations of the poppy crop and field reports were used to plan the timing of image acquisition but this was not an exact process because of flying constraints imposed by weather conditions and logistics. Imagery acquisitions were achieved for the growth stages shown in table 6.2. There were visible differences in crop morphology at the imagery acquisition dates in 2004 resulting from the seven week delayed planting date and the increased planting density of field No34 compared with Aero4. Poppy plants in field No34 had single, smaller capsules and were shorter in height. The timing of progression through growth stages was accelerated, with the poppy in No34 moving through leaf production, stem extension to flowering, faster than Aero4. The capsules in No34 had less time to grow and develop, as both fields reached senescence around the same date.

6.3.3 *Processing of aerial digital photography*

Near vertical aerial photography was acquired with digital cameras mounted in the fuselage of a light aircraft. The ADP system was the same as used by Taylor et al. (1997b) and Wood et al. (2003) and comprised of two Kodak DCS 420 digital cameras, fitted with optical band-pass filters used to simultaneously acquire images in the red (R, 640 nm centre, 10.4 nm band width at half maximum transmission) and near infrared (NIR, 840 nm centre, 11.7 nm width) wavebands. The above ground flying heights of 1200 m (4000 ft) and 500 m (1650 ft) were used to achieve ground pixel resolutions of 0.6 m and 0.25 m, respectively. The cameras were set manually to the same exposure (f-stop and shutter speed) and ISO settings to achieve the correct relative magnitudes of the red and near infrared but the settings were adjusted according to flying height and ambient light. The shutter speed was fixed according to flying height, 1/125 for 1200 m and 1/250 for 500 m, to control motion blur. The raw digital numbers (DNs) of each pixel were recorded onto removable storage inside each camera.

The ADP imagery collected from the R-NIR camera pair were co-registered and geometrically corrected to the UK Ordnance Survey of Great Britain (OSGB) map coordinate system to within 1 m accuracy. A grey and white reference panel (both 1.6 m by 1.6 m) were used to radiometrically normalise the DN values between dates. The NDVI was calculated from the normalised DN values using the equation:

$$\mathrm{NDVI} = \frac{N - R}{N + R} \tag{6.4}$$

where N is the near infrared and R is the red response of the camera. A low pass filter was applied to each image (7x7 and 5x5 kernels used with 0.25 m and 0.6 m resolution respectively) to reduce small-scale variations in NDVI and differences in colocation between image pixels and ground measurements (Wood et al., 2003).

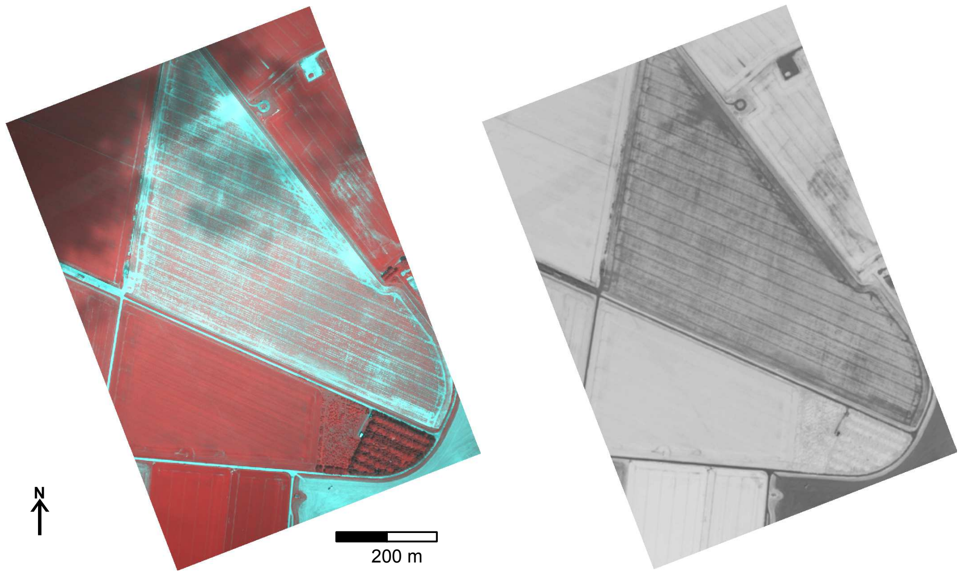
Examples of two-band false colour composites (FCC) of Aero4 and No34 with NIR in red and R in blue and green, acquired on 11 June 2004 are shown in figure 6.1 along with the respective NDVI images. Both FCC images show areas to be in cloud shadow which could not be avoided at the time. Closer visual inspection of NDVI values in and out of shadow in uniform crop areas showed that the NDVI calculation greatly reduced cloud shadow effects (figure 6.1) to the point where they could be ignored. The other image dates were not affected by cloud.

6.3.4 *Selection of ground calibration sites*

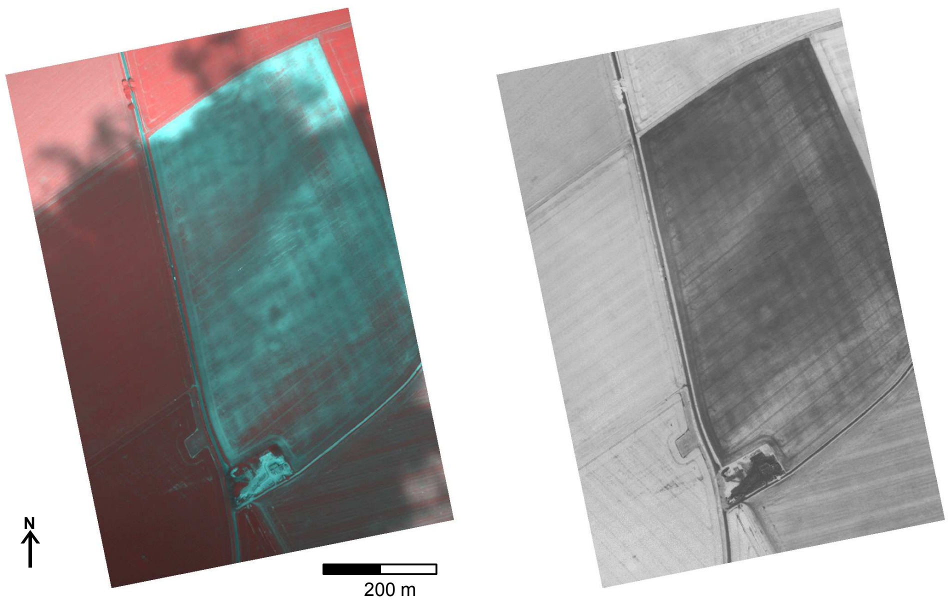
The rapid calibration methodology proposed by Wood et al. (2003) was implemented to select eight sites representing the range of NDVI within the field. To achieve this, the NDVI values were stratified into eight equal ranges and a site was randomly selected from within each stratum. Figure 6.2 shows an example of the stratification of NDVI applied to No34 and the location of the calibration sites. The same procedure was used to select calibration sites in Aero4. In 2005 eight calibration sites were selected across the two fields, to calibrate a total of 40 ha. One additional calibration site was added using a later NDVI image, to provide extra data representing low to average biomass poppy. In 2010 six calibration sites were selected in each of the Haseley fields.

6.3.5 *Crop measurements*

Crop measurements were made on the same dates as image acquisition in three 1 m^2 quadrats at each calibration site, positioned in a triangle formation as shown in figure 6.3(a) and orientated so that the diagonal was aligned with the direction of planting to avoid aliasing with plant rows. Spatial averaging of the triplets was used to match the field observations to the imagery resolution and reduce any error in co-location.



(a)



(b)

Figure 6.1. Presence of cloud shadow in original false colour composite ADP (left) and after calculation of NDVI (right) for (a) Aero4 and (b) No34. Imagery collected 11 June 2004 in Hampshire, UK.

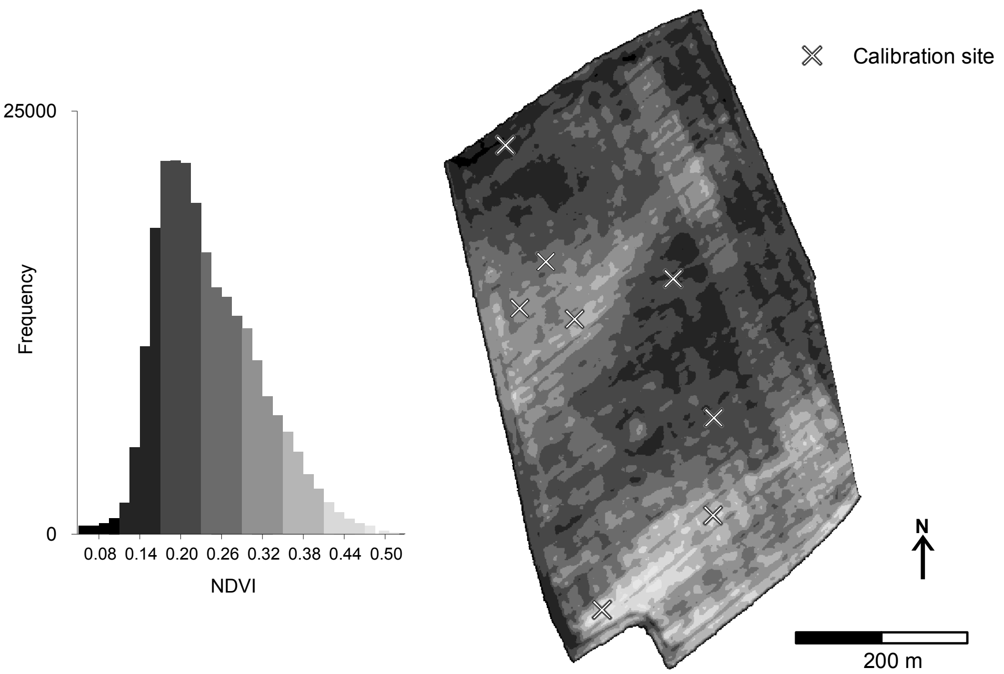


Figure 6.2. Stratification of field No34 into eight classes based on equal intervals of the NDVI image histogram. The location of selected calibration sites within each strata are marked. Image aquired on 11 June 2004.

Depending on the growth stage, the measurements made were: plant stand density, weed counts, bud and capsule counts, and capsule dimensions. Capsule height was measured between the stigmatic rays to the base of the ovary (figure 6.3(b)). On the final date the capsules were harvested from each of the 1 m^2 quadrats and oven dried for 3 days at 75 °C, to determine the dry capsule yield.

A digital photo of each sub-sample at each date was taken from a vertical height of approximately 3 m using a compact digital camera mounted on a wooden pole (figure 6.3(c)). These images were rectified and provided a visual record of the individual quadrats (figure 6.3(d)).

Timing within the crop growth cycle was established by visually estimating the predominant growth stage and assigning a numerical value based on the scale given in table 3. Typically plants in a poppy crop have a mixture of stages such as flower buds, flowers and capsules occurring at the same time. If there was no clear majority growth stage, an intermediate numerical value was assigned. For example, between leaf production and stem extension, the value 1.5 was used.

6.3.6 *Crop yield indicators and NDVI*

The empirical relationship between measured crop parameters and NDVI was determined using linear regression as follows:

$$y = a(\text{NDVI}) + b \tag{6.5}$$

where y is the crop parameter to be estimated, NDVI is the normalised difference vegetation index (equation (6.4)), a is the slope and b is the offset. The regression

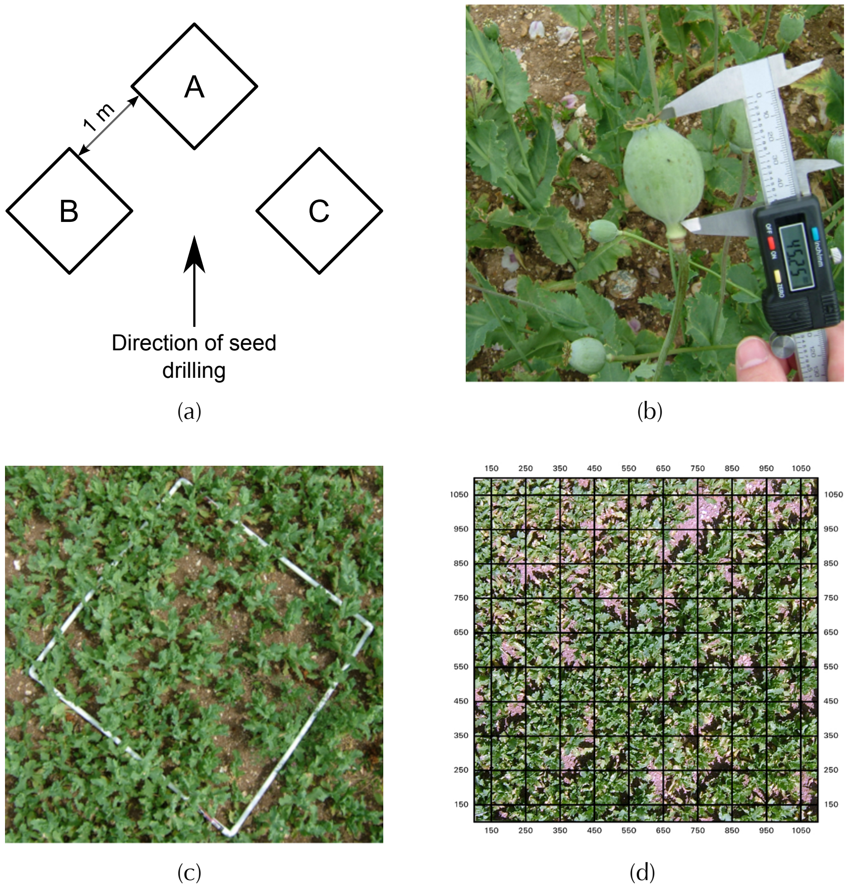
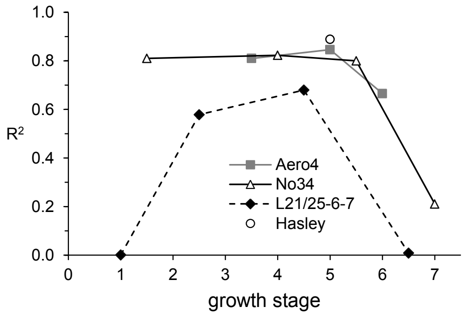


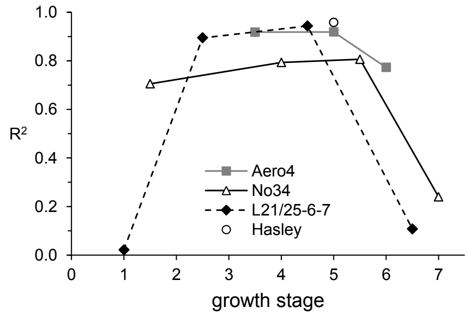
Figure 6.3. Field measurements: (a) Orientation of 1 m^2 quadrats in sample triplet; (b) height of capsule measured with callipers between stigmatic rays and base of ovary; (c) near vertical ground photograph of quadrat; and (d) rectified near vertical ground photograph.

Table 6.3. Summary of the poppy growth stages in sequential order.

Poppy growth stage	Date sequence
Emergence (cotyledons)	0
Leaf production (cabbage stage)	1
Stem extension	2
Flower bud development (hook stage)	3
Flowering	4
Capsule development	5
Seed development	6
Senescence	7



(a) Mature capsule volume



(b) Dry capsule yield

Figure 6.4. Summary of coefficients of determination (R^2) for the empirical linear relationship between NDVI at different poppy growth stages with (a) mature capsule volume and (b) final dry capsule yield, for study fields. Poppy growth stages are: (0) emergence, (1) leaf production, (2) stem extension, (3) flower bud development, (4) flowering, (5) capsule development, (6) seed development, (7) senescence.

parameters were applied to the NDVI values in the whole image to estimate a chosen crop parameter for any image pixel. Maps showing the within-field variation of the crop parameter can then be produced.

Figure 6.4(a) shows the coefficient of determination (R^2) between NDVI and mature green capsule volume at different crop growth stages, using equation (6.5). The highest correlations occurred during the 3–4 week period around flowering. The equivalent relationship between NDVI and final dry capsule yield is shown in figure 6.4(b) with R^2>0.9 during flowering to capsule development for Aero4 and L21/25–6–7, and R^2=0.793 and 0.806 at flowering and seed development respectively in No34.

The correlations are better for dry capsule yield than mature capsule volume for most of the growth stages. This is attributed to the total dry mass of the harvested capsules within each quadrat containing less measurement error compared to the subsample of capsule volume measured in the field. The timing of capsule measurements also effects the accuracy of the estimate of mature capsule volume as there may be capsules at different stages of maturity within any single quadrat that make identifying the optimum time for survey subjective.

In figure 6.5 data from the three study sites are shown grouped by growth stage: (a) leaf production to stem extension, (b) flowering and (c) capsule development to seed development. NDVI data was plotted against mature capsule volume (left) and dry capsule yield (right). The NDVI relationships at earlier growth stages (figure 6.5(a)) show greater variation in slope and offset for the different field sites because of rapid changes in the canopy biomass. There are differences in crop growth stage between fields. The growth stage in field L21/25–6–7 was leaf production, whereas No34 was between leaf production and stem extension. At the later growth stages (figure 6.5(c)) there is a reduction in correlation post flowering because of the onset of crop senescence. These results are consistent with findings for wheat (Aase and Siddoway, 1981; Tucker et al., 1980; 1981) and opium poppy in North-Western China (Jia et al., 2011a). At flowering (figure 6.5(b)) the NDVI relationships for individual fields converge for mature capsule volume and dry capsule yield, indicating the possibility of generalised fits. Homogeneity of slope tests confirmed there were no significant differences (P=0.41, P=0.71 respectively) and figure 6.6 shows single regression lines through the data for NDVI against mature capsule volume (R^2=0.70) and NDVI against dry capsule yield (R^2=0.87).

6.3.7 *Yield estimate and mapping*

The field average poppy NDVI calculated from the image has no sampling error and when substituted into the regression relationship in equation (6.5) allows an un-biased estimate of the average mature capsule volume to be made. For L21 and 25–6–7, the average NDVI (excluding experimental areas) was 0.362 and when substituted into equation (6.6) gives an estimate of 1,481 $cm^3\ m^{-2} \pm 11.6\%$ (95% CI) for the two fields. For comparison, the average mature capsule volume calculated from the sample alone is 1,376 $cm^3\ m^{-2} \pm 20.7\%$ (95% CI), a lower estimate with wider confidence intervals than the regression estimate.

Estimates of dry capsule yield are similarly calculated by substituting the average NDVI (0.362) into the regression equation for dry capsule yield (R^2=0.70), shown in figure 6.6, which gives 2.60 t $ha^{-1} \pm 5.8\%$ (95% CI), a narrower confidence interval than the mature capsule volume regression estimate ($\pm$11.6 %). Similarly to assess sample error, the sample dry capsule yield estimate is 2.44 t $ha^{-1} \pm 16.0\%$ (95% CI), a lower estimate with wider confidence intervals than the regression estimate. For both yield indicators the regression estimate has a lower variance than the sample estimate.

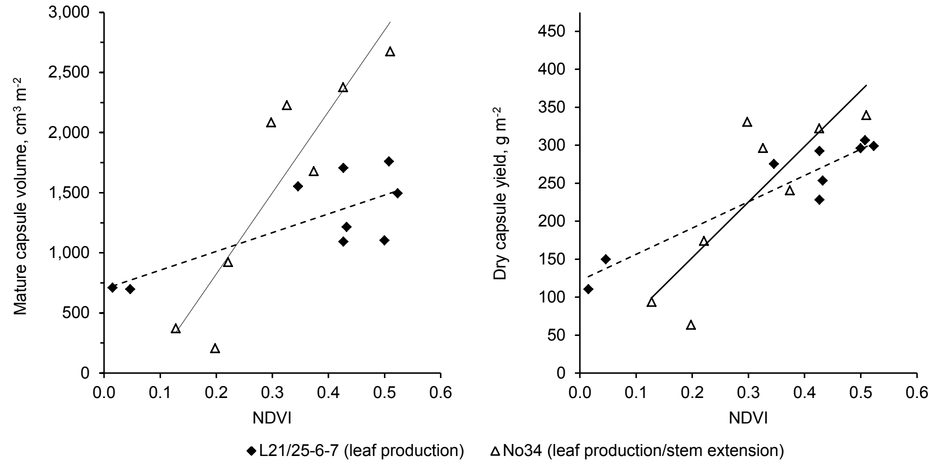
A map showing the spatial variation of poppy yield indicator can be produced by calculating the NDVI for each pixel in the ADP using the linear relationship from equation (6.5). As an example the generalised equation for mature capsule volume

$$V_c = 5051.5(\mathrm{NDVI}) - 347.61 \tag{6.6}$$

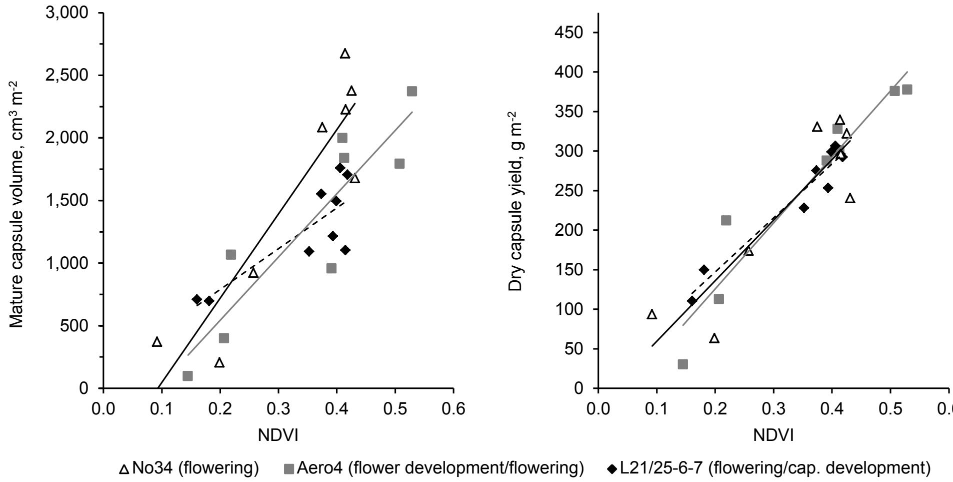
from figure 6.6 (R^2=0.70) was applied pixel-by-pixel to produce the yield indicator distribution map for fields L21 and 25–6–7 (figure 6.7). Negative values of NDVI were assumed to have zero yields. The mature capsule volume ranged from 0 to 2,464 $cm^3\ m^{-2}$, the lower yielding areas are shown in dark brown through to higher yielding areas in dark green. The tractor wheelings are visible at 28 m spacing as lower yielding light green lines. Two groups of experimental plots are seen in the south of the smaller field L21, and on the east side of the larger field 25–6–7. The southern half of field 25–6–7 yields better than the north. A curved linear feature of lower yield is visible across the middle of 25–6–7, which follows the course of a filled-in ditch.

6.4 Application in Afghanistan

The relationship between opium yield indicators and NDVI has practical significance for improving the yield estimate from the small, non-random sample collected in Afghanistan. The UNODC/MCN already collect VHR satellite imagery – suitable for calculating NDVI – at locations across Afghanistan for image interpretation of poppy crops. Images blocks are selected at random from a sample grid



(a)



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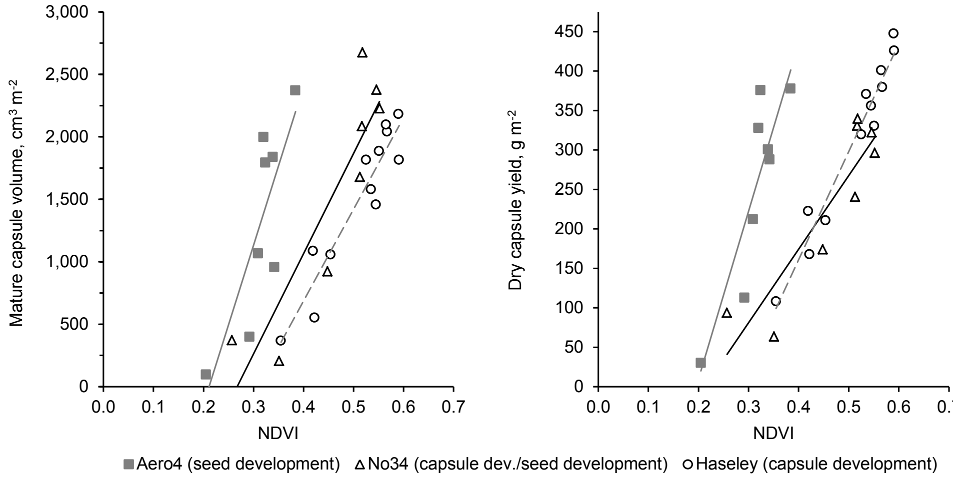

(c)

Figure 6.5. The empirical relationship between the poppy yield indicator mature capsule volume and NDVI (left), and dry capsule yield and NDVI (right) grouped by poppy growth stage: (a) leaf production/stem extension, (b) flowering and (c) capsule/seed development, for calibration sites.

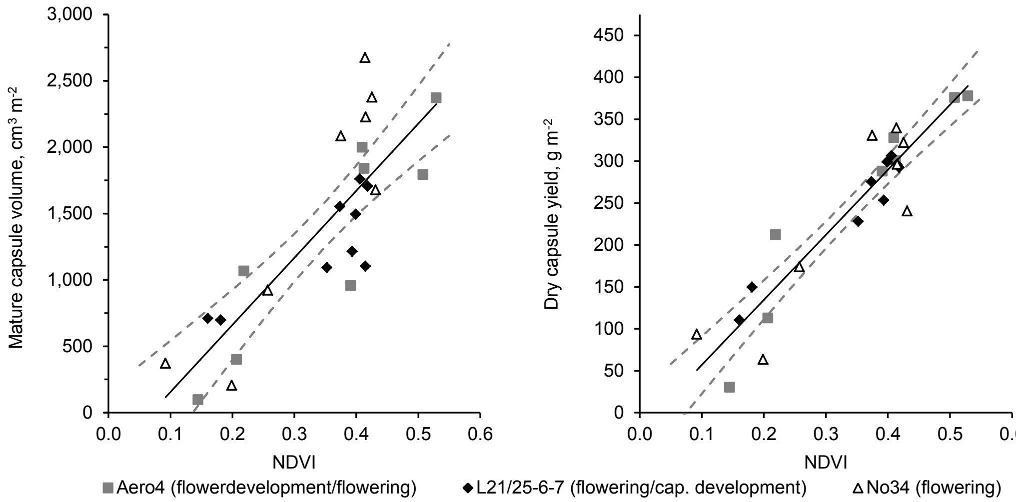

Figure 6.6. Generalised relationship between mature capsule volume and NDVI (left), and dry capsule yield and NDVI (right) from all calibration sites at flowering growth stage. Dashed lines show 95% confidence interval for the regression line.

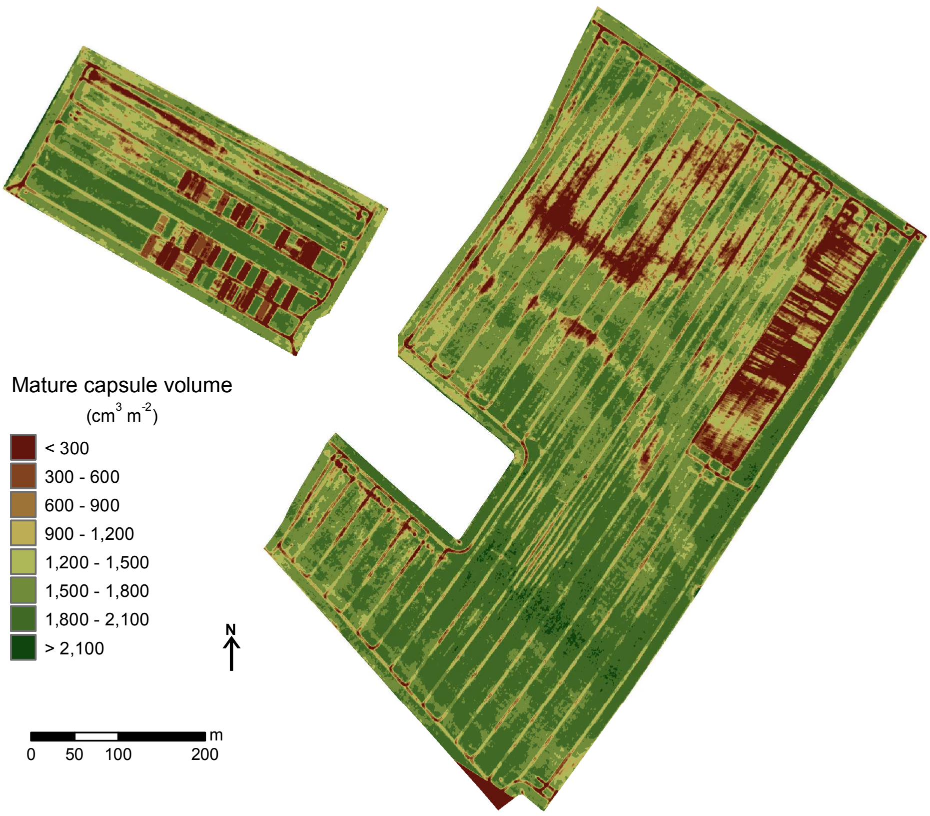

Figure 6.7. Poppy mature capsule volume for field L21 (left) and 25-6-7 (right) in Hampshire, UK. Two experimental plots (not discussed in this article) are visible in the south of L21 and east of 25-6-7, as variable yielding areas in regular block patterns between tractor tramlines.

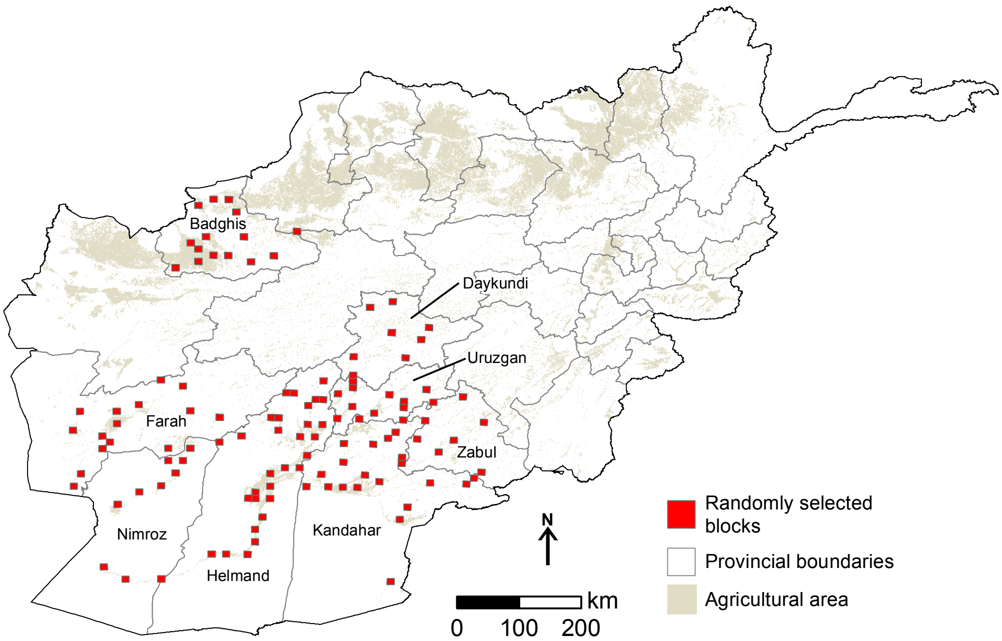

Figure 6.8. UNODC/MCN randomly selected image collection blocks in the main opium producing provinces of Afghanistan for 2011, adapted from UNODC (2011).

covering the agricultural areas of the main opium producing provinces (figure 6.8). An unbiased estimate of the average opium yield per image could be obtained by calibrating the NDVI for each VHR image using a small number of high quality field observations. As the image blocks are selected at random, unbiased regional and national yield estimates could be made by substituting the average mature capsule volume from the images into equation (6.1).

Although Afghan opium crops develop in a similar way to those in the UK, the growing conditions and poppy varieties are different. The VHR satellite sensor characteristics also differ from the ADP used in the UK field trials. The spatial resolution of the multi-spectral VHR imagery is coarser, ranging from 1.84 m to 3.22 m at nadir and the bandwidths in the R and NIR are wider (see table 6.4). The collection geometry is also more complex than the ADP as the sensors can be pointed off-nadir, acquiring images across and along the satellite track. To investigate the proposed remote sensing approach in Afghanistan, the UNODC/MCN provided data from their 2011 and 2012 yield surveys together with coincident collections of multispectral VHR imagery and image interpretations of the active poppy crop. The yield data comprised capsule measurements from 1 m^2 quadrats, ground photography and the GPS coordinates of the sampled fields. The field locations were verified by cross-referencing the field coordinates with pan-sharpened imagery and ground photography. Each VHR scene was evaluated for poppy growth stage using the crop information system described in Simms et al. (2014) together with available ground photography. Of the 2011 and 2012 data, 4 image sites (IKONOS, Worldview–2 and 2x Quickbird2) contained identifiable sample fields and coinci-

Table 6.4. Sensor ground sample distance (GSD) and bandwidths in the red (R) and near-infrared (NIR) for UNODC/MCN images selected for analysis.

Sensor	GSD m	Bandwidth, nm R	NIR	Province	Image date	Growth stage
WorldView-2	1.84	630–690	772–890	Herat	10-Apr-11	Flowering
IKONOS	3.28	632–698	757–853	Herat	17-Apr-11	Flowering
QuickBird2	2.44	630–690	760–900	Helmand	20-Apr-11	Capsule development
				Nangarhar	25-Apr-11	Capsule development

dent imagery collected within the leaf development to capsule development growth stages of the poppy crop (table 6.4). The multispectral images for these sites were calibrated to top-of-atmosphere reflectance to minimise the difference in radiometry between the sensors. An NDVI image was then calculated for each scene by substituting the reflectance values into equation (6.4). Pan-sharpened imagery was used for visual image interpretation of the poppy crop canopy.

Figure 6.9 shows an example from the Quickbird2 image, located in the province of Nangarhar, of the frequency and spatial distribution of field average NDVI of poppy fields (top) compared with image-interpretation of crop quality (bottom). The poppy field NDVI ranges from 0.33 to 0.64 over a small geographical area, which is consistent with the variation in the quality of crops seen in Afghanistan. Fields with lower than average NDVI (insert 1) have a canopy with patches of bare soil, indicating a lower planting density or poorer crop, compared to uniform fields that have a higher than average NDVI (inset 2). The surveyed fields (marked a and b) are adjacent to each other and have NDVI values 0.51 and 0.48 respectively, with field b having the same value as the mean of all poppy fields within the image (0.48). The results show variation in the field average NDVI consistent with the image-interpreted quality of the crop.

The field average of mature capsule volume per unit area (cm^3 m^{-2}) was calculated from the three 1 m^2 replicates within each ground surveyed field and plotted against the average NDVI for the field parcel. Field based averages of mature capsule volume were compared to field averages of NDVI because of insufficient support from the quadrat (3 per field on a random transect) observations to calibrate the VHR at the pixel scale (2–4 m). The results show an increase in NDVI with increased mature capsule volume at all 4 image sites but there were too few field observations per image to test the regression methodology.

Further analysis of the UNODC/MCN data were undertaken to investigate the suitability of the current ground observations for the calibration of VHR imagery. Within-field variation observed in the imagery, together with ground photography suggest that plot data might not be representative of the average capsule volume at the field scale in Afghanistan. In the UK field trials, spatial averaging of the quadrat triplet was used to match the field observations to the imagery resolution and reduce any error in co-location. Adopting a similar approach in Afghanistan, using the spatial average of multiple quadrats at each sample location, would increase the number of observations available for regression. However, this would require sample sites to be accurately geo-located using GPS.

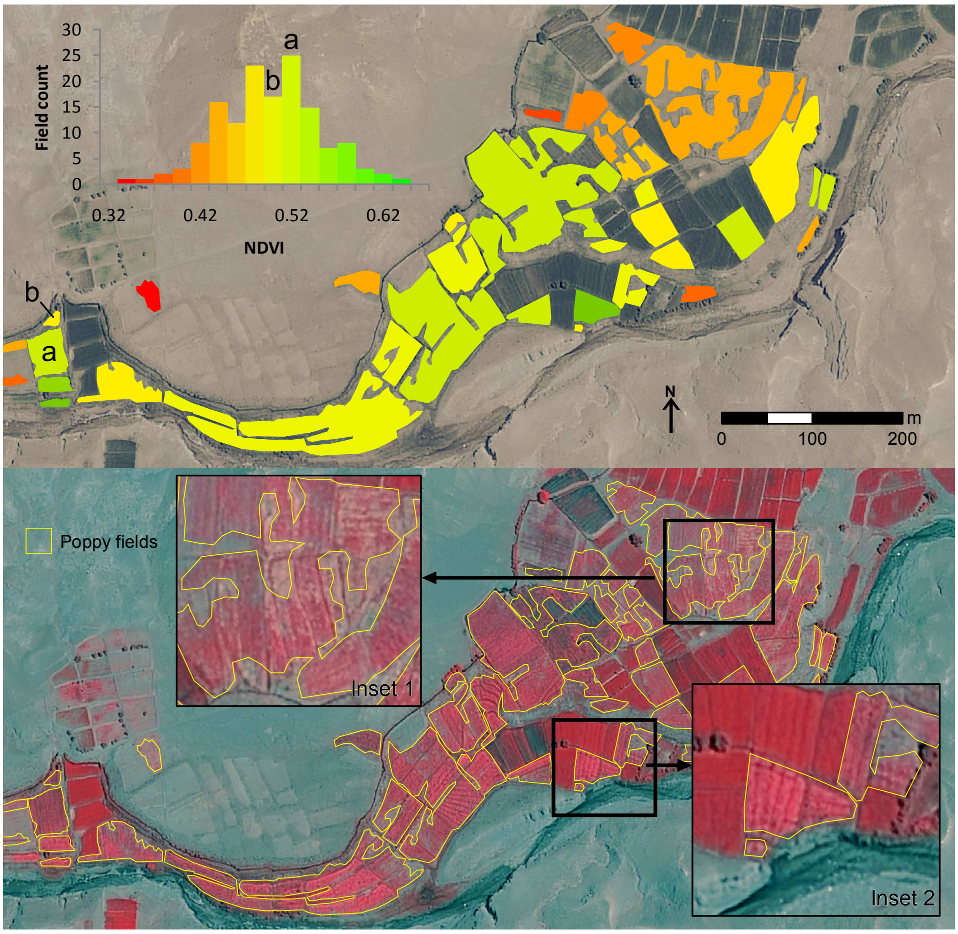

Figure 6.9. Spatial distribution of poppy field NDVI (top) and visual interpretation of crop quality (bottom), a subset of yield data from Nangarhar Province, eastern Afghanistan. Background image pan-sharpened true colour (top) and false colour (bottom) composite Quickbird2, 21 April 2011 (image ©UNODC/Ministry of Counter Narcotics, Government of Afghanistan).

Thorough examination of geo-tagged ground photography supplied for 2012 shows irregularities in the spatial distribution of the quadrats within the sampled fields. In some areas they were clustered at the edges of fields or under tree cover and did not follow the protocol for positioning using a field transect. It is likely that surveyors were trying to reduce risk by moving to concealed areas of the field to take measurements. From our experience with field survey data in Afghanistan, the accuracy of measurements and data recording are affected by the security of the field survey teams. It is important to consider that any modifications to the survey protocol that significantly increase the time spent in each field could increase the risk and reduce the quality of the field data.

The current UNODC/MCN methodology for the selection of sample fields (representing poor, medium and good crops) relies on a subjective assessment of quality made by the surveyor. Since the poppy field NDVI is correlated to the variation in potential yield, appropriately timed VHR imagery could be used to target fields for sampling. Having prior knowledge of crop quality across an image would allow surveyors flexibility in selecting safer locations to collect field data without biasing the sample. In extreme cases a surveyor could target a single field, with an NDVI close to the mean for all poppy fields, to collect a representative measurement for the image.

The UK data shows stability in the relationship between yield indicators and NDVI across fields and between years for imagery coinciding with the flowering growth stage. A generalised equation would be an advantage for survey implementation as it would reduce the number of sample sites required to calibrate each image. Further work in Afghanistan is required to determine if a generalised function for a satellite sensor could be developed and used for calibration across multiple image sites, including the effect of sun-sensor-target geometry and the atmosphere on the linear relationship between NDVI and yield indicator. Accurately determining VHR imagery collection windows to target the poppy flowering period would be essential for this approach.

The investigation of opium yield estimation using remote sensing is ongoing. To date there has been insufficient data to demonstrate a regression methodology in Afghanistan, partly due to uncertainty in the quality of ground based observations and the availability of suitably timed coincident VHR imagery. The UNODC/MCN are seeking to improve data quality through better training and surveyor supervision (UNODC, 2012). The use of cameras with automatic geo-tagging in 2012 highlighted previously unidentified data quality issues and are an important step for providing confidence in ground data collection going forward.

In order to integrate the UNODC/MCN's current yield sample and VHR imagery the following conditions must be met: (1) ground data must be accurately geo-referenced; (2) The selection of ground survey sites must be made at locations that are representative of the range of poppy crop variation, with respect to NDVI, but not spatially auto-correlated; (3) ground measurements of poppy crop parameters must be accurately co-registered with ortho-rectified imagery; and (4) imagery used to derive NDVI should be targeted for collection around the flowering growth stage to maximise the correlation between yield indicators and NDVI.

6.5 Conclusions

The UK field trials showed good empirical relationships between imagery-derived NDVI and poppy yield indicators (mature capsule volume and dry capsule yield) for individual fields. The results suggested a generalised relationship (R^2>0.7) across all sampled fields and years during the 3–4 week period including the flowering growth stage of the crop. The correlation of NDVI with dry capsule volume was found to be better (higher R^2) than NDVI with mature capsule volume. The relationship between yield indicators and NDVI was used to map the within-field yield variability of UK poppy crops.

The optimum timing for image collection is during the 3–4 week period including flowering, which corresponds with the highest R^2 and greatest stability of the empirical relationship between NDVI and yield indicator.

In the UK poppy fields, the regression estimator adjusted the yield estimate from the sample and reduced the variance. This approach will correct for the bias in the sample distribution and increase the precision of the small non-random sample collected in Afghanistan, improving the accuracy of the yield estimate.

The feasibility of applying the yield regression estimator methodology in Afghanistan was investigated using 2011 and 2012 ground data and VHR satellite imagery collected by UNODC/MCN. The initial results were promising but there were too few observations per image to validate the methodology. Further data are required to demonstrate the approach, to investigate generalised calibration equations, and the targeted sampling of representative fields using VHR satellite imagery.

The current limitations of developing a remote sensing approach are related to the ability of surveyors to collect accurate ground measurements in a challenging and dangerous environment. We believe that the integration of the existing yearly VHR imagery collection with a smaller, accurate and targeted ground sample represents the best solution for improving opium yield estimates in Afghanistan.

Acknowledgements

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Chapter 7
Conclusions

This chapter contains a synthesis of the research on remote sensing of opium poppy presented in the preceding chapters. The main findings are summarised and grouped according to the research objectives, followed by a statement of the contribution to knowledge. Ongoing investigations into the fusion of high frequency MODIS data and medium resolution imagery are presented in further work.

7.1 Summary of main findings

7.1.1 *Objective 1: comparison of remote sensing surveys of Afghanistan's opium monitoring programmes*

The initial comparisons of the UNODC and US survey methodologies took place during the project work presented in chapter 2. Investigations were conducted with both survey teams to understand discrepancies in published figures and to promote technical discussion. Survey methodology trials evolved into a parallel survey for selected provinces from 2006 to 2009. This work highlighted potential reasons for observed differences relating to the image interpretation of poppy from VHR imagery, the mapping of the total area of agriculture and stratification using full coverage medium resolution imagery.

Comparison of overlapping sample interpretations revealed systematic differences in the mapping of poppy field boundaries and the inclusion of within field features, such as irrigation ditches and bare patches within the crop canopy. There were also differences in the interpretation of thin or damaged crops relating to the spatial resolution of the imagery used for interpretation. The effect of interpretation keys and the resolution of the VHR imagery were the subject of debate between the survey teams.

Time-series profiles of NDVI, presented in chapter 3, were used to monitor the agricultural system because of a lack of reliable crop information. They revealed the significant variation in agricultural area between years caused by the rotation of large blocks of land and the expansion of cultivation into new areas. Differences in the mapped area of agriculture will affect cultivation estimates as the mask is used to extrapolate the proportion of poppy in the sample for the final estimates. The US survey also extend the area of their agricultural mask using a pixel buffer to ensure no poppy cultivation is excluded because of the resolution or geometric accuracy of the medium resolution imagery used to create the mask.

Profiles were also found to be indicative of the phenology of poppy despite the coarse resolution of MODIS, allowing the optimisation of collection windows for VHR and medium resolution imagery. The observed spatial variation in crop timing prompted investigation into how interpretation of VHR images collected outside of the optimal time windows affected the sampled area of poppy.

The results of parallel surveys found differences between direct expansion estimates, used by the UNODC, and the stratified estimates of the US survey. Stratified estimates, described in chapter 5, had lower confidence intervals and different best estimates.

7.1.2 *Objective 2: critical evaluation of how differences in survey methodologies impact opium estimates*

Image interpretation of crops was investigated as a source of bias within the sample. Chapter 4 examined the role of generalisation in sample interpretation, which increased estimates by up to 14% and is not accounted for in the confidence interval. Automatic segmentation and digital object classification were tested to increase the consistency of interpretation. The results of the segmentation were consistent with manual interpretation in terms of the measured area of poppy. However, digital classification caused a systematic labelling error that increased the final cultivation estimate by 30.2%.

The findings show the potential for differences in survey estimates between independent teams of interpreters relating to the source of imagery and the interpretation key. In the case of the US survey, interpretation includes all poppy area identified as a farmers' intention to cultivate and areas of thin crops that might not be visible in the lower resolution imagery used by the UNODC. This will lead to discrepancy between interpretations in years with poor crop establishment or in areas of marginal agriculture, where crop canopies are thin and contain patches of bare soil.

The results of the digital classification highlight the effect of error in the measurement of poppy from a sample on the final estimate. Unbiased interpretation is critical for accurate final estimates. The maturity of the crop at the time of image capture can lead to differences in the delineated area, while images collected outside of the optimum timing windows are more likely to contain errors as interpretation is less certain.

The effects of the definition of the agricultural mask and buffering on stratified and un-stratified estimates using different resolutions of imagery and sample fractions were investigated in chapter 5. Decreasing the resolution of the imagery and buffering both increased the final direct-expansion estimate, showing the definition of the agricultural mask as having the greatest impact on final estimates of poppy (up to 20% increase). For the UNODC's survey, where new agriculture is added to the mask of potential agriculture each year, there is a high risk of artificially increasing poppy cultivation estimates.

In contrast, stratification reduced the effect of image resolution and buffering by separating higher productivity areas with lower variance from areas of low production according to their spectral differences. Despite the highly mixed spectral strata, estimates were robust to changes in the agricultural mask and variation in the sample proportion. Buffered estimates were within 5% of unbuffered estimates for different mask resolutions and estimates using 40 strata had a similar precision to unstratified estimates with double the sample fraction.

The agricultural mask, sample interpretation and the use of stratification have been identified as the components of the UNODC and US surveys' that cause discrepancies in final estimates. It is clear from the results that any of these factors, or a combination of them, could lead to differences in final estimates that fall outside of confidence intervals. Provinces with highly mixed cultivation practices and large areas of marginal agriculture are particularly susceptible. This is also true of provinces with more uniform distribution of crops in abnormal years.

7.1.3 *Objective 3: identifying improvements to current methodologies for reducing error and bias in opium production estimates*

Stratification is recommended to reduce differences in the definition of the agricultural mask caused by annual changes in active agriculture, buffering and the pixel size of medium resolution imagery. Also, the increased precision of stratified estimates reduces confidence intervals (about 2 to 10%), or allows for a reduction in the number of samples compared to direct expansion. The extra cost of stratification is low as imagery already collected and processed for creating the agricultural mask can be reused. Also, the increased availability of free medium-resolution imagery from the European Commission's Copernicus programme will improve the chances of acquiring imagery timed to coincide with the poppy growth cycle.

The use of image segmentation for controlling the consistency of field delineation has been demonstrated (chapter 4). Automatic techniques will greatly increase the speed of interpretation and reduce measurement error in sample delineations of poppy. Other recommendations to share interpretations at intersecting samples and discuss uncertainties between survey teams have already been adopted.

Chapter 6 presents the development of a bias correction methodology for the small non-random yield sample collected as part of the UNODC's annual survey. The fundamental relationships between image derived NDVI and field measurements of mature capsule volume and dry yield were determined from 3 years of crop trials conducted on UK poppy crops. The results show a stable relationship with images collected around the flowering growth stage between years, prompting the development of the approach in the context of the UNODC's annual yield survey.

Timing of imagery collections is a key consideration in minimising measurement error, bias correction of yield observations, and definition of the agricultural mask. Optimal timing also maximises the spectral differences in medium resolution imagery used for stratification. MODIS provides information in near-real time for monitoring crop phenology and historical information on changes that, when used together with the single dated images, shows changes in production such as crop rotations and newly exploited desert areas. The extra effort in maintaining an imagery based monitoring system, such as that presented in chapter 3, must be weighed against the benefits of accurate information on phenology and inter-annual changes in cultivation caused by management practices, drought or flooding.

In light of the work presented in this thesis, the following methodology is suggested to minimise error and bias in final estimates of opium production in Afghanistan:

Wide-area crop monitoring – use of time-series NDVI to inform decisions on image timing (VHR and medium resolution) in relation to crop phenology and annual changes in cultivation practices.

Agricultural mask – yearly collection of full-coverage medium resolution imagery from Landsat-8 and Sentinel-2 for mapping the active agricultural area. Areas should be subdivided into zones using time-series NDVI for optimising the timing of medium resolution imagery in relation to the crop growth cycle.

Sample interpretation – use of automatic methods for image segmentation of VHR images to improve consistency in poppy field delineation and to improve the accuracy of visual interpretation.

Image-based stratification – stratified area frame sampling for robust estimates with lower confidence intervals that will be less affected by errors in the mapped area of agriculture. The strata created from the medium resolution imagery used to create the agricultural mask.

Yield estimate – bias correction of field measurements of poppy yield indicators using NDVI from satellite imagery at sample locations (VHR scenes) as an alternative to random sampling.

7.2 Contribution

The differences in the remote sensing methodologies of the UNODC and US Government explain the discrepancies in their opium figures. Interpretation keys, the mapping of the total area of agriculture and the timing of imagery collections in relation to the growth cycle of poppy crops can introduce measurement error and bias into estimates of opium production.

The evidence presented supports the use of imagery based stratification to reduce the effect of differences in the mapped area of agriculture on final estimates. It is not surprising that agricultural masks, from independent sources with differing assumptions on what constitutes poppy cultivation, disagree. Compounding this is the large yearly variation in the spatial distribution and area of cultivated land. Stratification is only a small increase in effort as medium resolution imagery is already part of the process of creating the agricultural mask.

A strong relationship in field observations of capsule volume and NDVI has been demonstrated in UK poppy crops over multiple growing seasons and in different locations. These findings have led to methodology trials using the UNODC's yield survey data. Provided the quality of field data can be improved, VHR imagery can be used to correct for bias in the non-random sample, leading to improved information on opium production.

All aspects of opium monitoring depend on the timing of image acquisition, specifically the period from stem elongation to the end of flowering. Sub-optimally timed VHR imagery makes interpretation uncertain, cannot be used for bias correction of yield observations, and affects the area of measured poppy in the sample. Timing windows vary across provinces with topography, elevation and latitude. Inter-annual variations also occur at the same locations, with crop development delayed by cold weather or damaged by frost. The interpretation of thin or damaged crops differs depending on the resolution of the VHR imagery and on the definition of a poppy field in the interpretation key. In years with poor crop establishment, there will be significant differences in the measured area of poppy when the field is the minimum mapping unit and within canopy bare soil and poor crops are included.

This work has contributed to the development of an operational methodology for bias correction of yield observations for the UNODC and the production of guidelines for the use of remote sensing for opium cultivation surveys (UNODC, 2015a). The findings have wider implications to global illicit crop monitoring where visiting field sites is limited by security conditions. Tree crops such as coca (*Erythroxylon coca*) do not follow the annual crop cycle of poppy, but timing of imagery collection is still important to maximise spectral differences during classification or defining the area where cultivation takes place. Also, the findings on the suitability of image datasets for accurately measuring crop areas at an appropriate scale and the use of stratified estimates are not limited to poppy in Afghanistan. The integrated approach presented for poppy, including wide-area monitoring at high temporal resolution, could be applied for other crops to improve confidence in statistical estimates from remote sensing based methodologies.

7.3 Further work

Provinces such as Kandahar have highly variable poppy cultivation practices, including: high density poppy monoculture; areas of vines intercropped with poppy; thin ribbon valleys; and areas of marginal agriculture with no cropping in some years. These areas display distinct temporal characteristics in NDVI profiles that could be used for improved sample design (pre-stratification) or post-stratification of the agricultural area.

Profiles can be characterised by decomposing the time series measurements of NDVI into magnitude and phase frequency components using a fast Fourier transform (FFT). This allows the separation of low frequency information relating to crop growth cycles from higher frequency noise (Geerken, 2009).

For example, figure 7.1 shows the magnitudes of the first three Fourier components of the 2007 MODIS NDVI stack as bands of a false-colour composite image. The Helmand river valley is green because of its consistent double crop cycle (band two). Marginal agricultural areas that support a single crop cycle appear as brown and the main area of Kandahar shows up as red because of its long single cycle (band one) that includes tree crops and vines.

The MODIS data used to extract temporal information has coarse spatial resolution unsuitable for mapping the agricultural area in Afghanistan. Further research into fusing crop cycle information with medium resolution imagery at an appropriate scale for generating the agricultural mask is required.

The results of clustering image data into separable information classes is dependant on the preselection of initial cluster means and the number of clusters. Further work into defining the appropriate clustering parameters could help improve the relationship between spectral classes and the probability of poppy cultivation. Also, including a spatial component in clustering could help to separate highly mixed strata. By further combining temporal information on crop cycles with spectral data, stratification could be improved to more accurately map the local distribution of poppy cultivation and improve district level estimates.

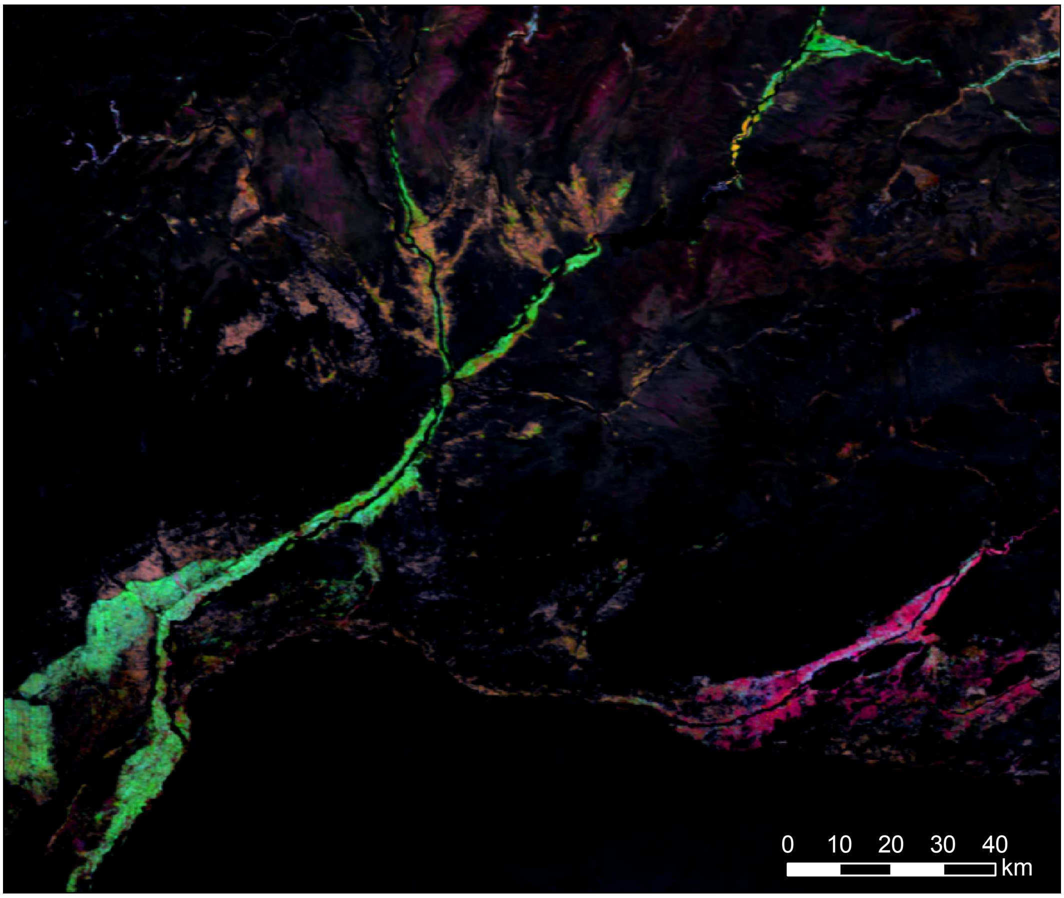

Figure 7.1. False-colour composite of magnitudes from the first three Fourier components of the fast Fourier transform of 2007 MODIS NDVI stack. Areas with double cropping in Helmand show as green, single crop cycles with tree crops and vines in Kandahar show as red.

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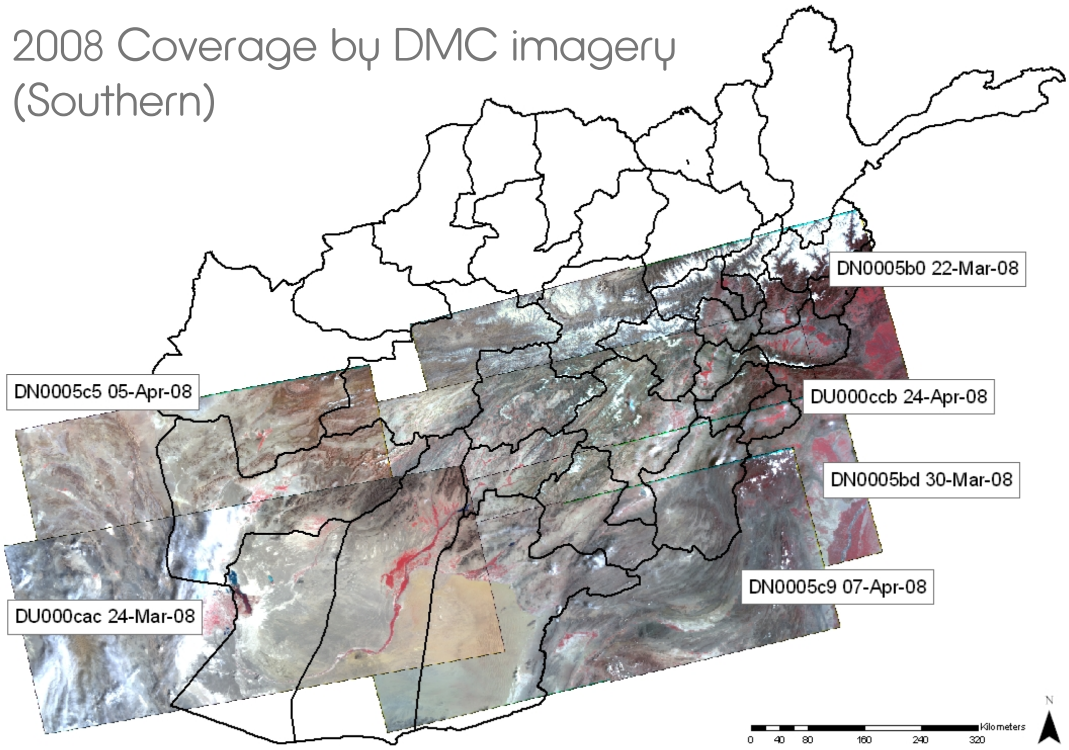
Appendix A
Data collections: 2008–2009

2008 Coverage by DMC imagery (Southern)



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IKONOS used in Hilmand

LOCATION	SOURCE	DATE
held_a1	CU	28/03/2008
held_a4	CU	28/03/2008
held_b0	CU	28/03/2008
held_c1	CU	28/03/2008
held_c4	CU	28/03/2008
held_d0	CU	28/03/2008
held_e0	CU	28/03/2008
held_f1	CU	28/03/2008
held_f2	CU	28/03/2008
held_f3	CU	28/03/2008
held_f6	CU	28/03/2008
held_h0	CU	28/03/2008
held000	UN	22/04/2008
held011	UN	30/05/2008
held040	UN	24/04/2008
held045	UN	08/05/2008
held054	UN	08/05/2008
held057	UN	27/04/2008
held059	UN	27/04/2008
held081	UN	27/04/2008
held087	UN	27/04/2008
held103	UN	08/05/2008
held108	UN	08/05/2008
held115	UN	27/04/2008
held124	UN	30/04/2008

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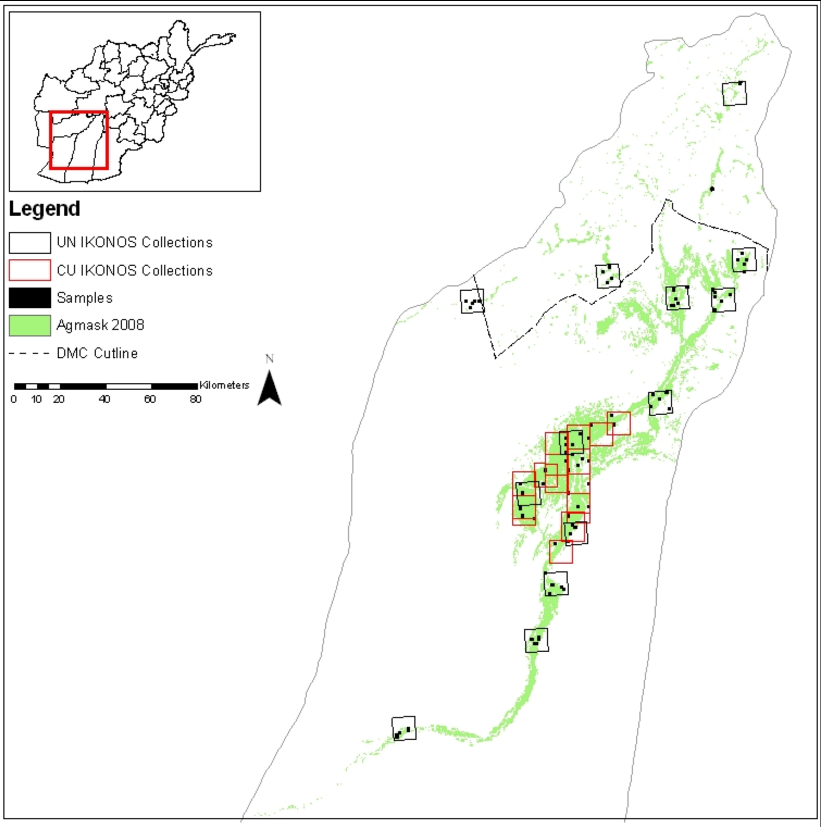
2008 Samples and Active Agriculture Hilmand



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IKONOS imagery used in Kandahar

LOCATION	SOURCE	DATE
kand_a3	CU	16/04/2008
kand_add_2	UN	05/04/2008
kand_b1	CU	16/04/2008
kand_c0	CU	16/04/2008
kand_d0	CU	24/04/2008
kand_e0	CU	16/04/2008
kand_f0	CU	22/04/2008
kand_g0	CU	16/04/2008
kand_h0	CU	05/05/2008
kand_k0	CU	24/04/2008
kand009	UN	05/05/2008
kand017	UN	08/05/2008
kand052	UN	24/04/2008
kand053	UN	16/04/2008
kand073	UN	16/04/2008
kand077	UN	27/04/2008
kand078	UN	16/05/2008
kand084	UN	16/04/2008
kand088	UN	05/05/2008
kand135	UN	24/04/2008
kand143	UN	05/04/2008
dand+	UN	16/04/2008

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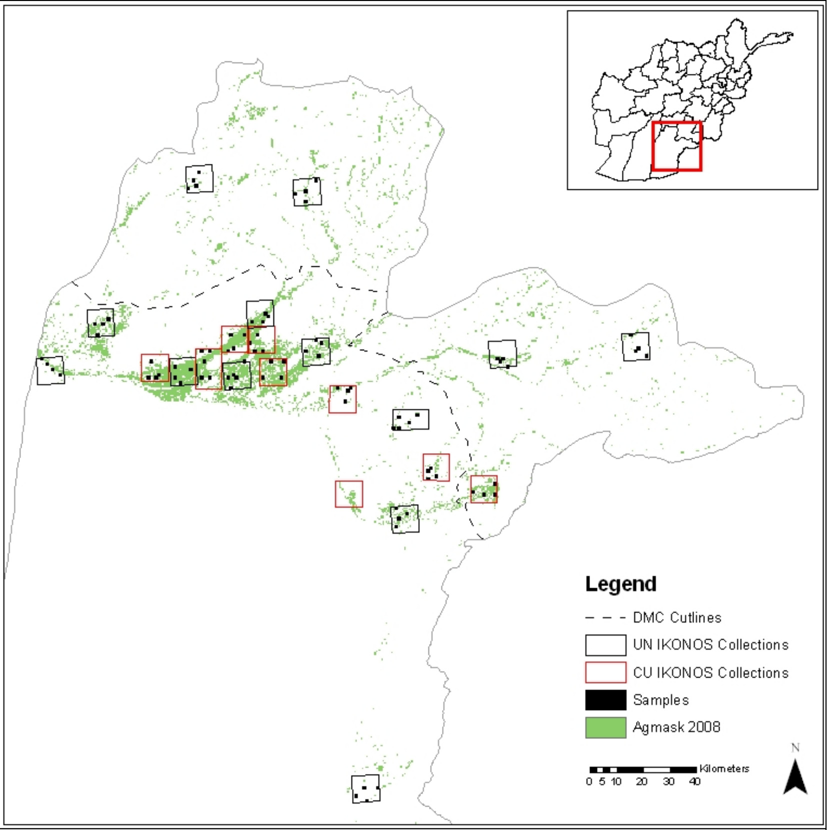
2008 Samples and Active Agriculture Kandahar



IKONOS imagery used in Uruzgan

Cranfield UNIVERSITY

LOCATION	SOURCE	DATE
uruz_a0	CU	13/04/2008
uruz_b0	CU	13/04/2008
uruz004	UN	16/04/2008
uruz005	UN	13/04/2008
uruz178	UN	22/05/2008
uruz199	UN	05/05/2008
uruz206	UN	13/04/2008

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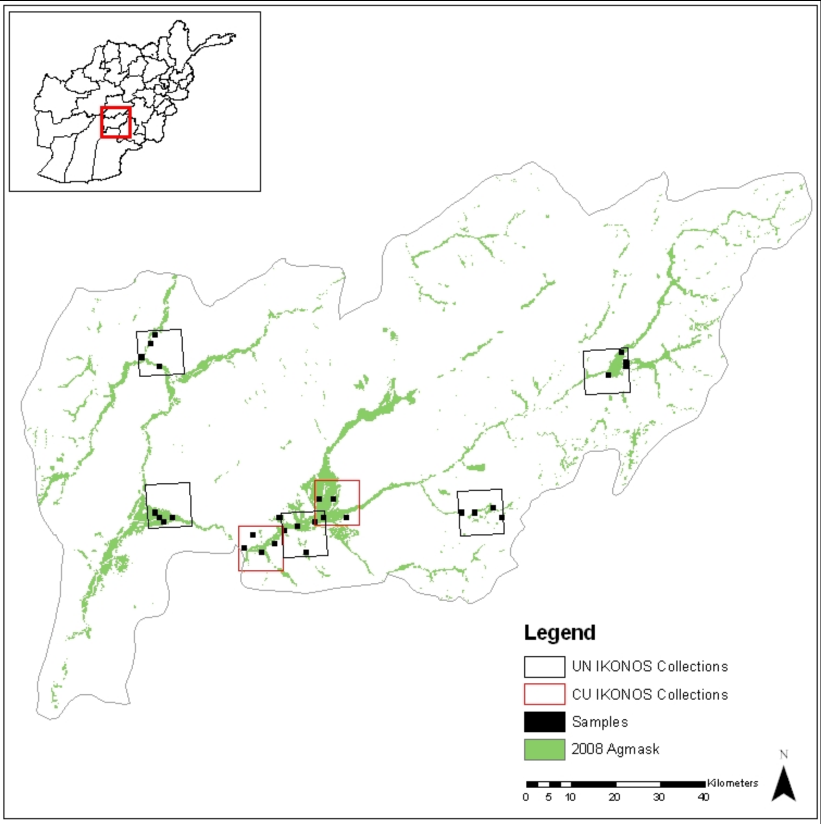
2008 Samples and Active Agriculture Uruzgan



IKONOS imagery used in Nangarhar

Cranfield UNIVERSITY

LOCATION	SOURCE	DATE
nan_a0	CU	28/03/2008
nan_d0	CU	30/03/2008
nan_i0	CU	18/04/2008
nan_j0	CU	18/04/2008
nan_k0	CU	02/05/2008
nan02	UN	27/04/2008
nan07	UN	16/04/2008
nan11	UN	02/04/2008
nan12	UN	27/03/2008
nan25	UN	02/04/2008
nan29	UN	27/03/2008
nan34	UN	16/04/2008
nan39	UN	02/04/2008
nan46	UN	27/04/2008
nazyan	UN	30/03/2008

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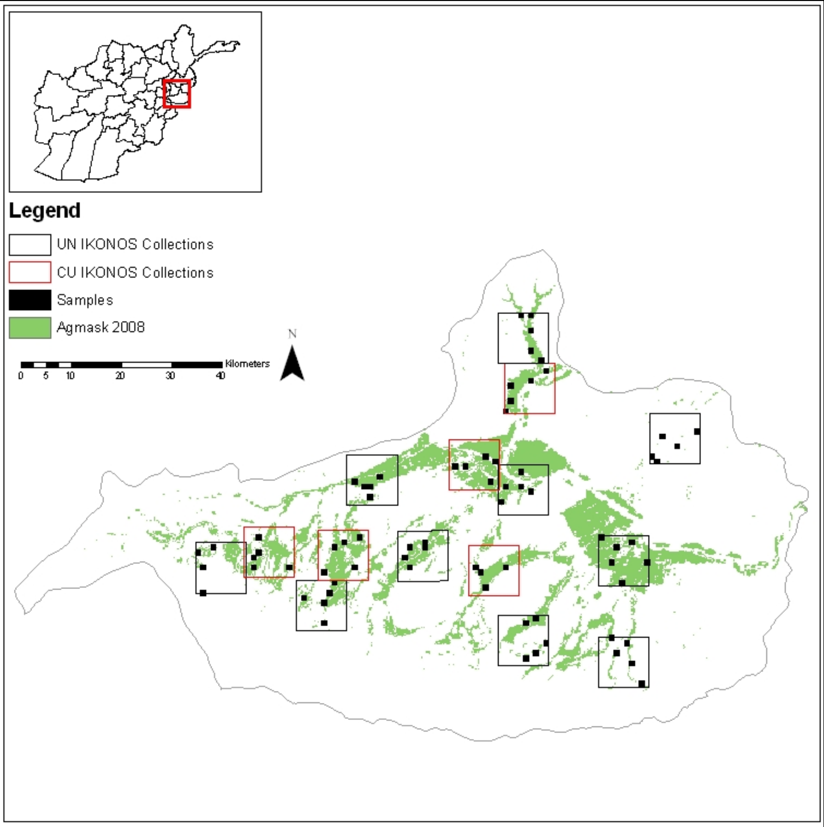
2008 Samples and Active Agriculture Nangarhar



IKONOS used in Farah and Nimroz

LOCATION	SOURCE	DATE
Farah001	UN	11/05/08
Farah018	UN	11/05/08
Farah052	UN	11/05/08
Farah057	UN	11/05/08
Farah098	UN	11/05/08
Farah100	UN	08/05/08
Kompsat2	CU	02/04/08

LOCATION	SOURCE	DATE
Nimr_g0	CU	28/03/08
Nimroz1	UN	23/03/08
Nimroz1	UN	23/03/08
Nimroz1	UN	23/03/08
Nimroz1	UN	11/05/08

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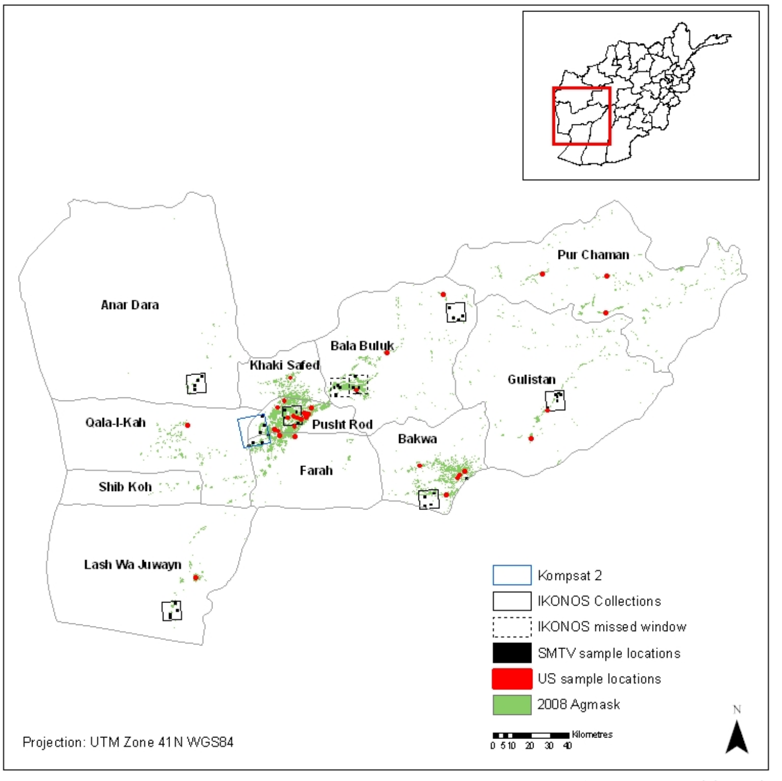
2008 Samples and Active Agriculture Farah



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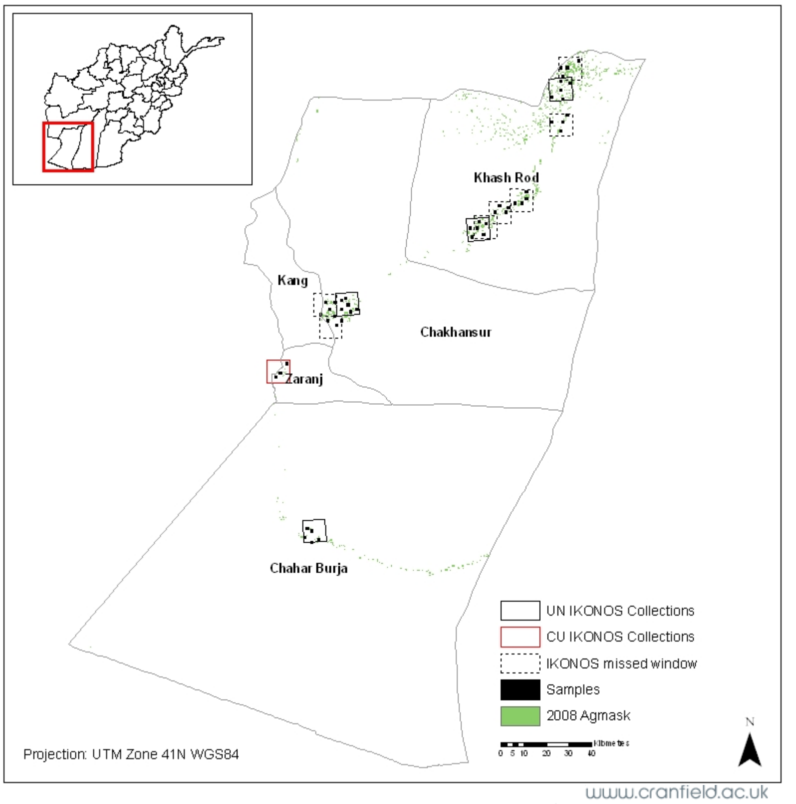
2008 Samples and Active Agriculture Nimroz



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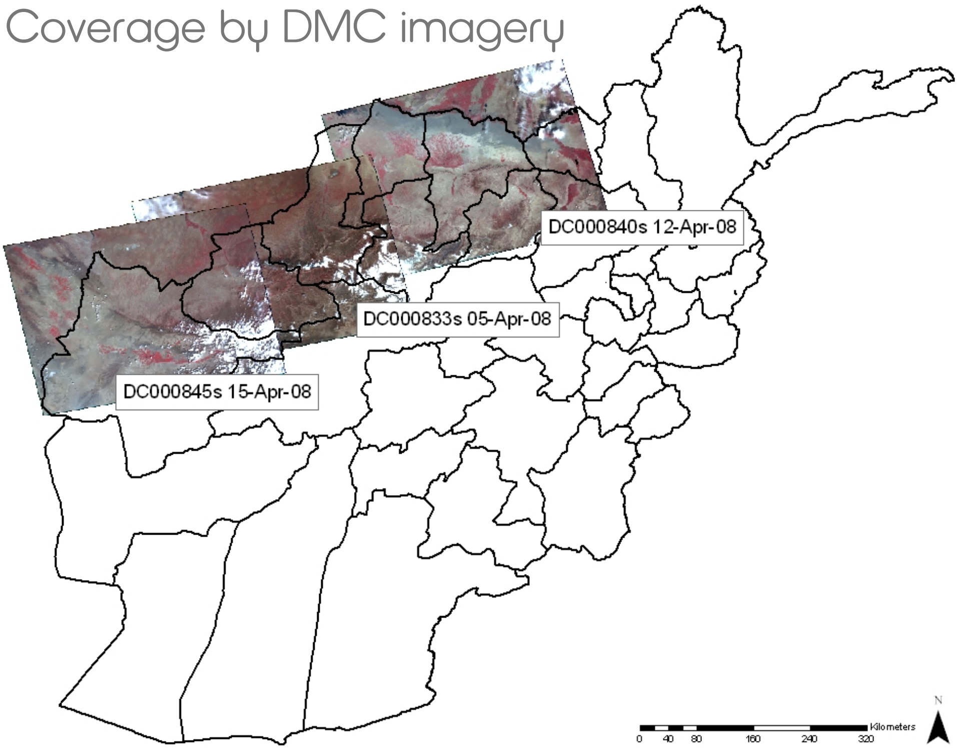
2008 Coverage by DMC imagery



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IKONOS used in Badghis

Cranfield UNIVERSITY

LOCATION	SOURCE	DATE
Badghis1	UN	14/05/2008
Badghis2	UN	14/05/2008
Badghis3	UN	14/05/2008
Badghis4	UN	14/05/2008

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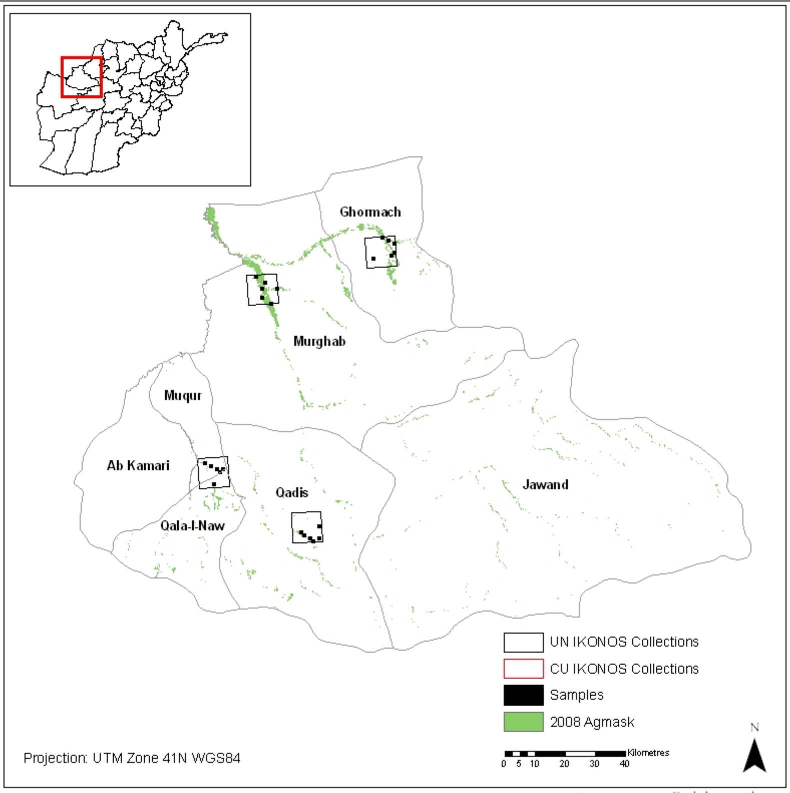
2008 Samples and Active Agriculture Badghis



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IKONOS imagery used in Balkh

Cranfield UNIVERSITY

LOCATION	SOURCE	DATE
Balkh01	CU	30/04/2008
Balkh02	UN	30/04/2008
Balkh03	CU	30/04/2008
Balkh04	CU	05/05/2008
Balkh05	UN	05/05/2008
Balkh06	UN	05/05/2008
Balkh07	CU	30/04/2008
Balkh10	UN	11/04/2008
Balkh11	UN	11/05/2008
Balkh_a	CU	05/07/2008
Balkh_b	CU	29/06/2008

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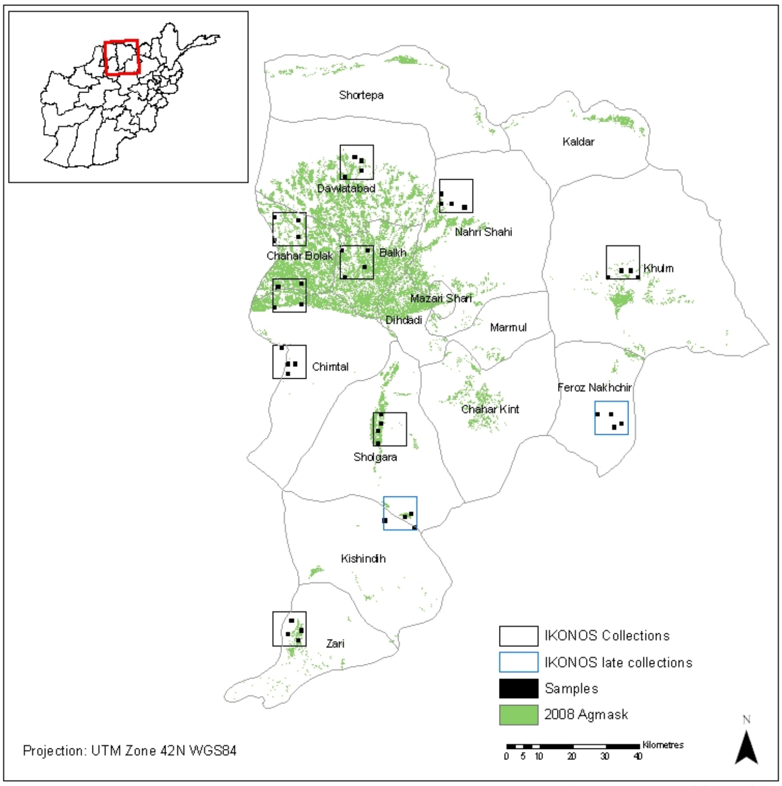
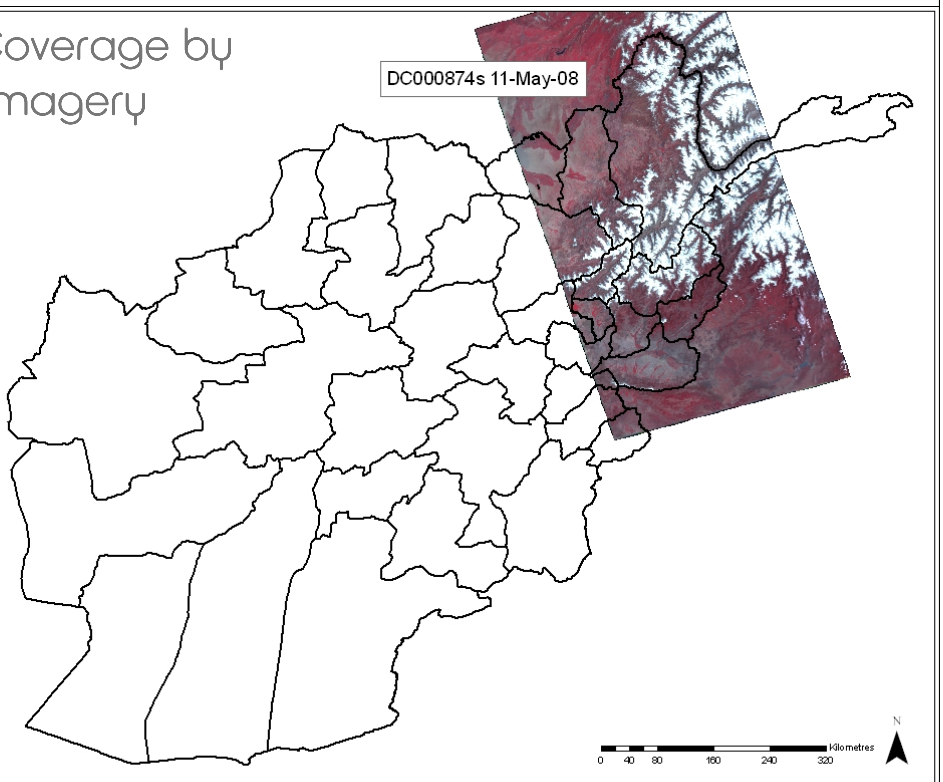
2008 Samples and Active Agriculture Balkh



www.cranfield.ac.uk

2008 Coverage by DMC imagery



www.cranfield.ac.uk

IKONOS used in Badakhshan

LOCATION	SOURCE	DATE
Bada01	UN	02/06/08
Bada02	UN	02/06/08
Bada05	UN	30/05/08
Bada12	UN	02/06/08
Bada26	UN	02/06/08
Bada31	UN	02/06/08
Bada44	UN	04/06/08
Bada55	UN	08/05/08
Bada79	UN	04/06/08
Bada_b0	CU	18/06/08
Bada_c0	CU	02/06/08

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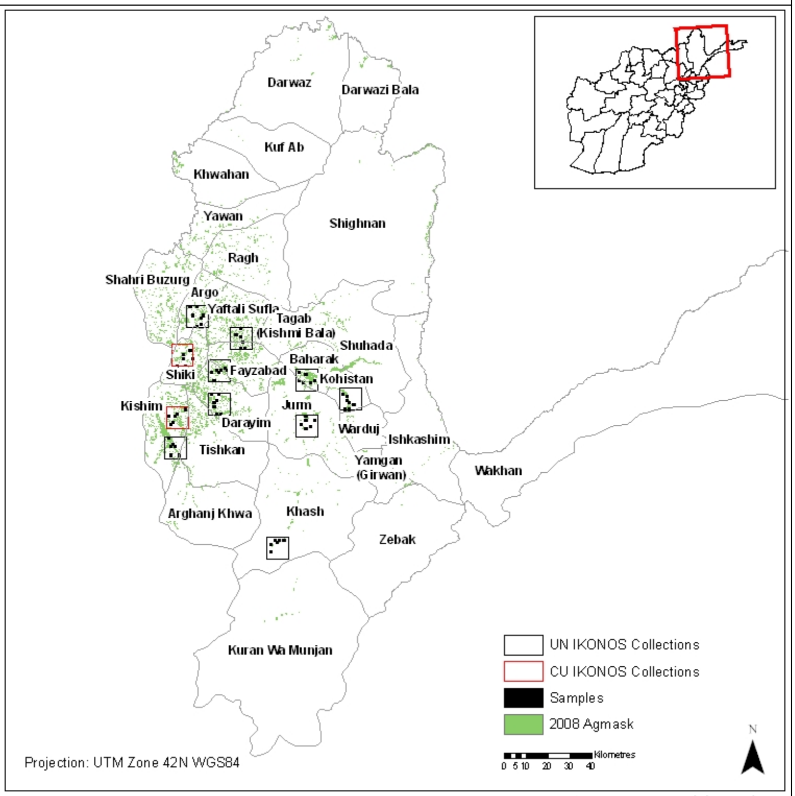
2008 Samples and Active Agriculture Badakhshan



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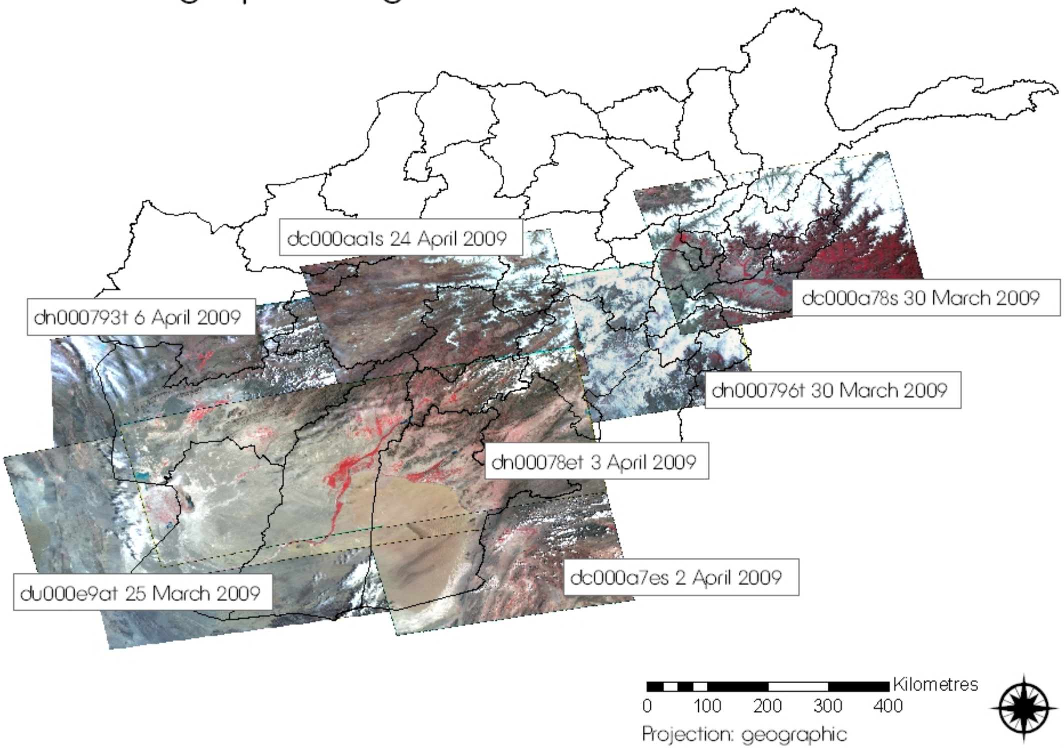
DMC imagery coverage 2009

Cranfield UNIVERSITY



IKONOS image collections

Cranfield UNIVERSITY

Helmand

Location	Source	Date
held_c01	CU	25/03/2009
held_c02	CU	25/03/2009
held_c03	CU	25/03/2009
held_c04	CU	25/03/2009
held_c05	CU	25/03/2009
held_c06	CU	25/03/2009
held_c07	CU	25/03/2009
held_c08	CU	25/03/2009
held_c09	CU	25/03/2009
held_c10	CU	25/03/2009
held_c11	CU	03/04/2009
held_c12	CU	03/04/2009
held000	UN	08/04/2009
held115	UN	08/04/2009
held124	UN	08/04/2009
held005	UN	11/04/2009
held057	UN	11/04/2009
held059	UN	11/04/2009
held081	UN	11/04/2009
held087	UN	11/04/2009
held045	UN	14/04/2009
held006	UN	25/04/2009
held007	UN	25/04/2009
held054	UN	25/04/2009
held103	UN	25/04/2009
held108	UN	25/04/2009
held004	UN	30/04/2009
held011	UN	30/04/2009
held040	UN	06/05/2009
held001	UN	25/05/2009
held002	UN	25/05/2009
held003	UN	25/05/2009

Kandahar

Location	Source	Date
kand_c01	CU	29/04/2009
kand_c03	CU	14/04/2009
kand_c06	CU	02/04/2009
kand001	UN	30/04/2009
kand002	UN	14/04/2009
kand003	UN	30/04/2009
kand004	UN	19/05/2009
kand005	UN	19/05/2009
kand006	UN	16/05/2009
kand007	UN	22/05/2009
kand008	UN	08/05/2009
kand009	UN	06/05/2009
kand010	UN	08/04/2009
kand017	UN	05/05/2009
kand052	UN	17/05/2009
kand053	UN	14/04/2009
kand073	UN	05/05/2009
kand077	UN	17/05/2009
kand078	UN	16/05/2009
kand084	UN	30/04/2009
kand088	UN	05/05/2009
kand135	UN	08/04/2009
kand143	UN	02/04/2009

Uruzgan

Location	Source	Date
uruz_c01	CU	27/04/2009
uruz_c03	CU	27/04/2009
uruz_c04	CU	05/05/2009
uruz001	UN	05/05/2009
uruz002	UN	08/04/2009
uruz003	UN	08/04/2009
uruz004	UN	08/04/2009
uruz005	UN	05/05/2009
uruz006	UN	08/04/2009
uruz007	UN	03/04/2009
uruz178	UN	08/05/2009
uruz199	UN	03/04/2009
uruz206	UN	05/05/2009

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IKONOS image collections

Farah

Location	Source	Date
fara_c01	CU	03/04/2009
fara_c07	CU	30/04/2009
fara001	UN	17/04/2009
fara002	UN	30/04/2009
fara003	UN	09/04/2009
fara004	UN	17/05/2009
fara005	UN	17/05/2009
fara006	UN	17/05/2009
fara007	UN	17/05/2009
fara008	UN	09/04/2009
fara009	UN	09/04/2009
fara018	UN	30/04/2009
fara052	UN	09/04/2009
fara057	UN	09/04/2009
fara098	UN	17/05/2009
fara100	UN	22/05/2009

Nimroz

Location	Source	Date
nimr_c03	CU	03/04/2009
nimr001	UN	26/03/2009
nimr002	UN	20/03/2009
nimr003	UN	20/03/2009
nimr004	UN	03/04/2009
nimr005	UN	20/03/2009
nimr006	UN	20/03/2009
nimr007	UN	20/03/2009
nimr008	UN	03/04/2009
nimr009	UN	08/04/2009
nimr010	UN	08/04/2009

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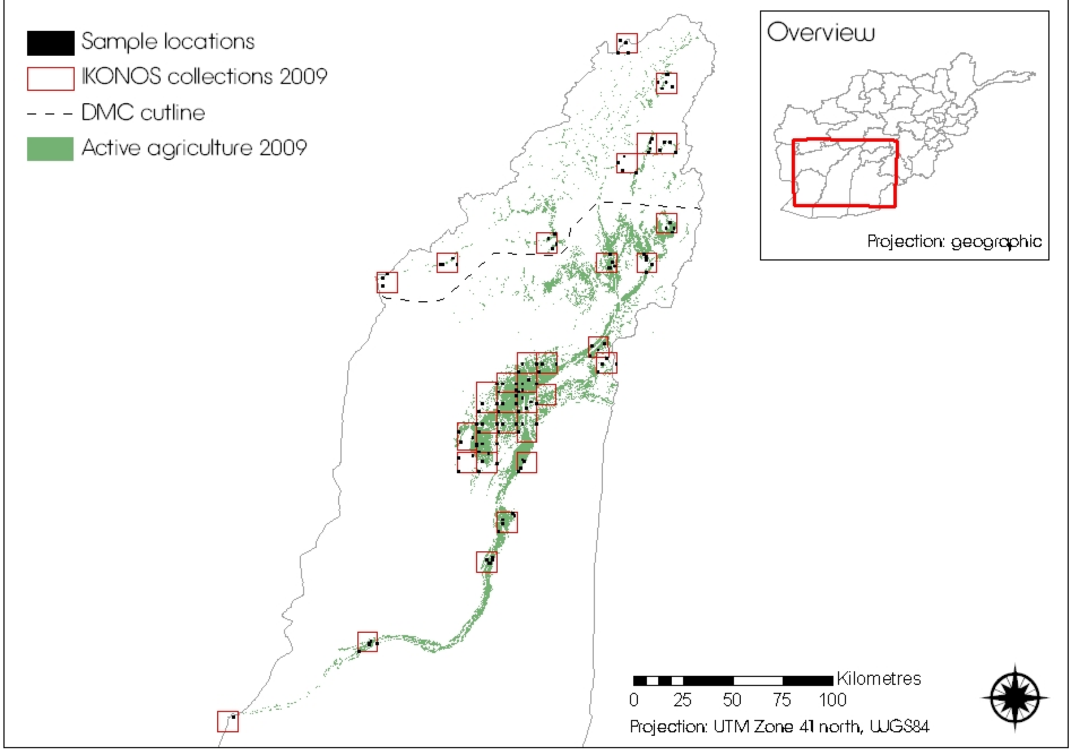
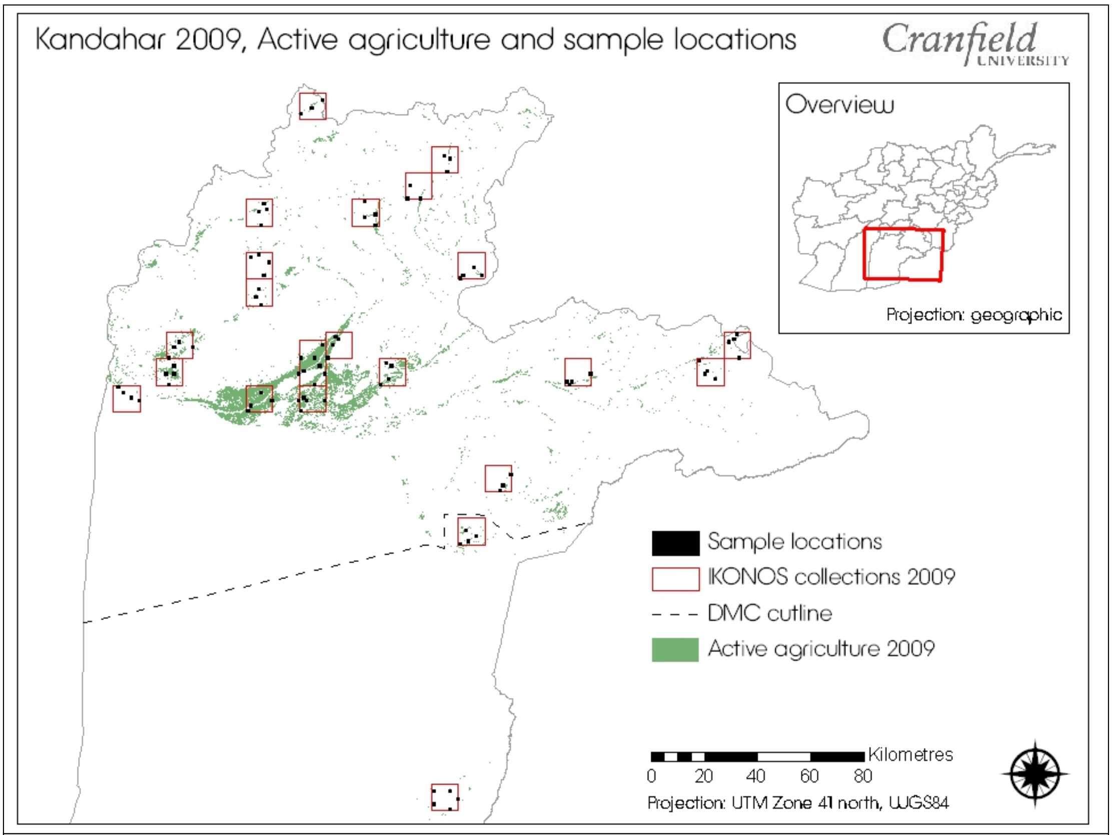
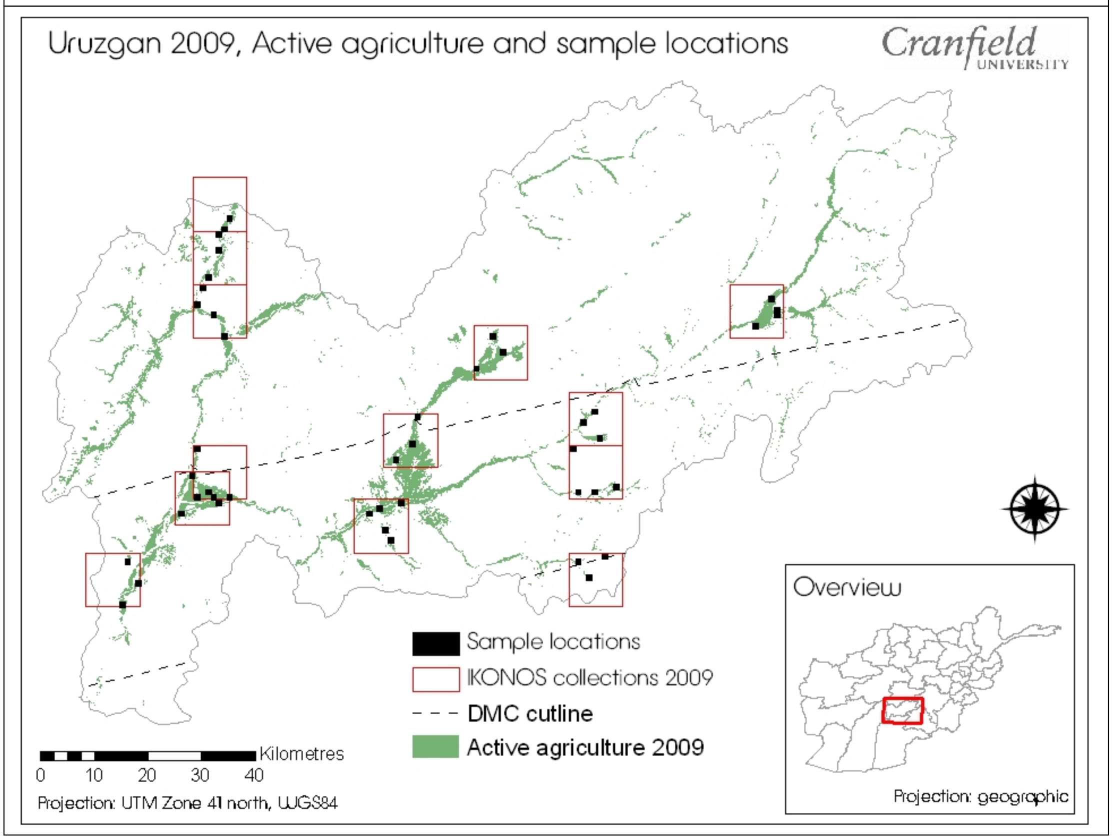
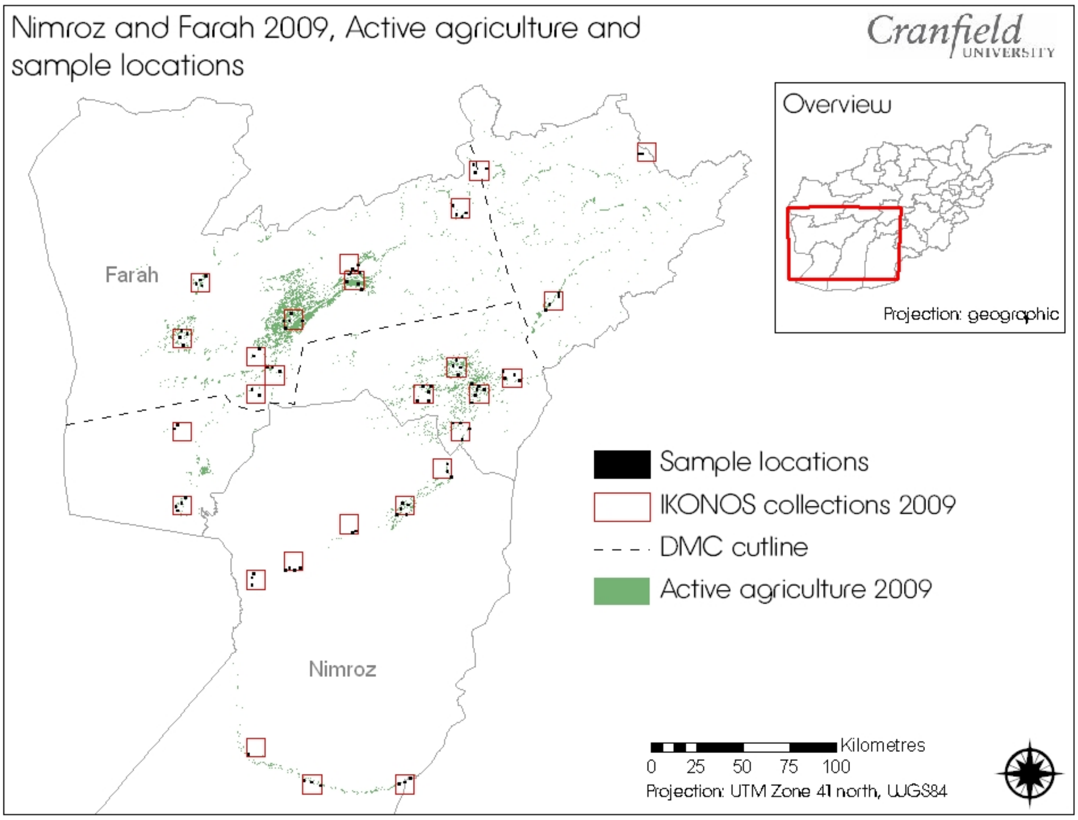
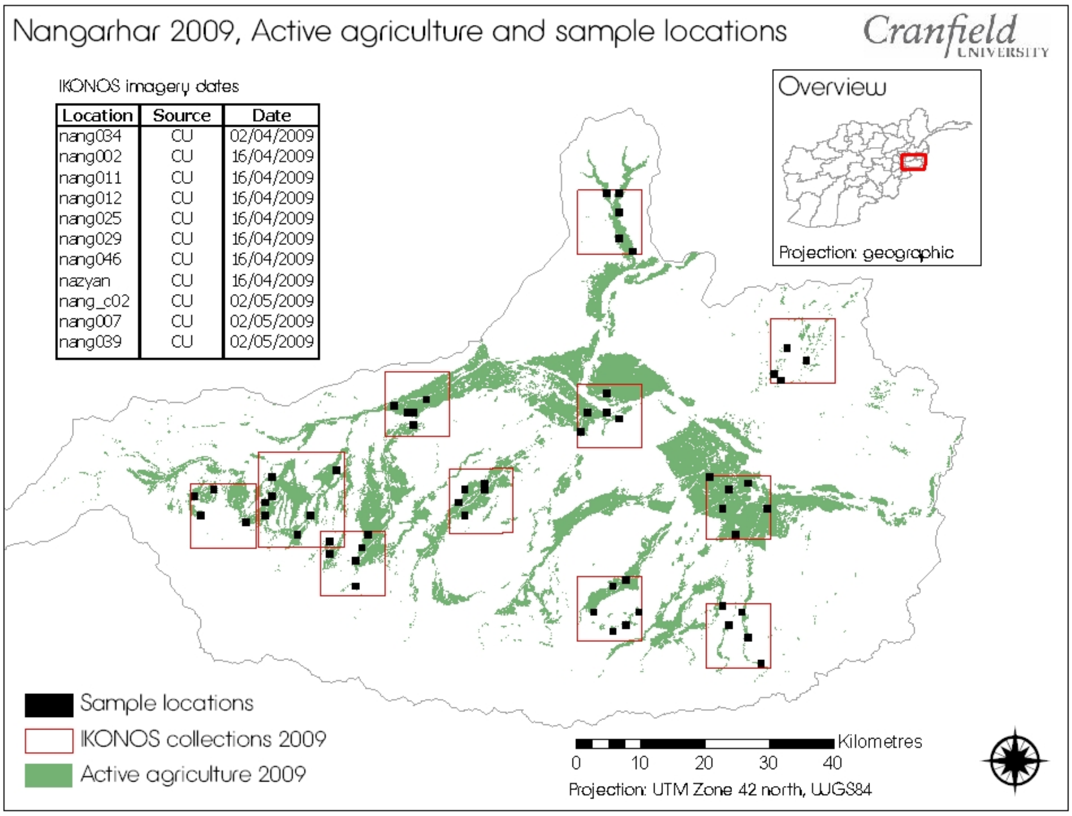
Helmand 2009, Active agriculture and sample locations




Kandahar 2009, Active agriculture and sample locations
Cranfield UNIVERSITY
Overview
Projection: geographic
Sample locations
IKONOS collections 2009
DMC cutline
Active agriculture 2009
Kilometres
0 20 40 60 80
Projection: UTM Zone 41 north, WGS84

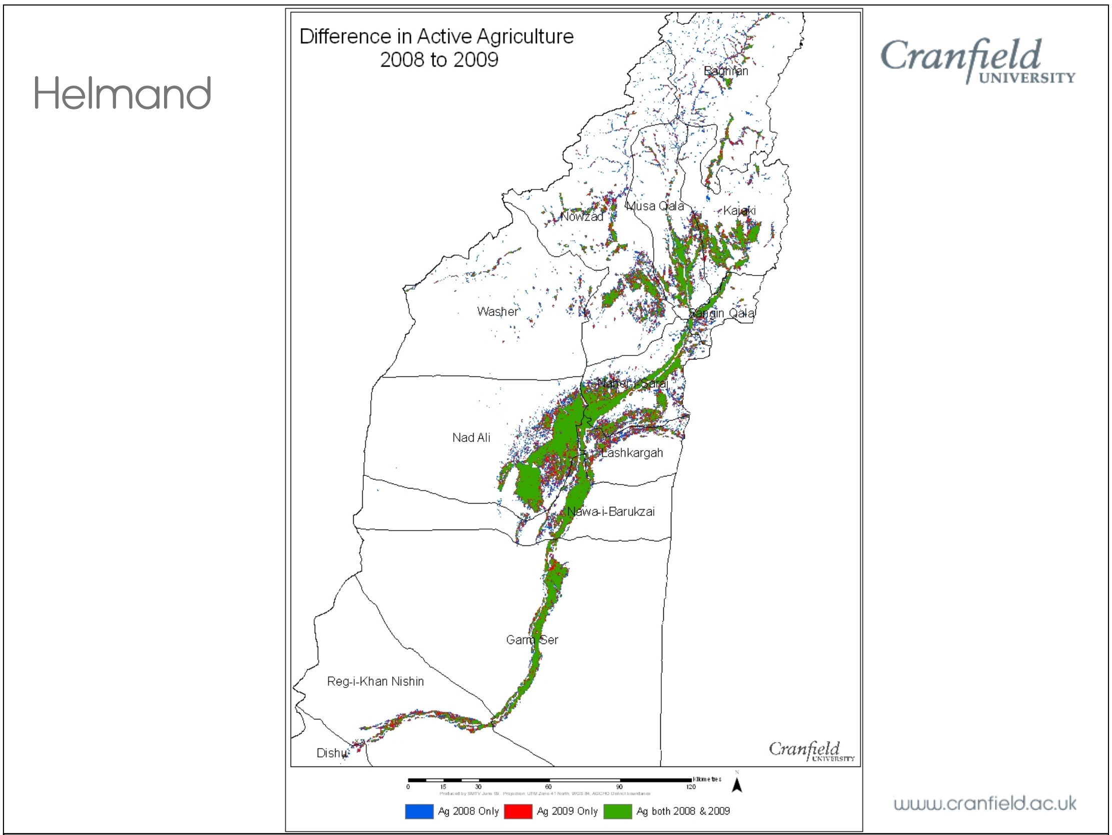

Uruzgan 2009, Active agriculture and sample locations
Cranfield UNIVERSITY
Overview
Projection: geographic
Sample locations
IKONOS collections 2009
DMC cutline
Active agriculture 2009
Kilometres
0 10 20 30 40
Projection: UTM Zone 41 north, WGS84

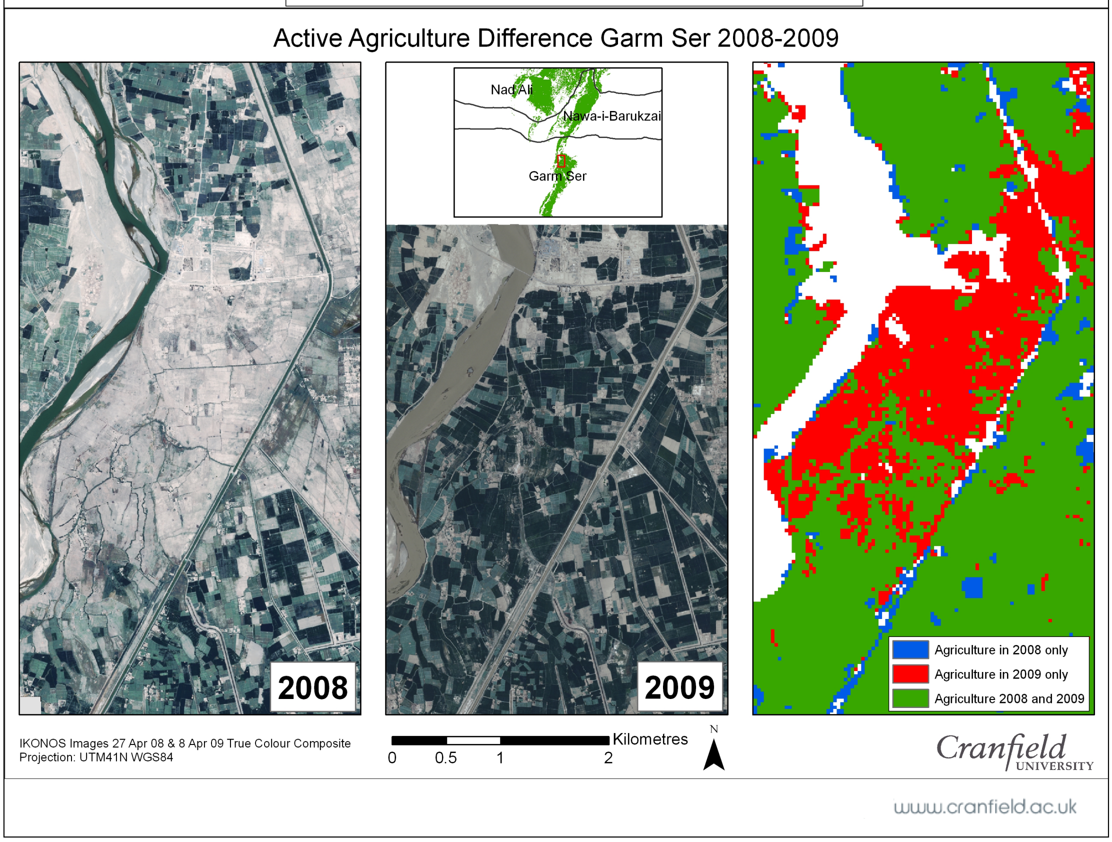


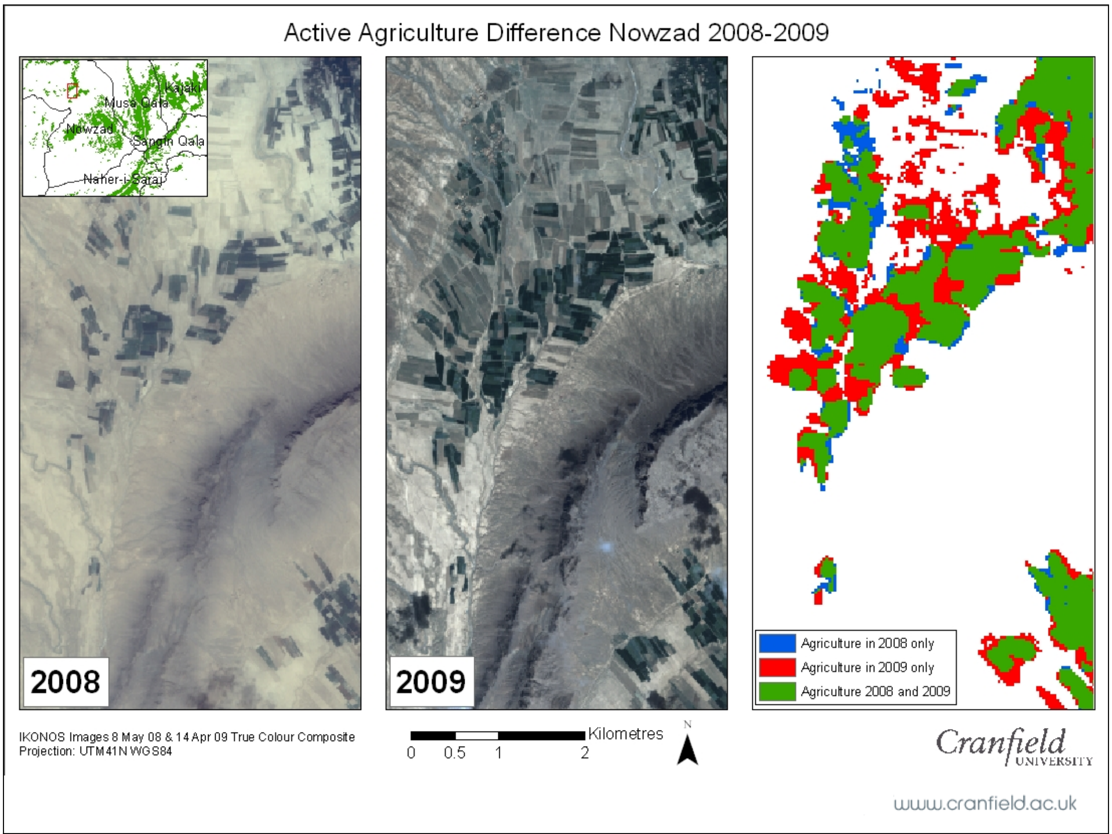


Location	Source	Date
nang034	CU	02/04/2009
nang002	CU	16/04/2009
nang011	CU	16/04/2009
nang012	CU	16/04/2009
nang025	CU	16/04/2009
nang029	CU	16/04/2009
nang046	CU	16/04/2009
nazyan	CU	16/04/2009
nang_c02	CU	02/05/2009
nang007	CU	02/05/2009
nang039	CU	02/05/2009

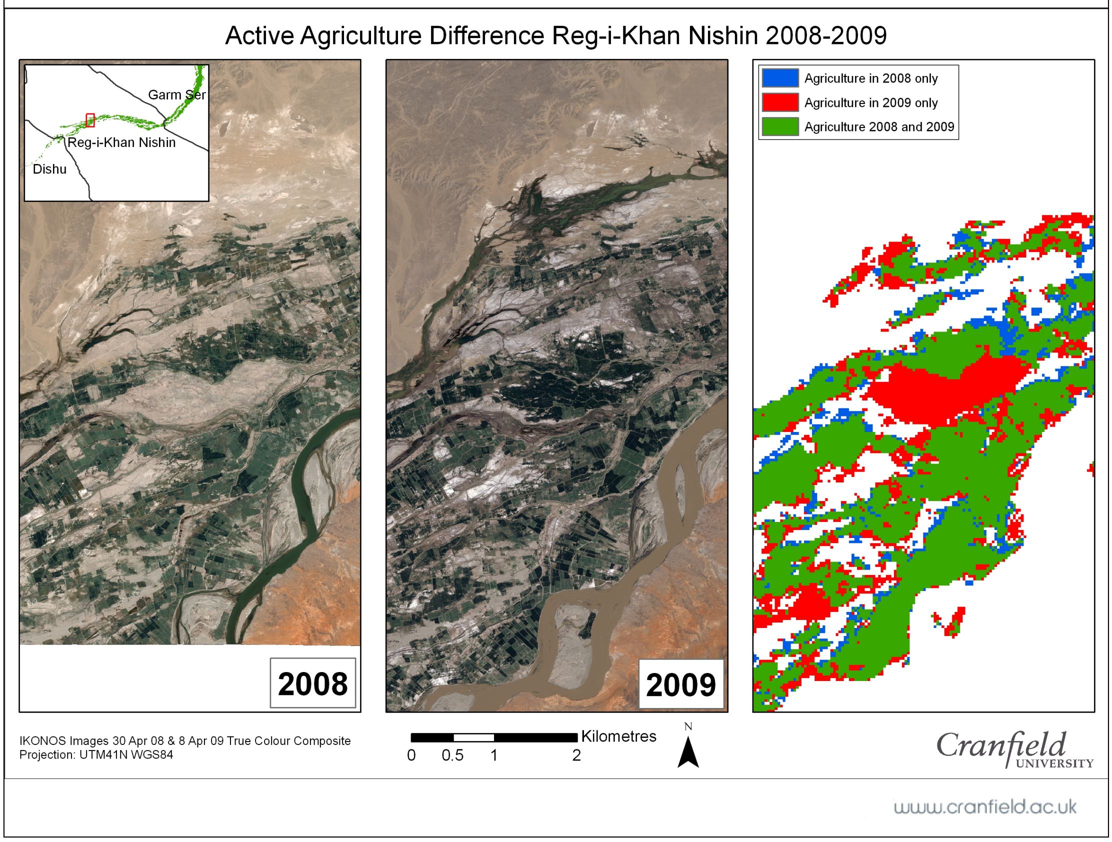
Appendix B
Changes in agricultural masks: 2008–2009


Helmand
Difference in Active Agriculture
2008 to 2009
Baghran
Musa Qala
Kajaki
Nowzad
Washer
Sangin Qala
Nad Ali
Lashkargah
Nawa-i-Barukzai
Garm Ser
Reg-i-Khan Nishin
Dishu
Cranfield UNIVERSITY
Ag 2008 Only
Ag 2009 Only
Ag both 2008 & 2009
Cranfield UNIVERSITY
www.cranfield.ac.uk

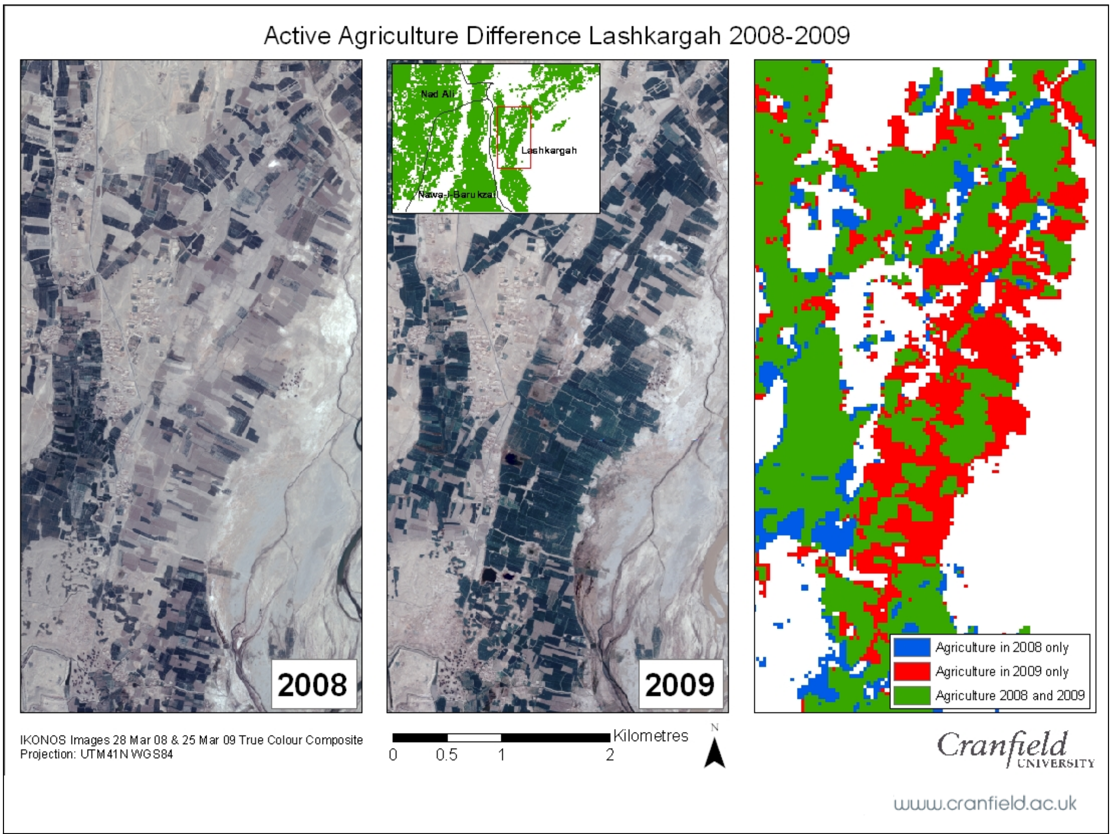

Active Agriculture Difference Garm Ser 2008-2009
Nad Ali
Nawa-i-Barukzai
Garm Ser
2008
2009
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 and 2009
IKONOS Images 27 Apr 08 & 8 Apr 09 True Colour Composite
Projection: UTM41N WGS84
Kilometres
0 0.5 1 2
N
Cranfield UNIVERSITY
www.cranfield.ac.uk

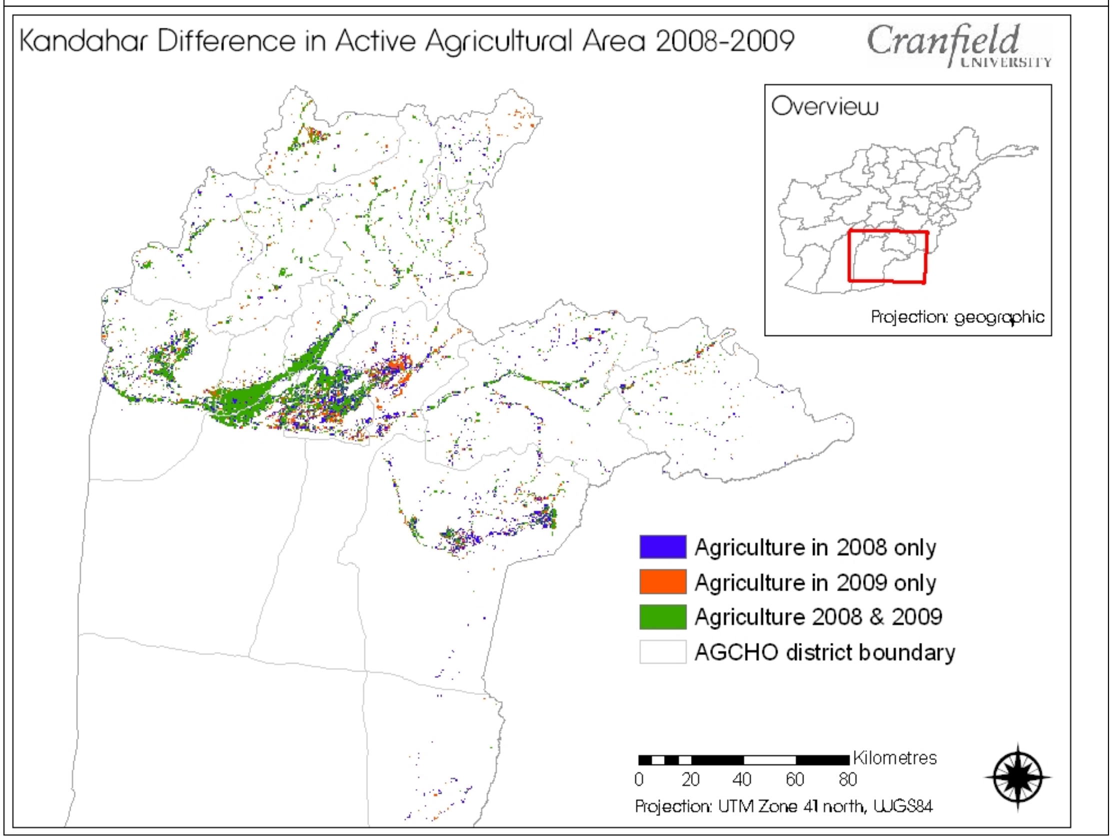


Active Agriculture Difference Nowzad 2008-2009
Kajaki
Musa Qala
Nowzad
Sangin Qala
Naher-i-Saraj
2008
2009
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 and 2009
IKONOS Images 8 May 08 & 14 Apr 09 True Colour Composite
Projection: UTM41N WGS84
Kilometres
0 0.5 1 2
N
Cranfield UNIVERSITY
www.cranfield.ac.uk

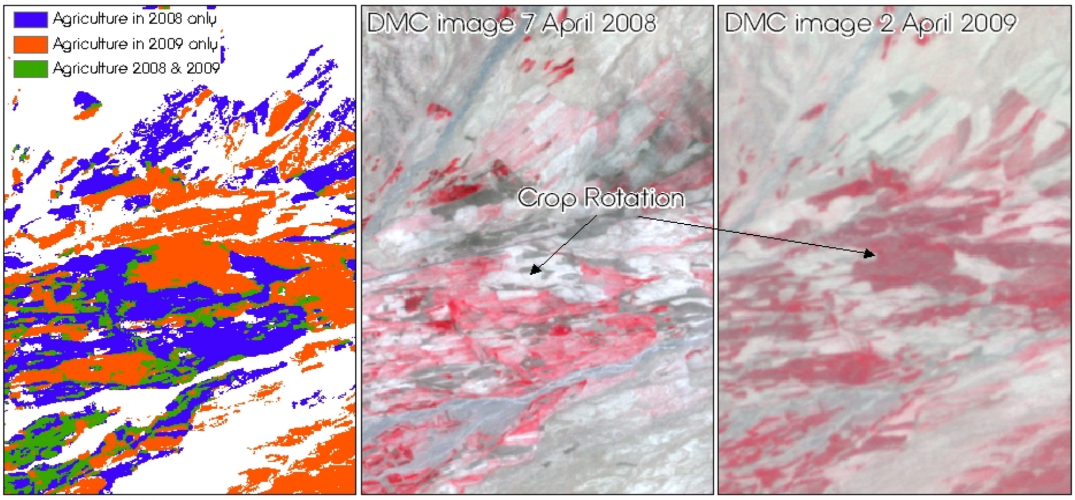


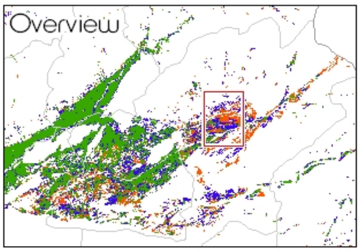
Active Agriculture Difference Reg-i-Khan Nishin 2008-2009
Garm Ser
Reg-i-Khan Nishin
Dishu
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 and 2009
2008
2009
IKONOS Images 30 Apr 08 & 8 Apr 09 True Colour Composite
Projection: UTM41N WGS84
Kilometres
0 0.5 1 2
N
Cranfield UNIVERSITY
www.cranfield.ac.uk


Active Agriculture Difference Lashkargah 2008-2009
Nad Ali
Lashkargah
2008
2009
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 and 2009
IKONOS Images 28 Mar 08 & 25 Mar 09 True Colour Composite
Projection: UTM41N WGS84
0 0.5 1 2 Kilometres
N
Cranfield UNIVERSITY
www.cranfield.ac.uk


Kandahar Difference in Active Agricultural Area 2008-2009
Cranfield UNIVERSITY
Overview
Projection: geographic
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 & 2009
AGCHO district boundary
0 20 40 60 80 Kilometres
Projection: UTM Zone 41 north, WGS84

Kandahar Difference in Active Agricultural Area 2008-2009



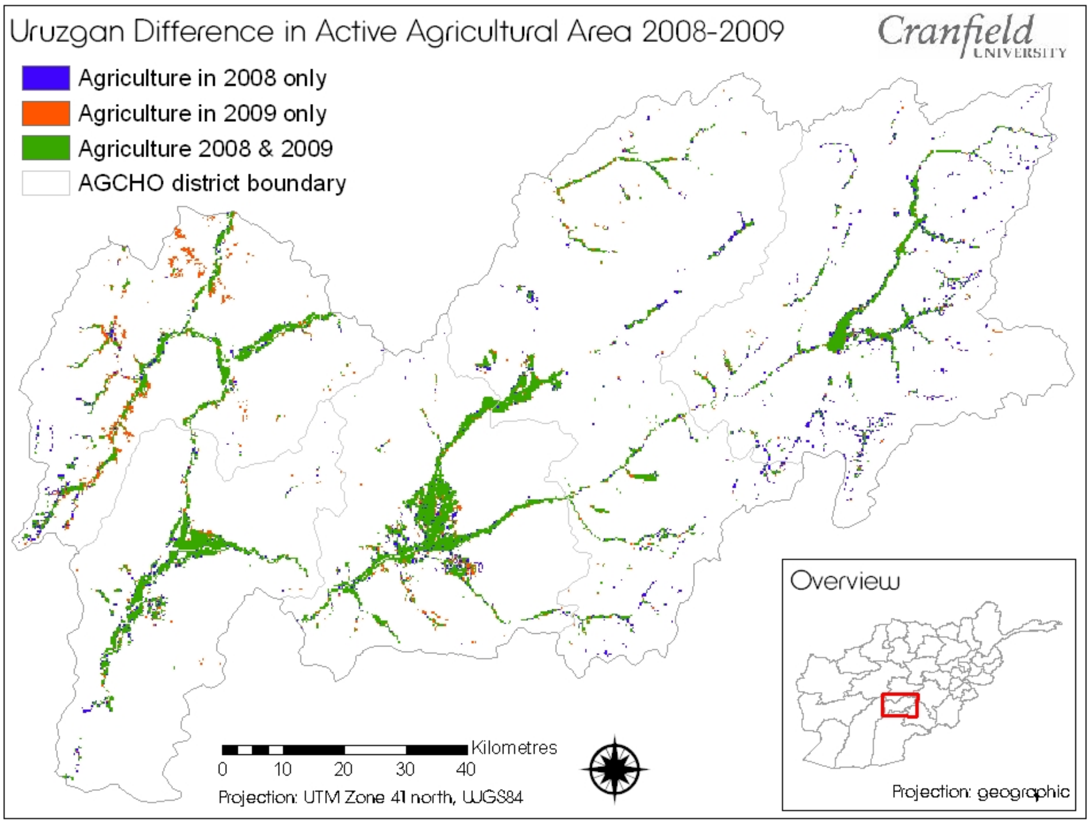


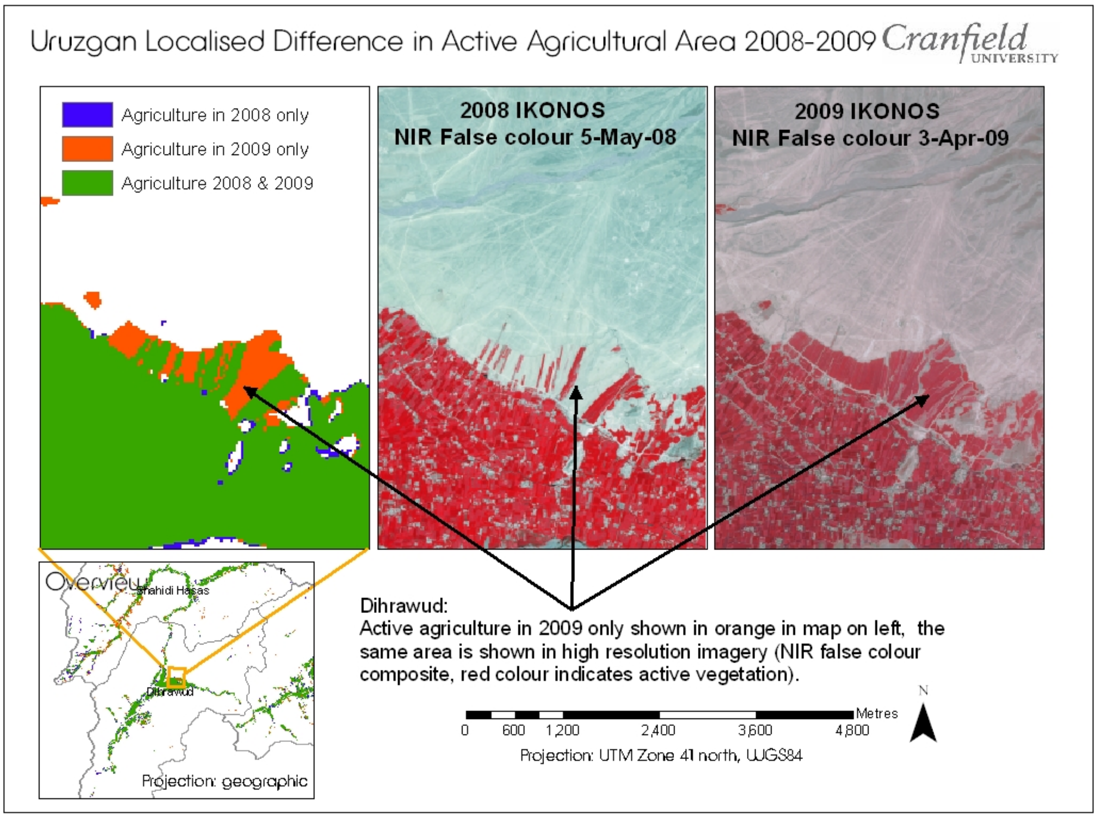
A significant rotation of agricultural land can be seen in this area of Kandahar in the difference map produced from the active agricultural areas in 2008 and 2009. The DMC imagery from 2008 shows a weaker near-infrared response in the vegetated areas than in 2009, which is attributed to the poor growing conditions of the 2008 season.

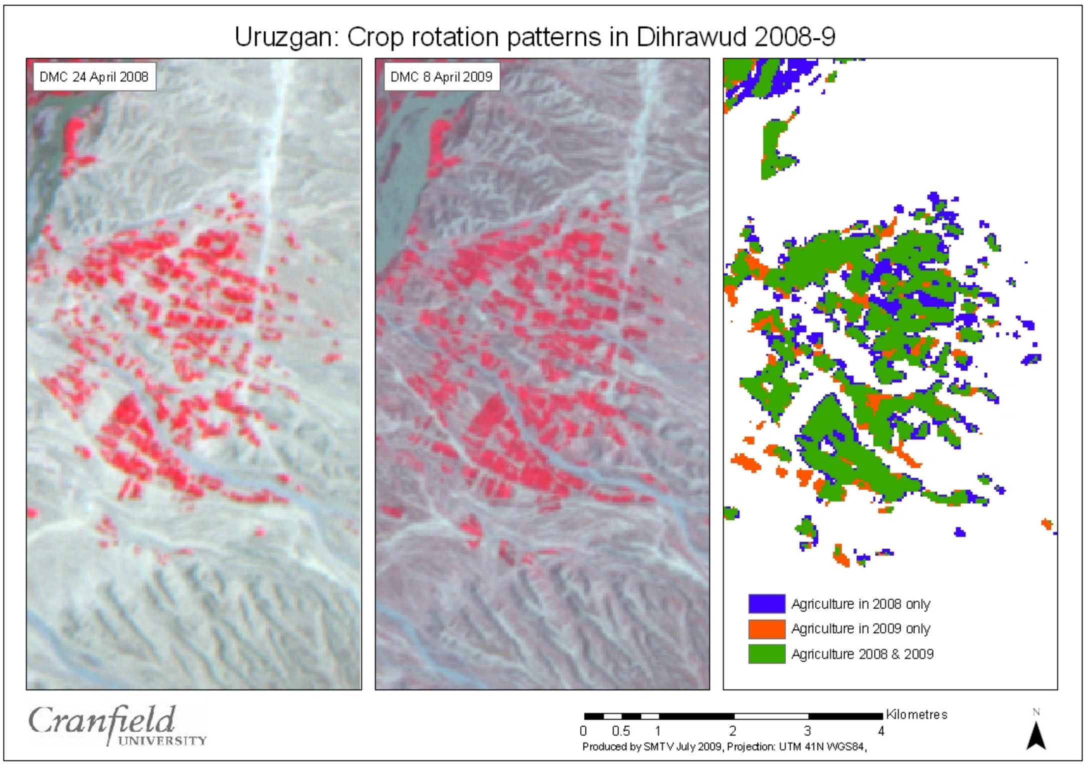
Kilometres 0 1 2 3 4

Projection: UTM Zone 41 north, WGS84

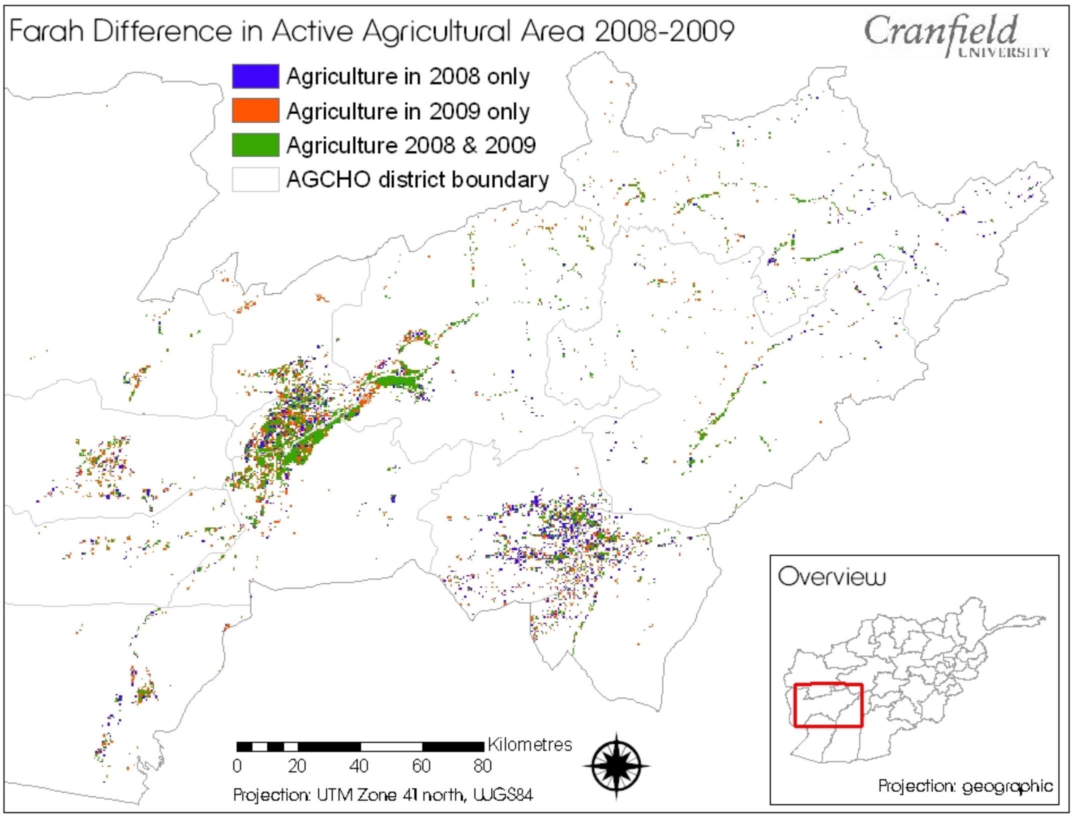
Uruzgan Difference in Active Agricultural Area 2008-2009

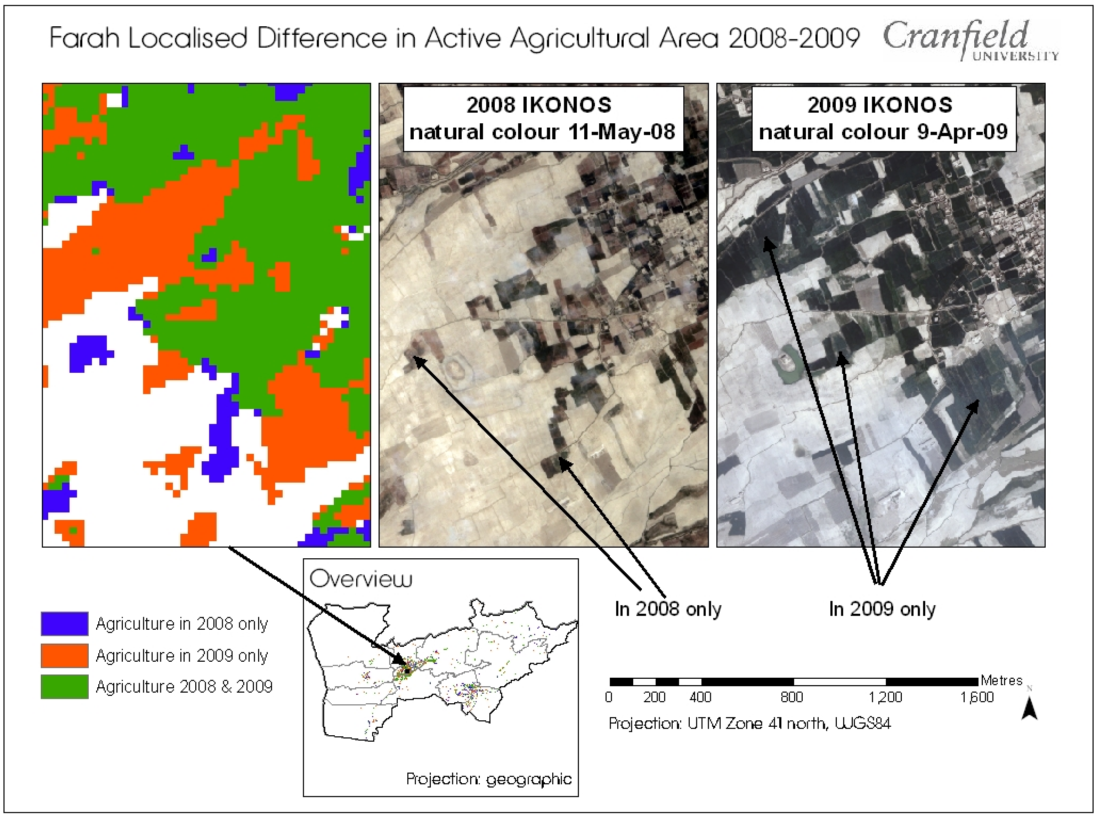


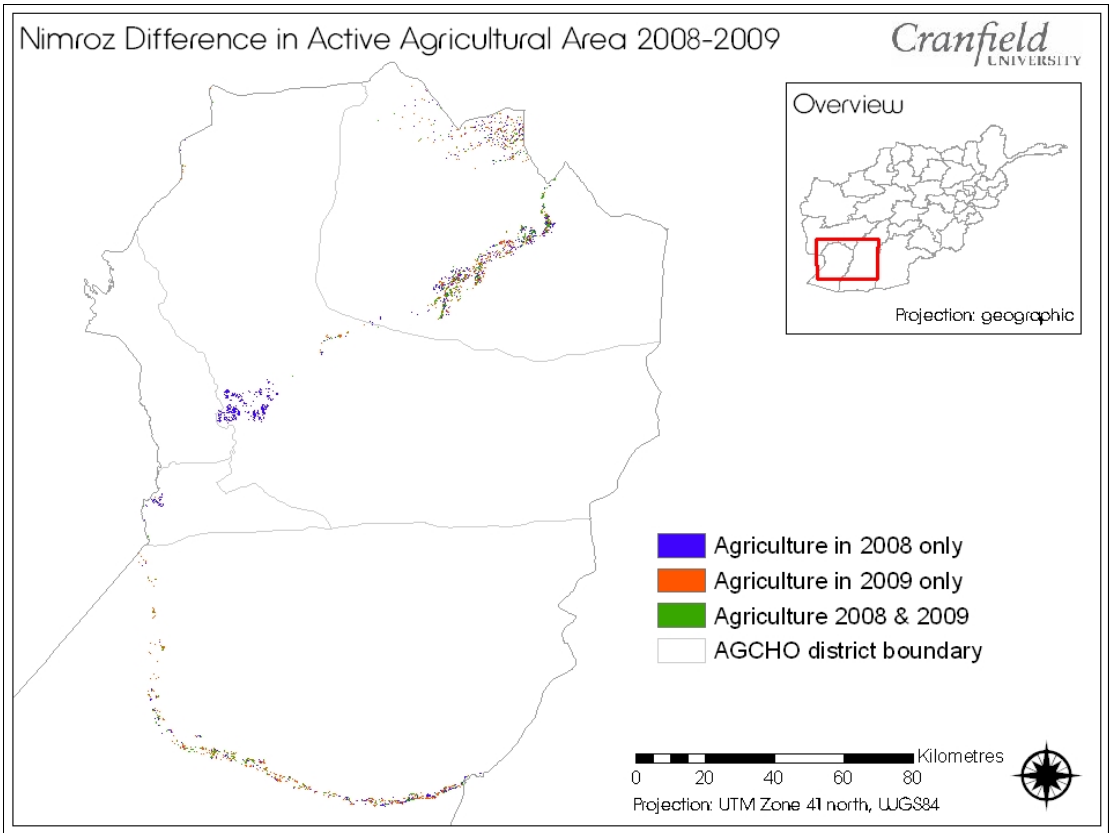


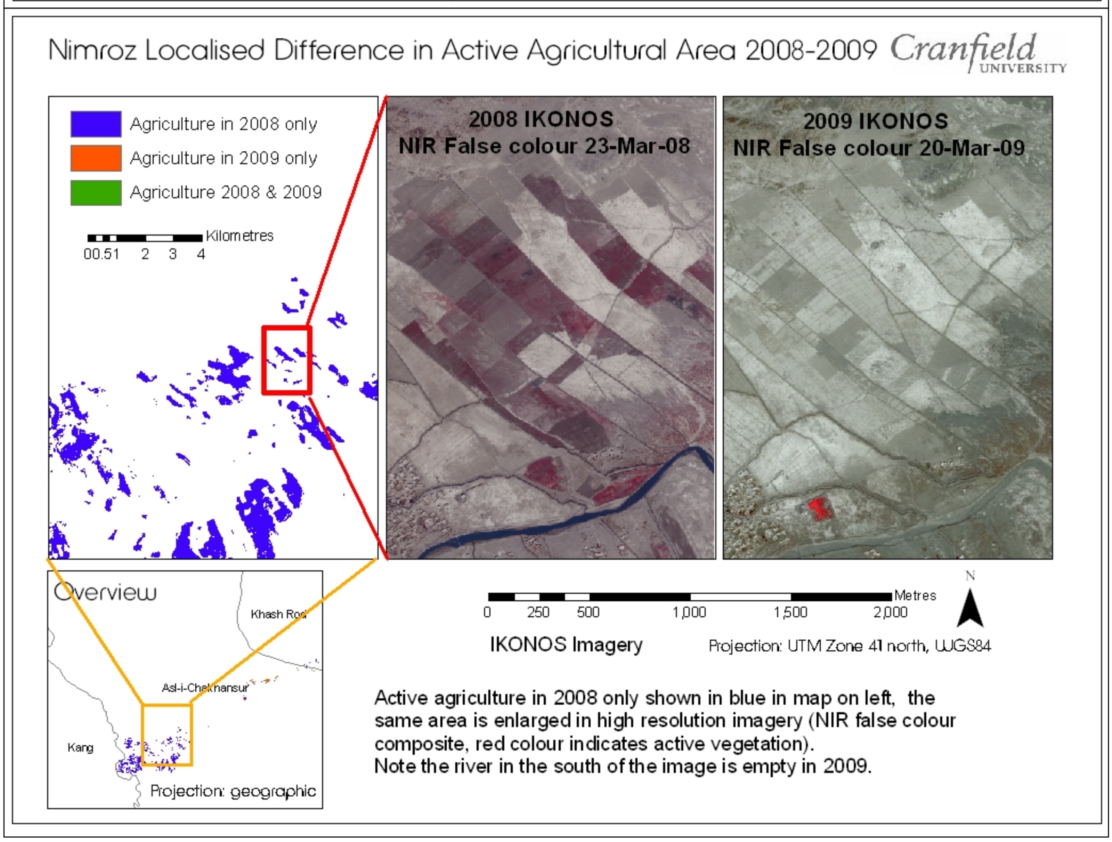


www.cranfield.ac.uk

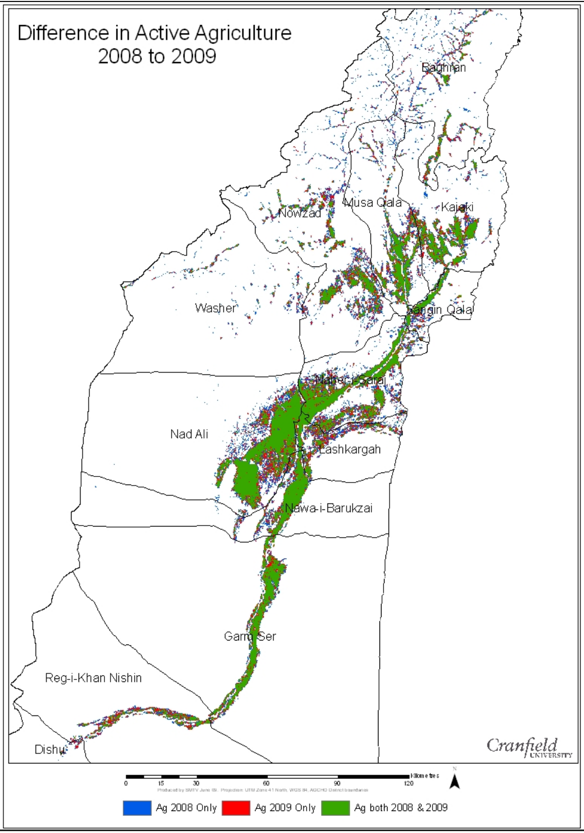

Farah Difference in Active Agricultural Area 2008-2009
Cranfield UNIVERSITY
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 & 2009
AGCHO district boundary
Kilometres
0 20 40 60 80
Projection: UTM Zone 41 north, WGS84
Overview
Projection: geographic


Farah Localised Difference in Active Agricultural Area 2008-2009
Cranfield UNIVERSITY
2008 IKONOS
natural colour 11-May-08
2009 IKONOS
natural colour 9-Apr-09
In 2008 only
In 2009 only
Overview
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 & 2009
Metres
0 200 400 800 1,200 1,600
Projection: UTM Zone 41 north, WGS84
Projection: geographic


Nimroz Difference in Active Agricultural Area 2008-2009
Cranfield UNIVERSITY
Overview
Projection: geographic
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 & 2009
AGCHO district boundary
Kilometres
0 20 40 60 80
Projection: UTM Zone 41 north, WGS84


Nimroz Localised Difference in Active Agricultural Area 2008-2009
Cranfield UNIVERSITY
Agriculture in 2008 only
Agriculture in 2009 only
Agriculture 2008 & 2009
Kilometres
0 0.5 1 2 3 4
2008 IKONOS
NIR False colour 23-Mar-08
2009 IKONOS
NIR False colour 20-Mar-09
Overview
Khash Rod
Asl-i-Chakhansur
Kang
Projection: geographic
Metres
0 250 500 1,000 1,500 2,000
N
IKONOS Imagery
Projection: UTM Zone 41 north, WGS84
Active agriculture in 2008 only shown in blue in map on left, the same area is enlarged in high resolution imagery (NIR false colour composite, red colour indicates active vegetation).
Note the river in the south of the image is empty in 2009.

Helmand



Cranfield UNIVERSITY

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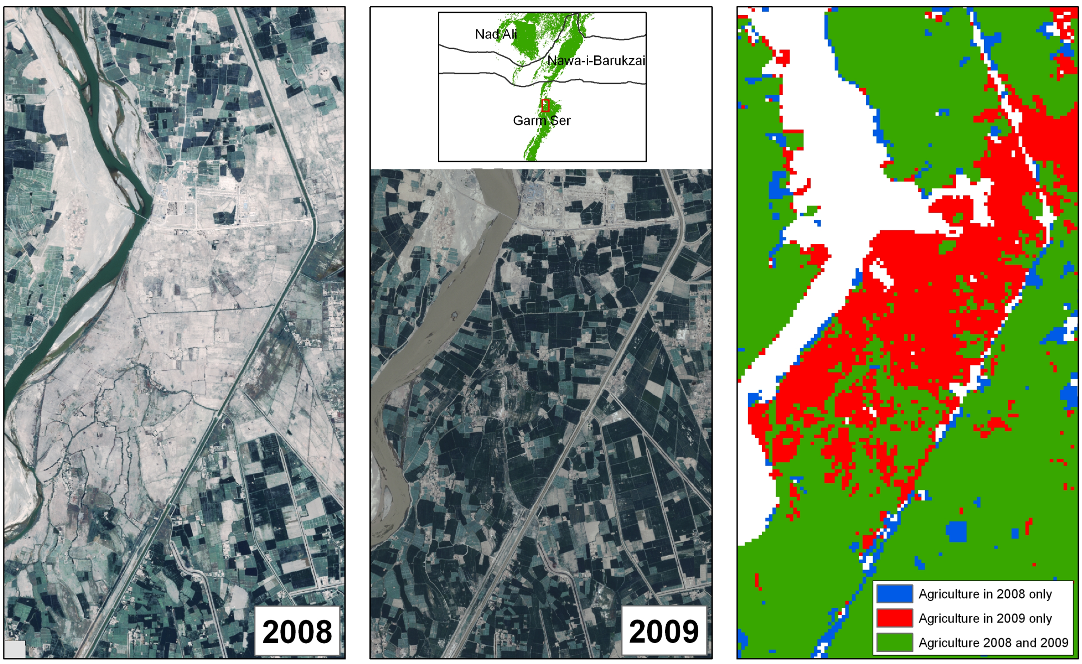
Active Agriculture Difference Garm Ser 2008-2009



IKONOS Images 27 Apr 08 & 8 Apr 09 True Colour Composite
Projection: UTM41N WGS84

Kilometres
0 0.5 1 2
N

Cranfield UNIVERSITY

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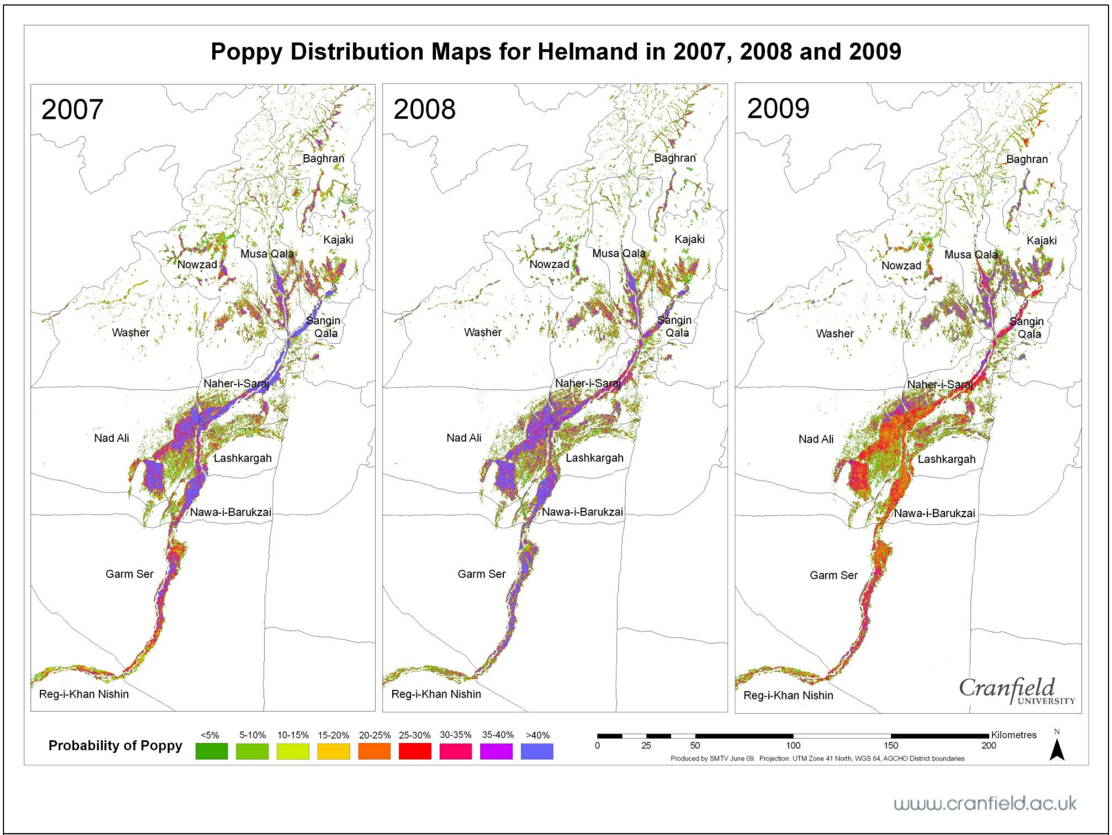
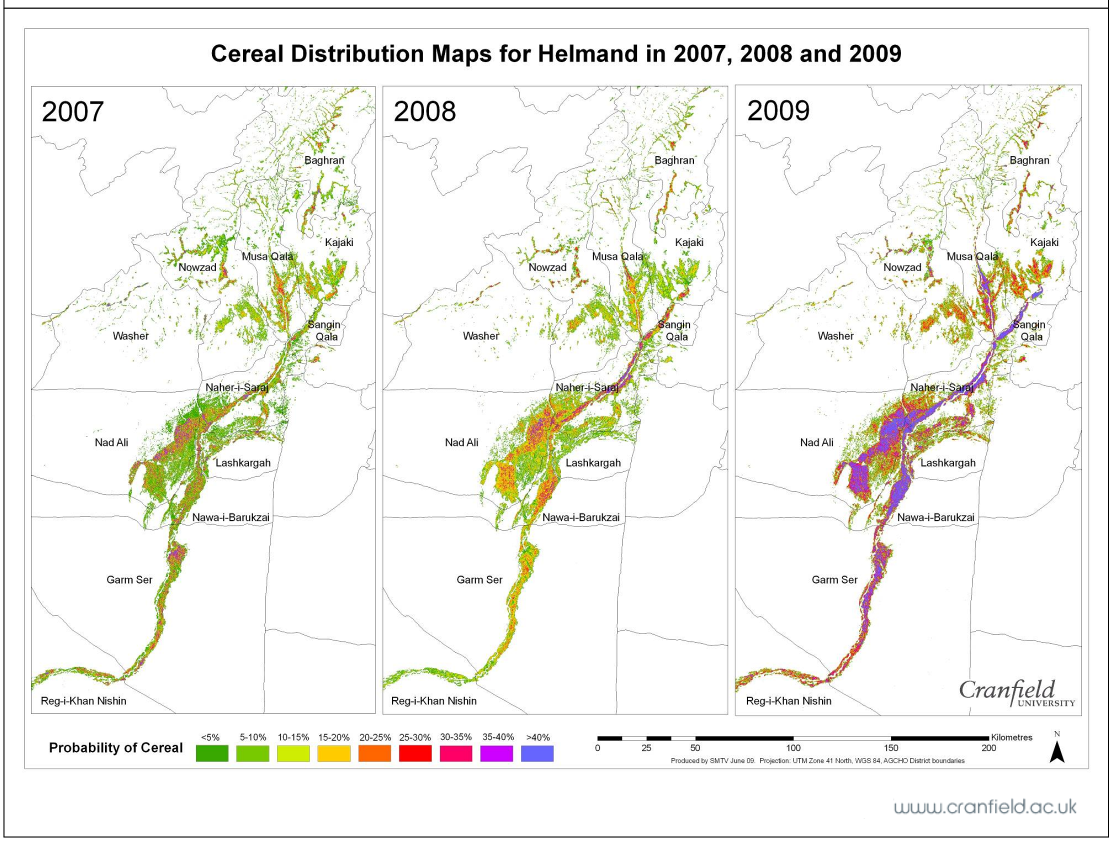
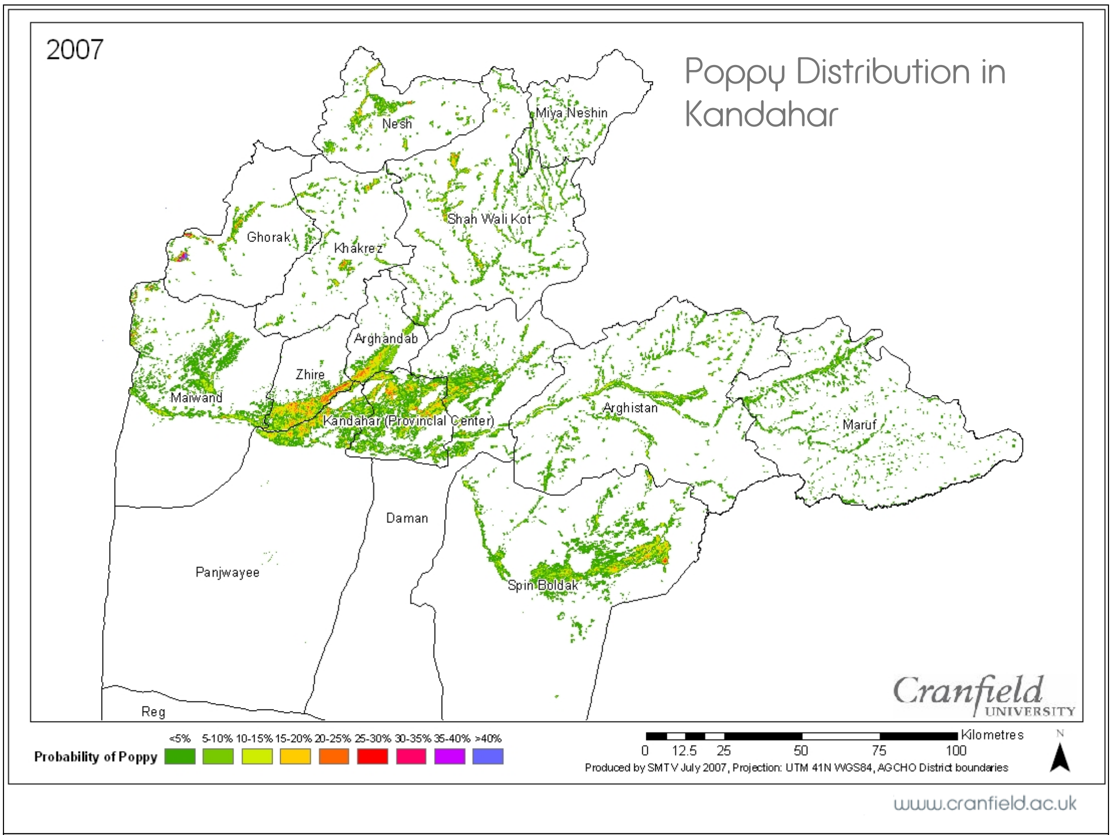
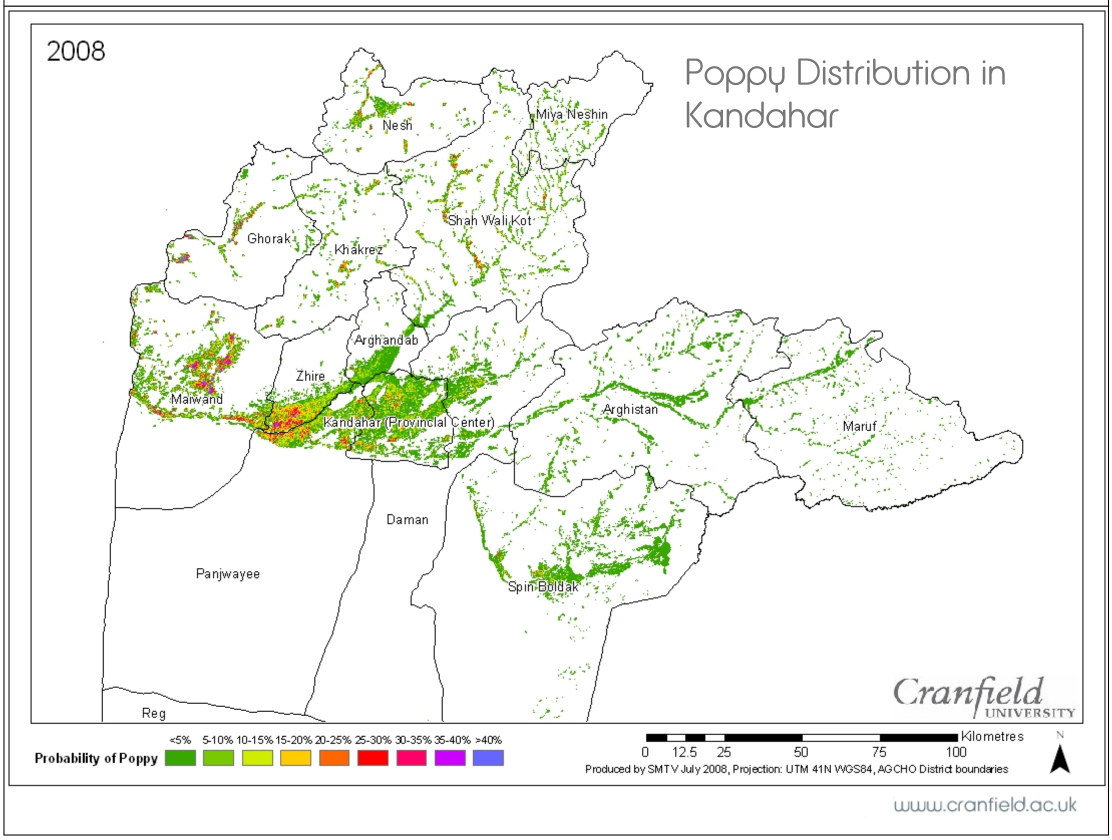
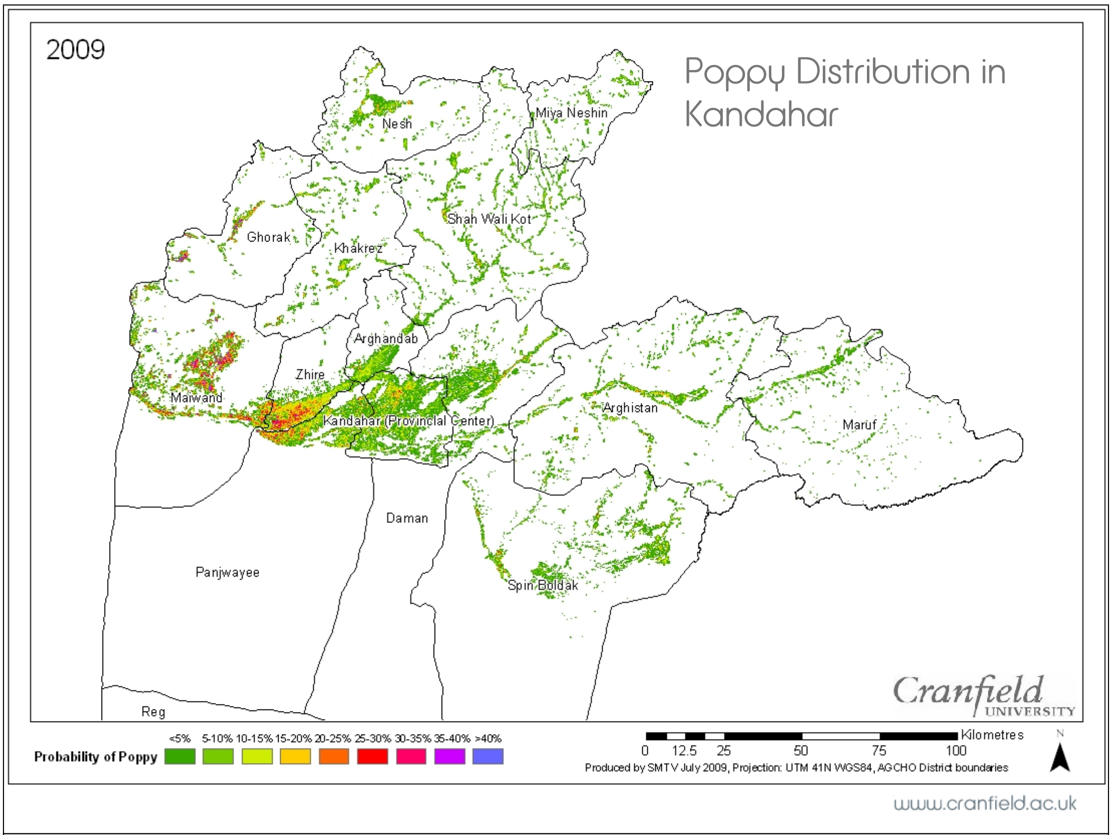
Appendix C
Distribution maps: 2007–2009

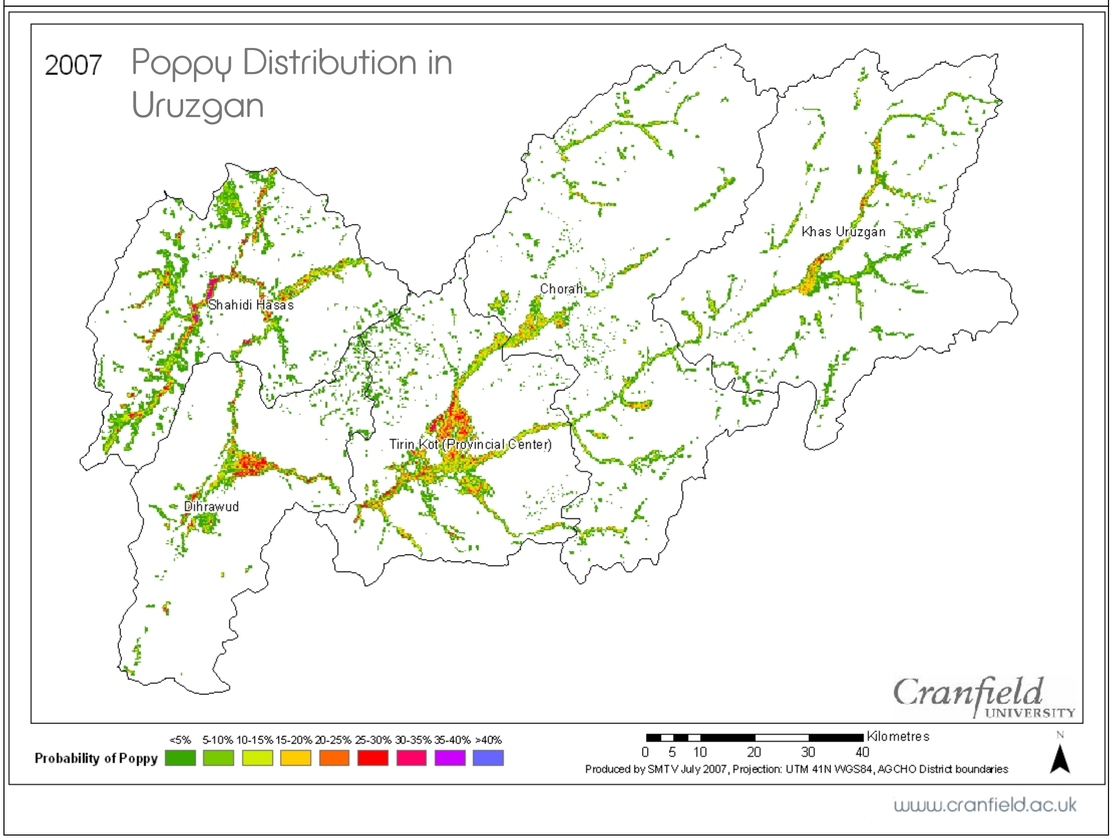

Poppy Distribution Maps for Helmand in 2007, 2008 and 2009
2007
2008
2009
Baghran
Kajaki
Musa Qala
Nowzad
Washer
Sangin Qala
Naher-i-Saraj
Nad Ali
Lashkargah
Nawa-i-Barukzai
Garm Ser
Reg-i-Khan Nishin
Cranfield UNIVERSITY
Probability of Poppy
<5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
>40%
0 25 50 100 150 200 Kilometres
N
Produced by SMTV June 09. Projection: UTM Zone 41 North, WGS 84, AGCHO District boundaries
www.cranfield.ac.uk

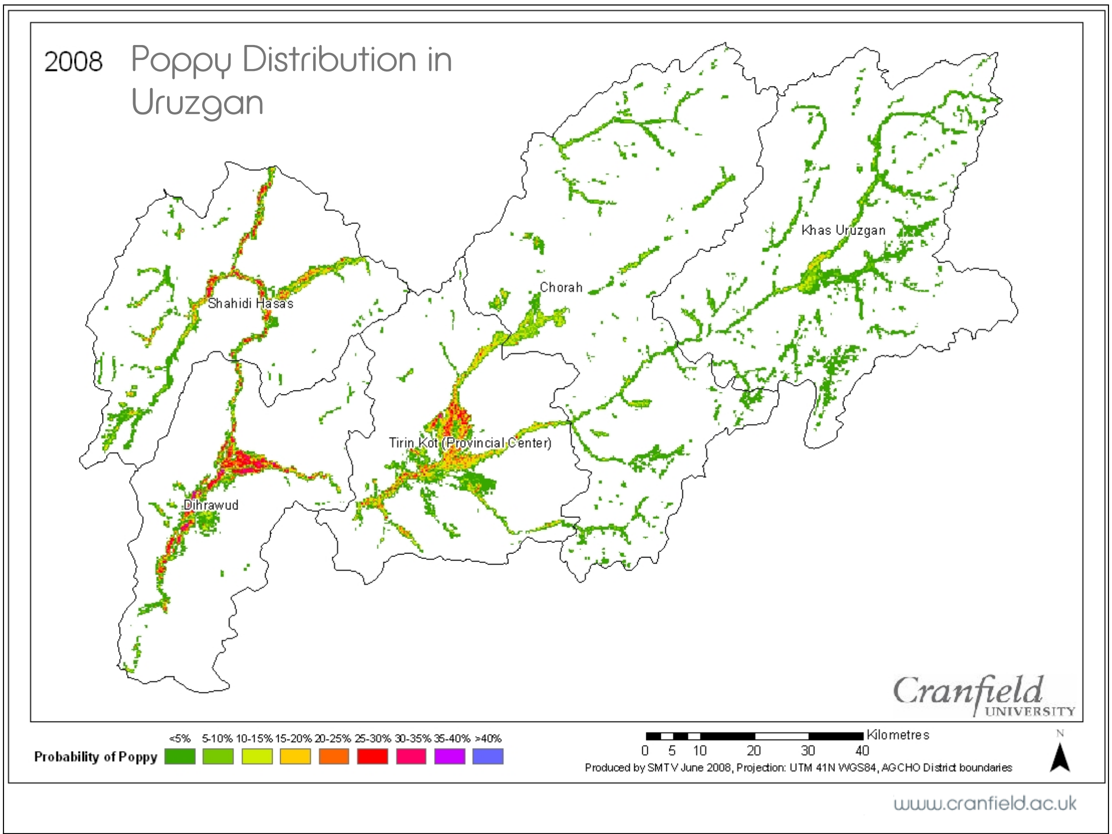

Cereal Distribution Maps for Helmand in 2007, 2008 and 2009
2007
2008
2009
Baghran
Kajaki
Musa Qala
Nowzad
Washer
Sangin Qala
Naher-i-Saraj
Nad Ali
Lashkargah
Nawa-i-Barukzai
Garm Ser
Reg-i-Khan Nishin
Cranfield UNIVERSITY
Probability of Cereal
<5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
>40%
0 25 50 100 150 200 Kilometres
N
Produced by SMTV June 09. Projection: UTM Zone 41 North, WGS 84, AGCHO District boundaries
www.cranfield.ac.uk

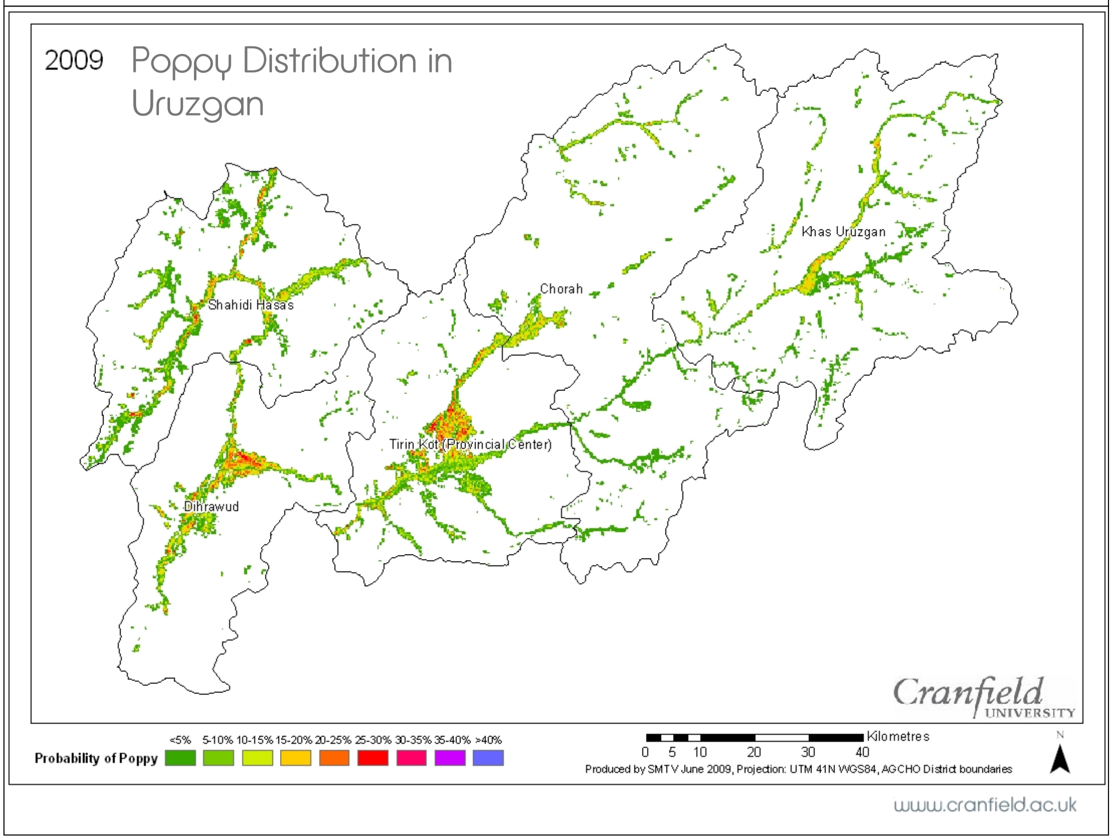

2007
Poppy Distribution in Kandahar
Nesh
Miya Neshin
Shah Wali Kot
Ghorak
Khakrez
Arghandab
Zhire
Maiwand
Kandahar (Provincial Center)
Arghistan
Maruf
Daman
Panjwayee
Spin Boldak
Reg
Cranfield UNIVERSITY
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Probability of Poppy
0 12.5 25 50 75 100 Kilometres
N
Produced by SMTV July 2007, Projection: UTM 41N WGS84, AGCHO District boundaries
www.cranfield.ac.uk

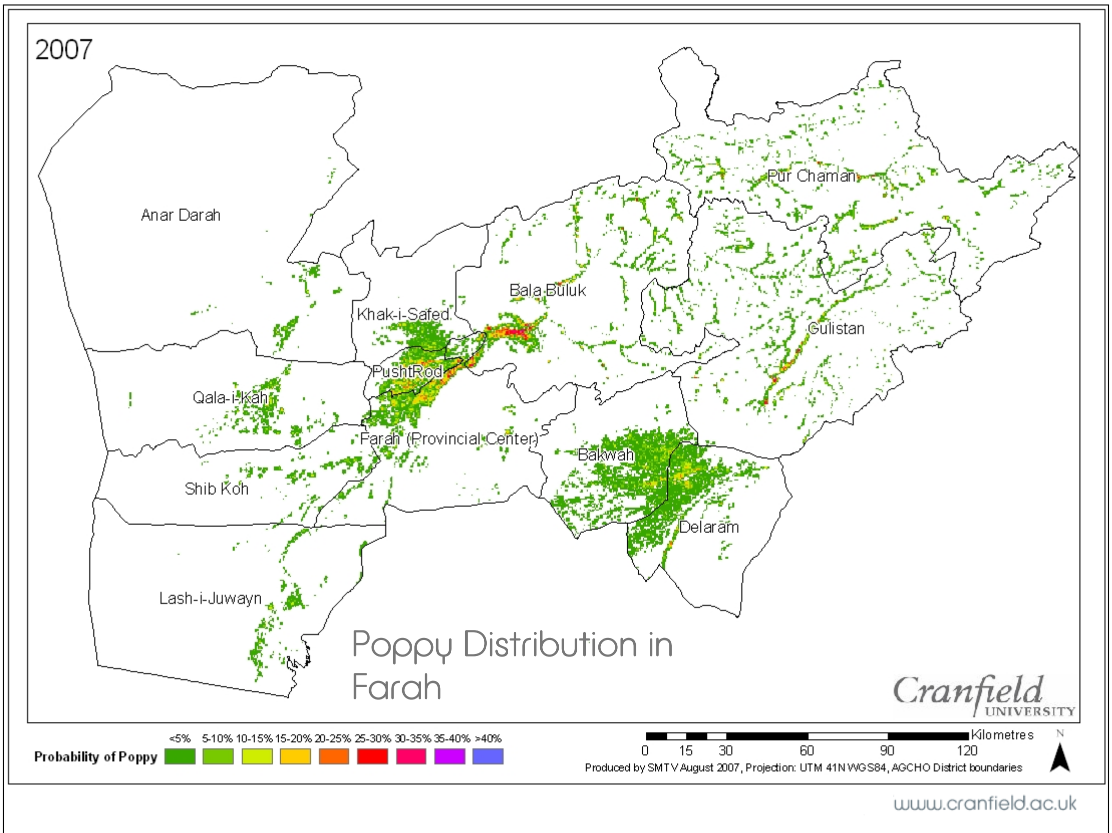

2008
Poppy Distribution in Kandahar
Nesh
Miya Neshin
Shah Wali Kot
Ghorak
Khakrez
Arghandab
Zhire
Maiwand
Kandahar (Provincial Center)
Arghistan
Maruf
Daman
Panjwayee
Spin Boldak
Reg
Cranfield UNIVERSITY
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Probability of Poppy
0 12.5 25 50 75 100 Kilometres
N
Produced by SMTV July 2008, Projection: UTM 41N WGS84, AGCHO District boundaries
www.cranfield.ac.uk

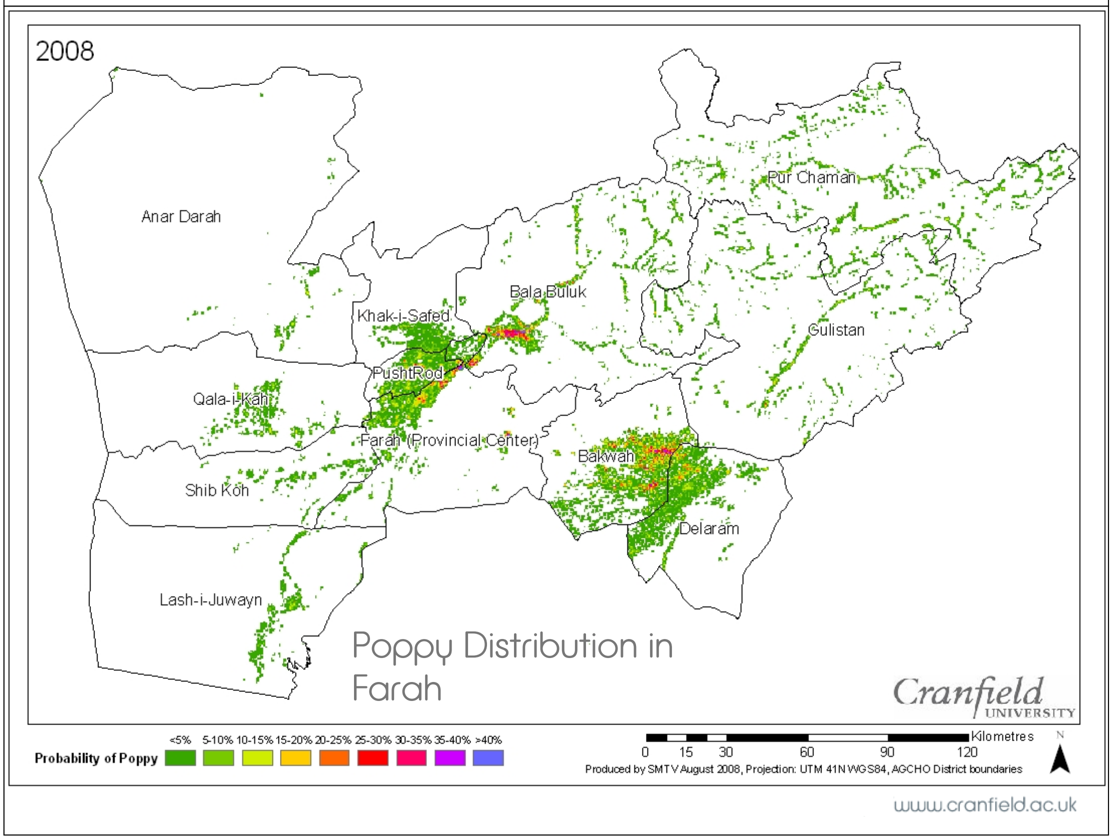

2009
Poppy Distribution in Kandahar
Nesh
Miya Neshin
Shah Wali Kot
Ghorak
Khakrez
Arghandab
Zhire
Maiwand
Kandahar (Provincial Center)
Arghistan
Maruf
Daman
Panjwayee
Spin Boldak
Reg
Cranfield UNIVERSITY
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Probability of Poppy
Kilometres
0 12.5 25 50 75 100
Produced by SMTV July 2009, Projection: UTM 41N WGS84, AGCHO District boundaries
N
www.cranfield.ac.uk

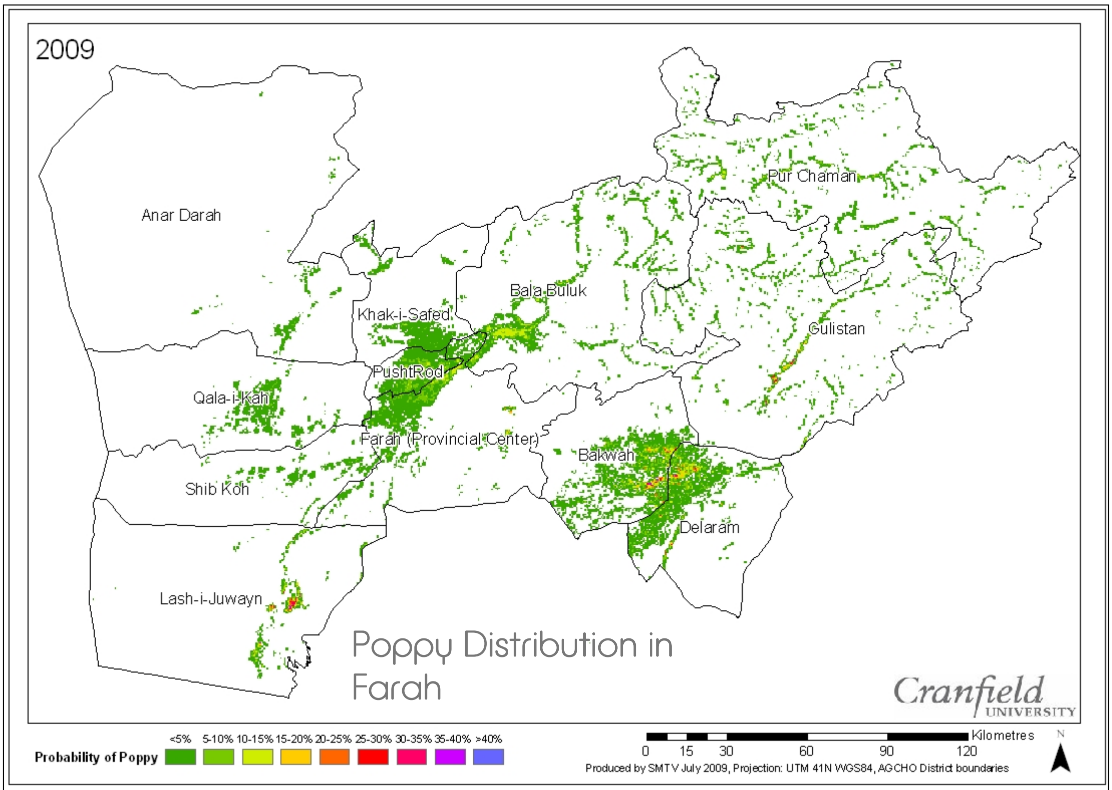

2007
Poppy Distribution in Uruzgan
Khas Uruzgan
Shahidi Hasas
Choran
Tirin Kot (Provincial Center)
Dihrawud
Cranfield UNIVERSITY
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Probability of Poppy
Kilometres
0 5 10 20 30 40
Produced by SMTV July 2007, Projection: UTM 41N WGS84, AGCHO District boundaries
N
www.cranfield.ac.uk


2008
Poppy Distribution in Uruzgan
Shahidi Hasas
Chorah
Khas Uruzgan
Tirin Kot (Provincial Center)
Dihrawud
Cranfield UNIVERSITY
Probability of Poppy
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Kilometres
0 5 10 20 30 40
Produced by SMTV June 2008, Projection: UTM 41N WGS84, AGCHO District boundaries
N
www.cranfield.ac.uk

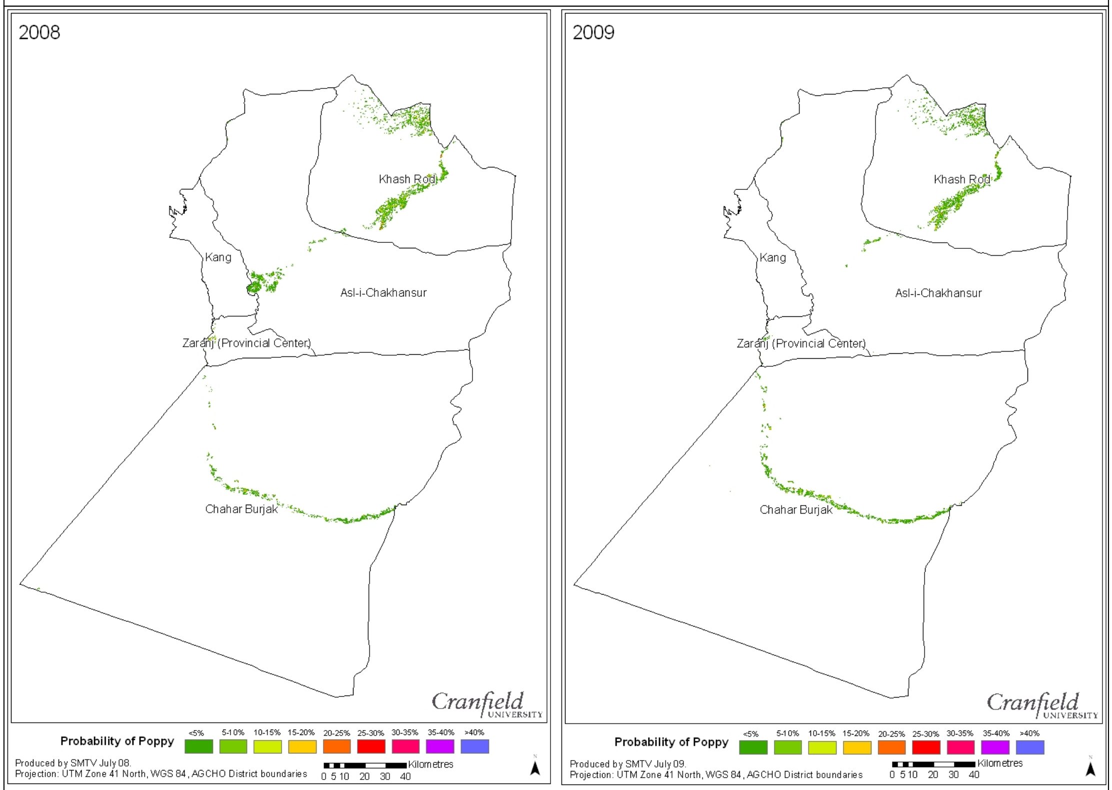

2009
Poppy Distribution in Uruzgan
Shahidi Hasas
Chorah
Khas Uruzgan
Tirin Kot (Provincial Center)
Dihrawud
Cranfield UNIVERSITY
Probability of Poppy
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Kilometres
0 5 10 20 30 40
Produced by SMTV June 2009, Projection: UTM 41N WGS84, AGCHO District boundaries
N
www.cranfield.ac.uk


2007
Anar Darah
Pur Chaman
Bala Buluk
Khak-i-Safed
Gulistan
PushtRod
Qala-i-Kah
Farah (Provincial Center)
Bakwah
Shib Koh
Delaram
Lash-i-Juwayn
Poppy Distribution in Farah
Cranfield UNIVERSITY
Probability of Poppy
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
0 15 30 60 90 120 Kilometres
N
Produced by SMTV August 2007, Projection: UTM 41N WGS84, AGCHO District boundaries
www.cranfield.ac.uk


2008
Anar Darah
Pur Chaman
Bala Buluk
Khak-i-Safed
Gulistan
PushtRod
Qala-i-Kah
Farah (Provincial Center)
Bakwah
Shib Koh
Delaram
Lash-i-Juwayn
Poppy Distribution in Farah
Cranfield UNIVERSITY
Probability of Poppy
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
0 15 30 60 90 120 Kilometres
N
Produced by SMTV August 2008, Projection: UTM 41N WGS84, AGCHO District boundaries
www.cranfield.ac.uk

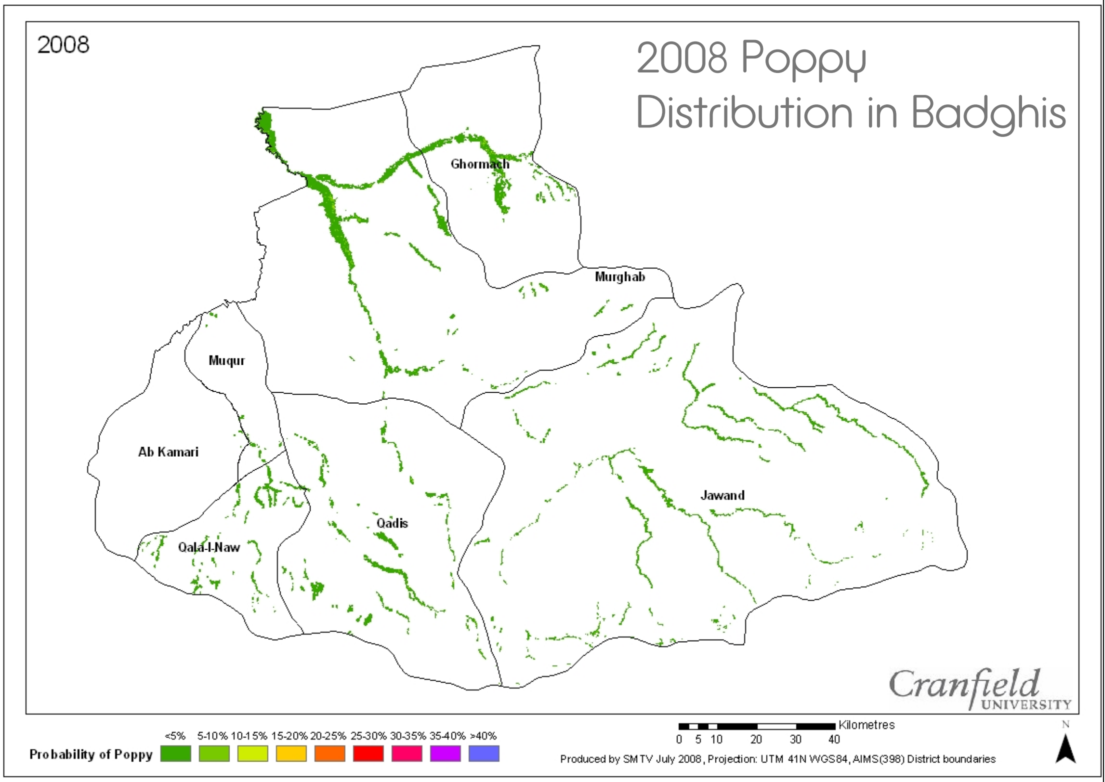


www.cranfield.ac.uk



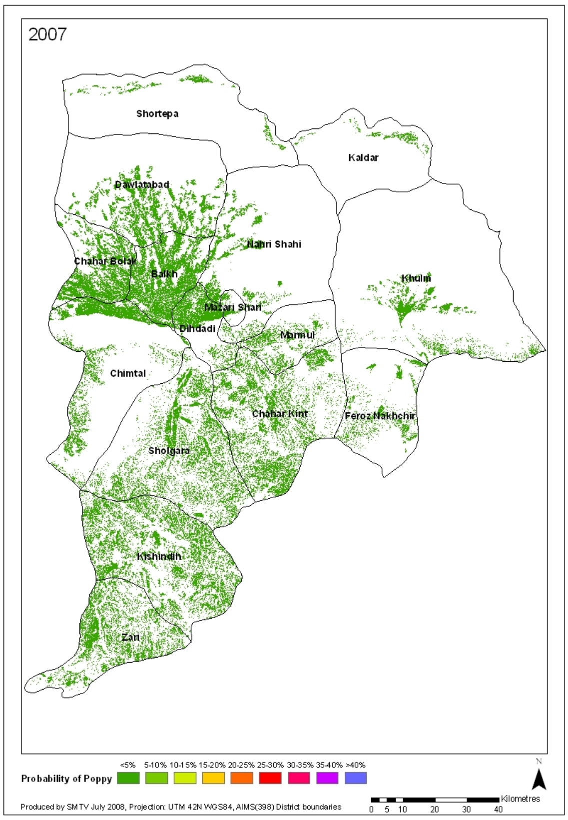
Poppy Distribution in Nimroz

www.cranfield.ac.uk



www.cranfield.ac.uk

2007 Poppy Distribution in Balkh



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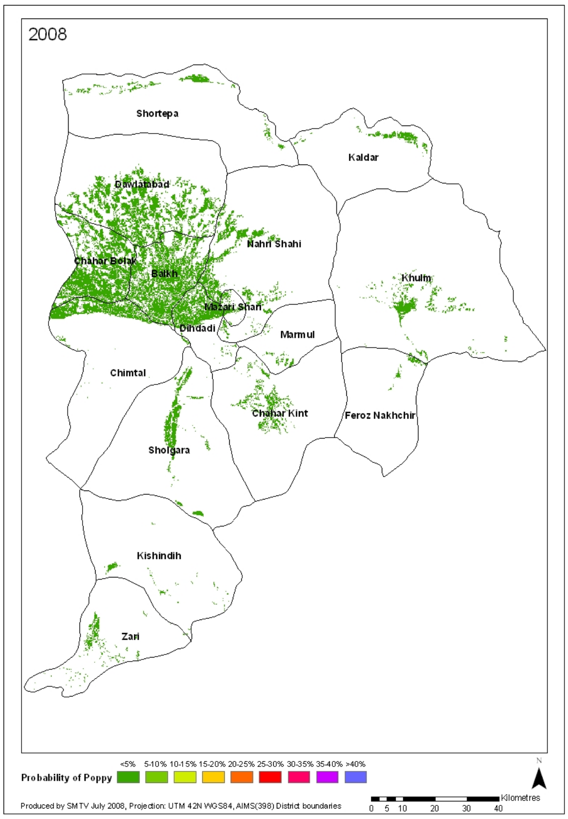
2008 Poppy Distribution in Balkh



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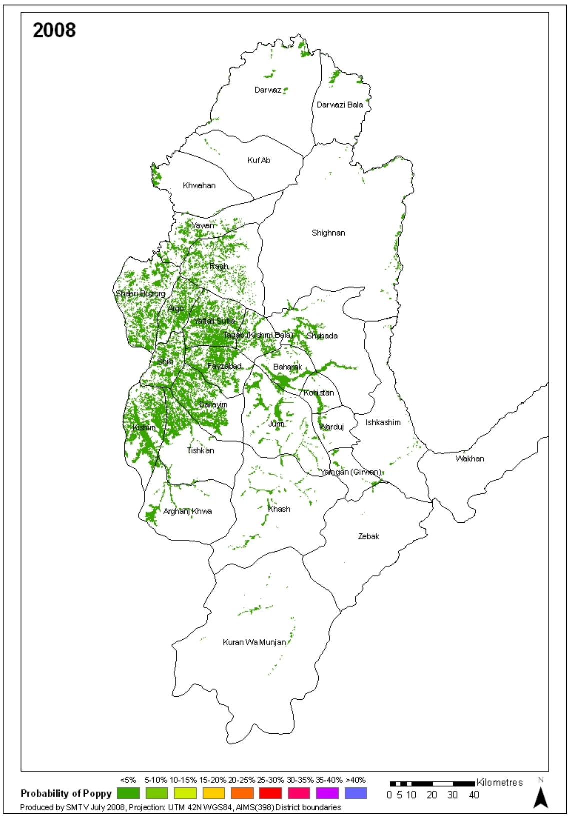
2008 Poppy Distribution in Badakhshan



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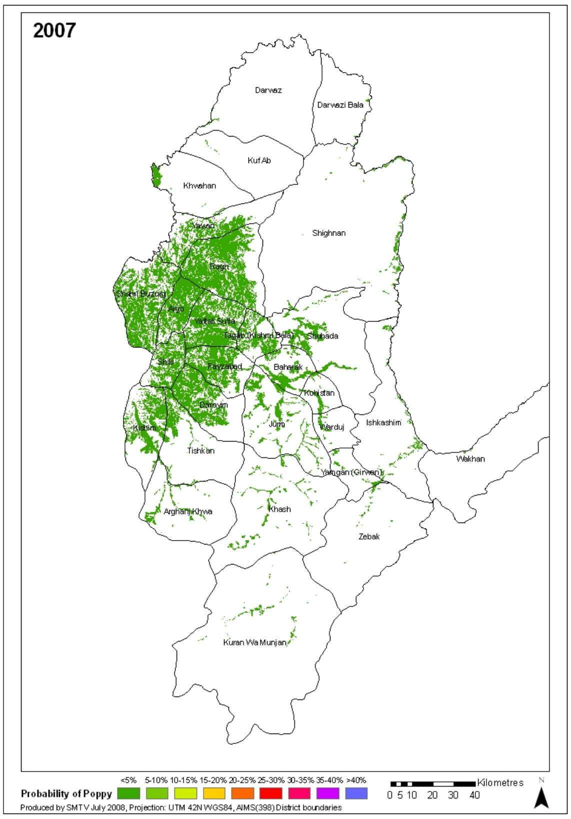
2007 Poppy Distribution in Badakhshan



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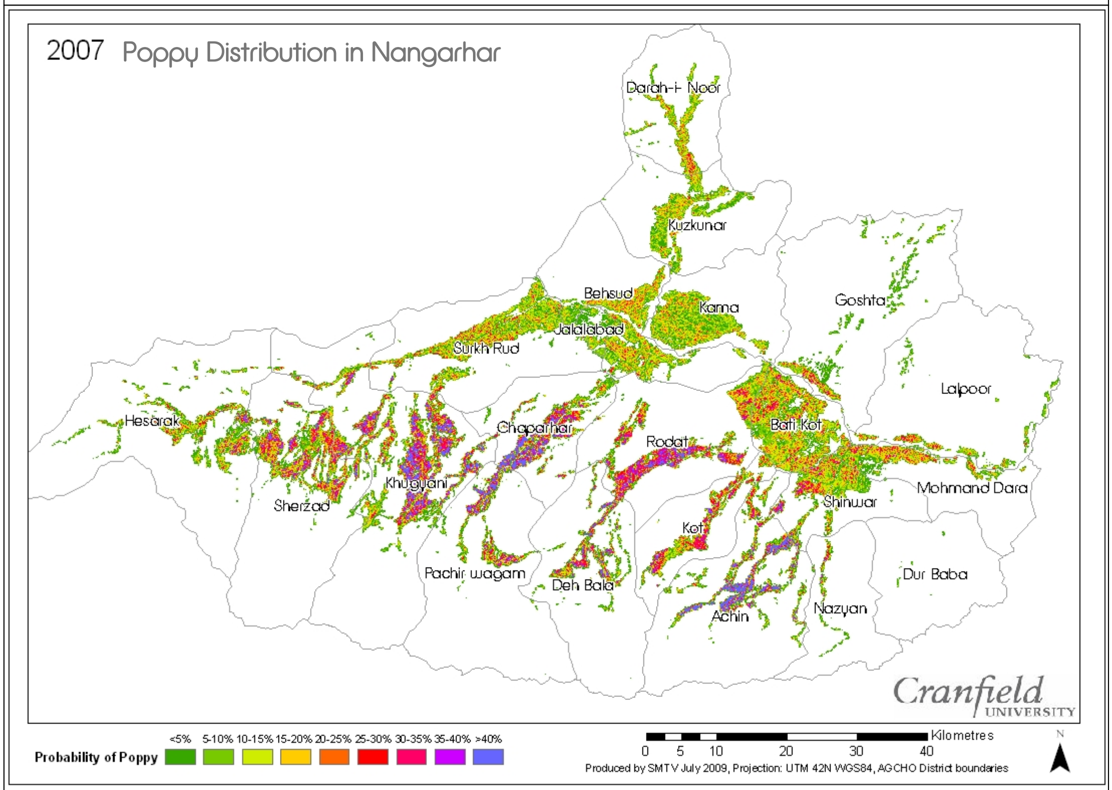
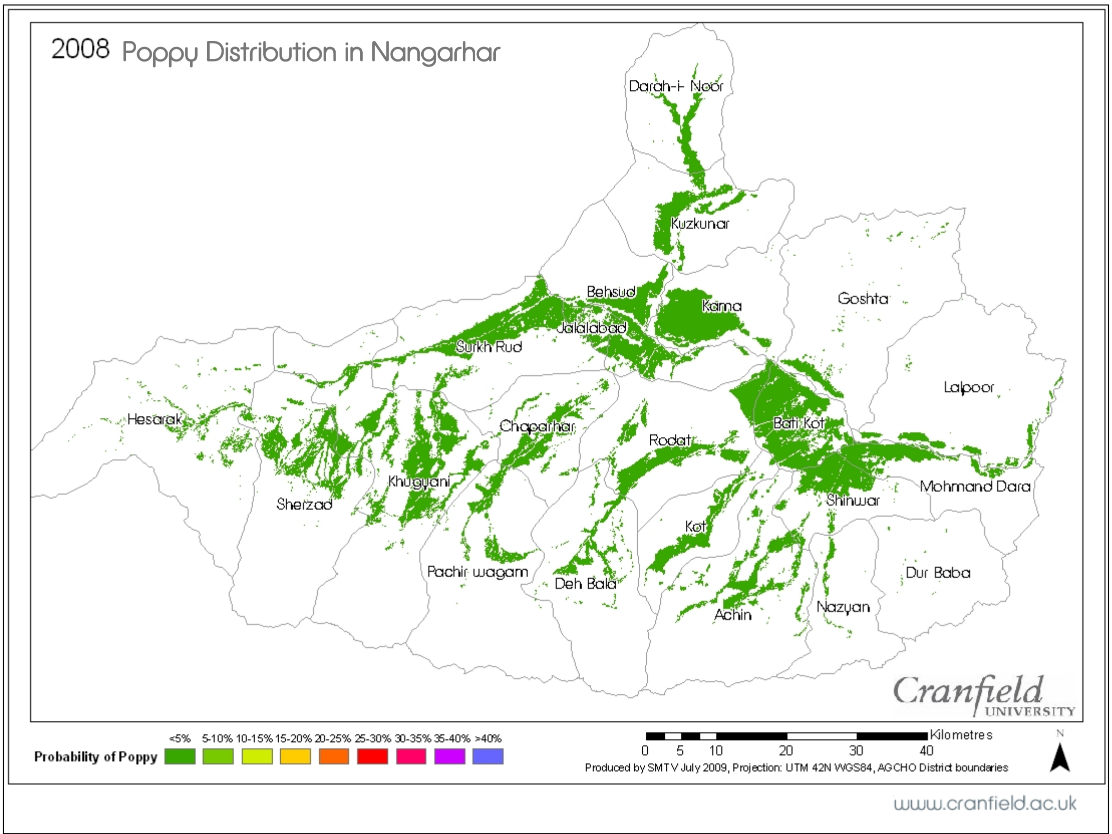
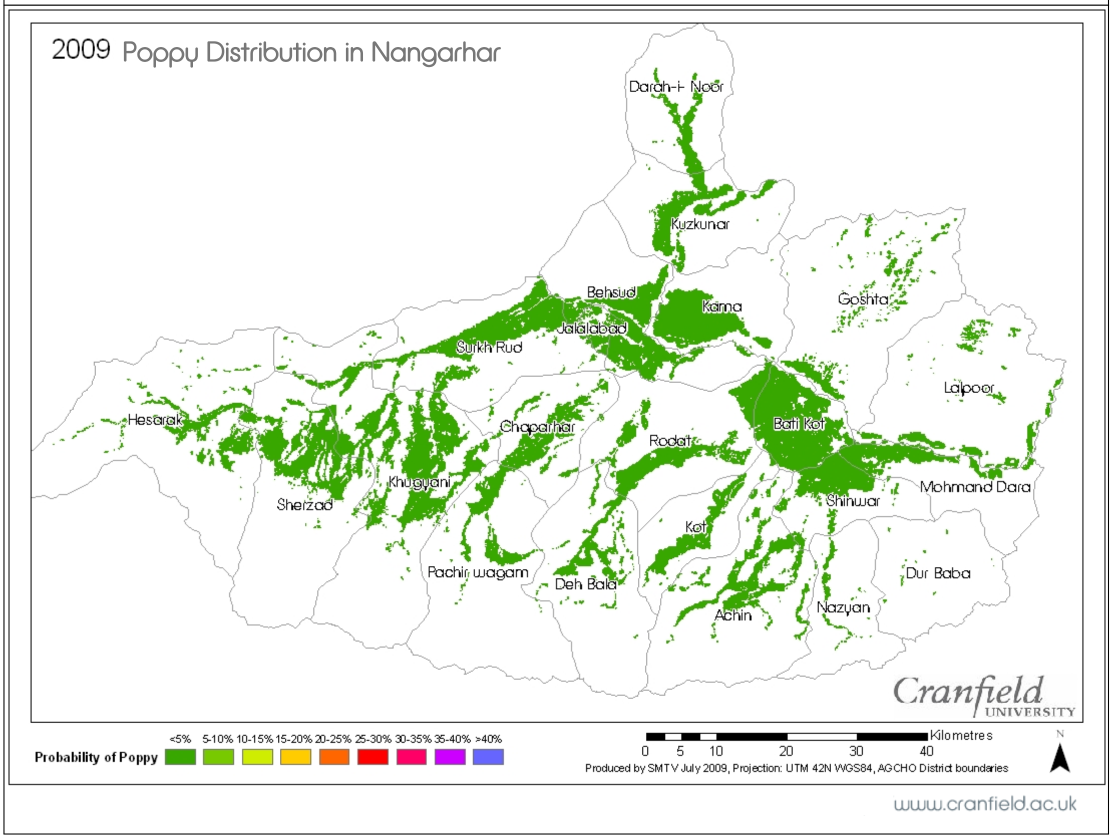
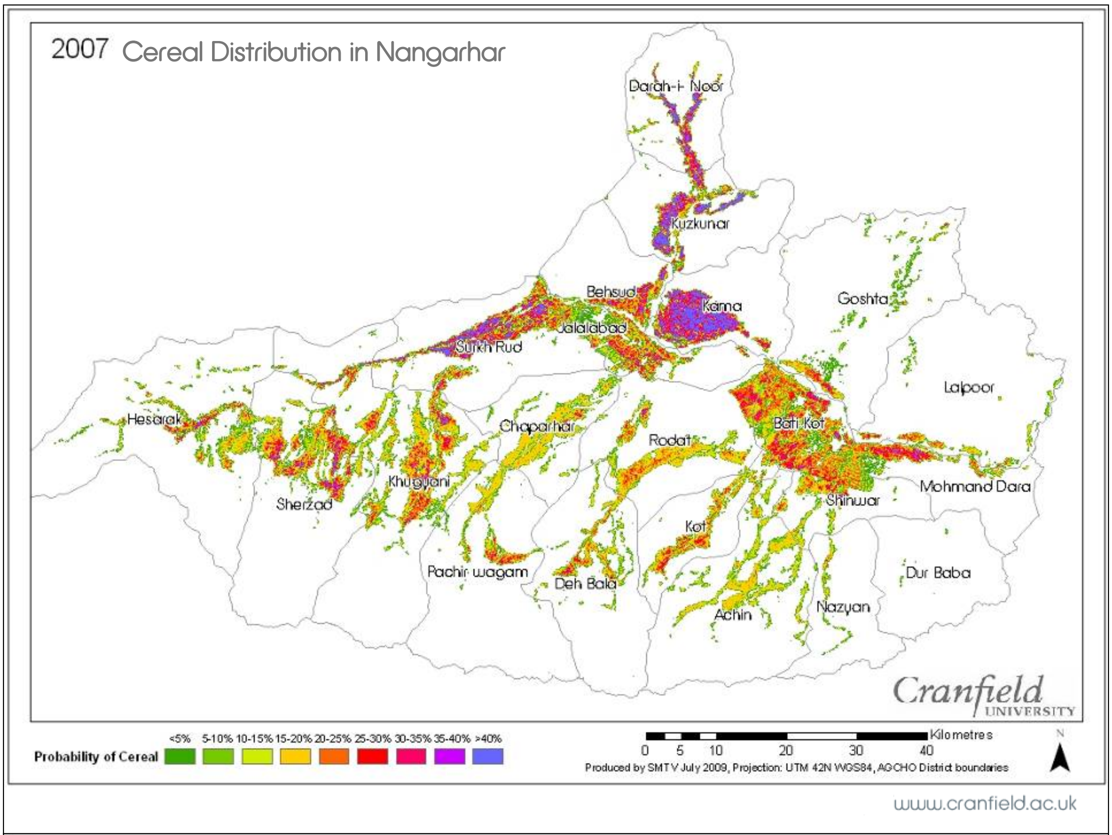
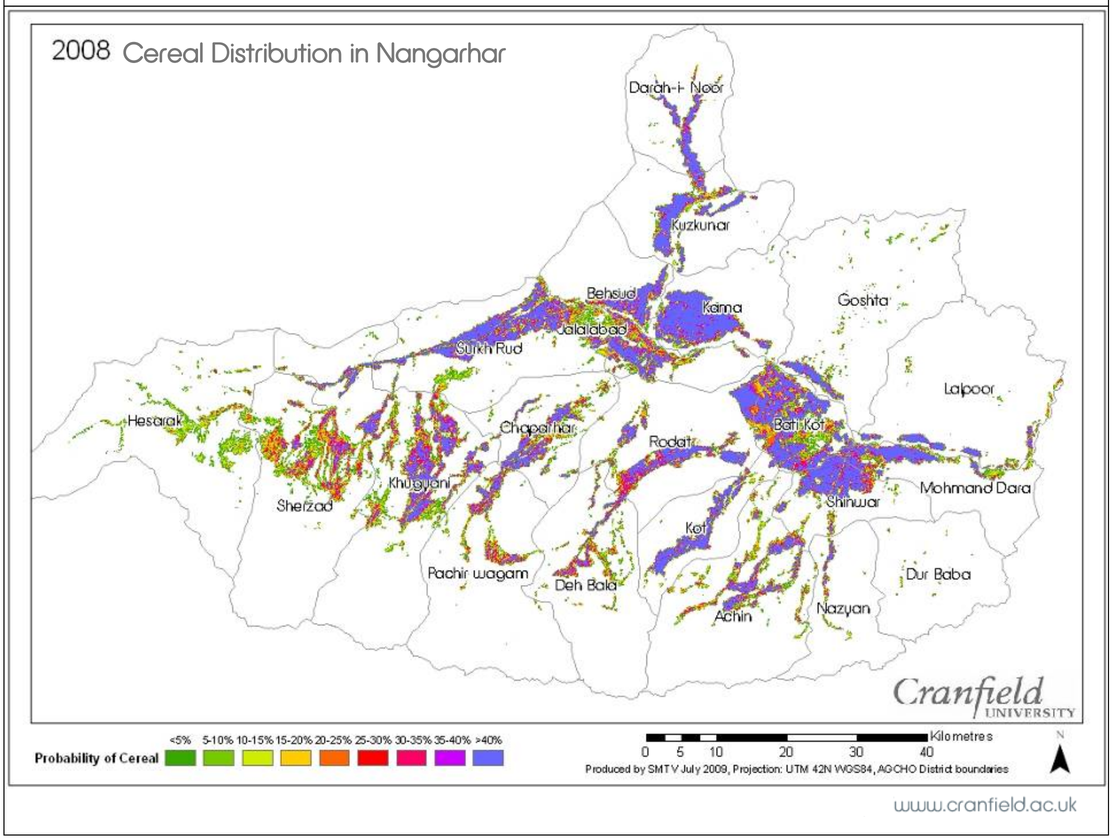


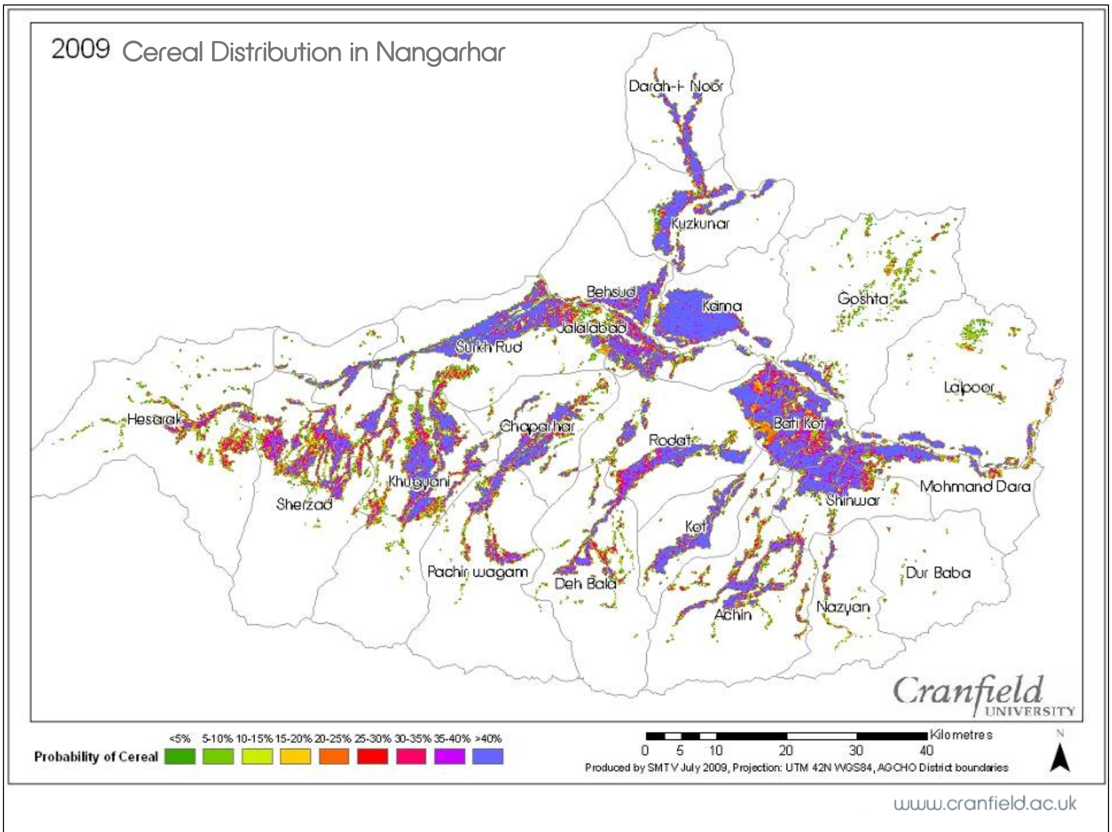
www.cranfield.ac.uk

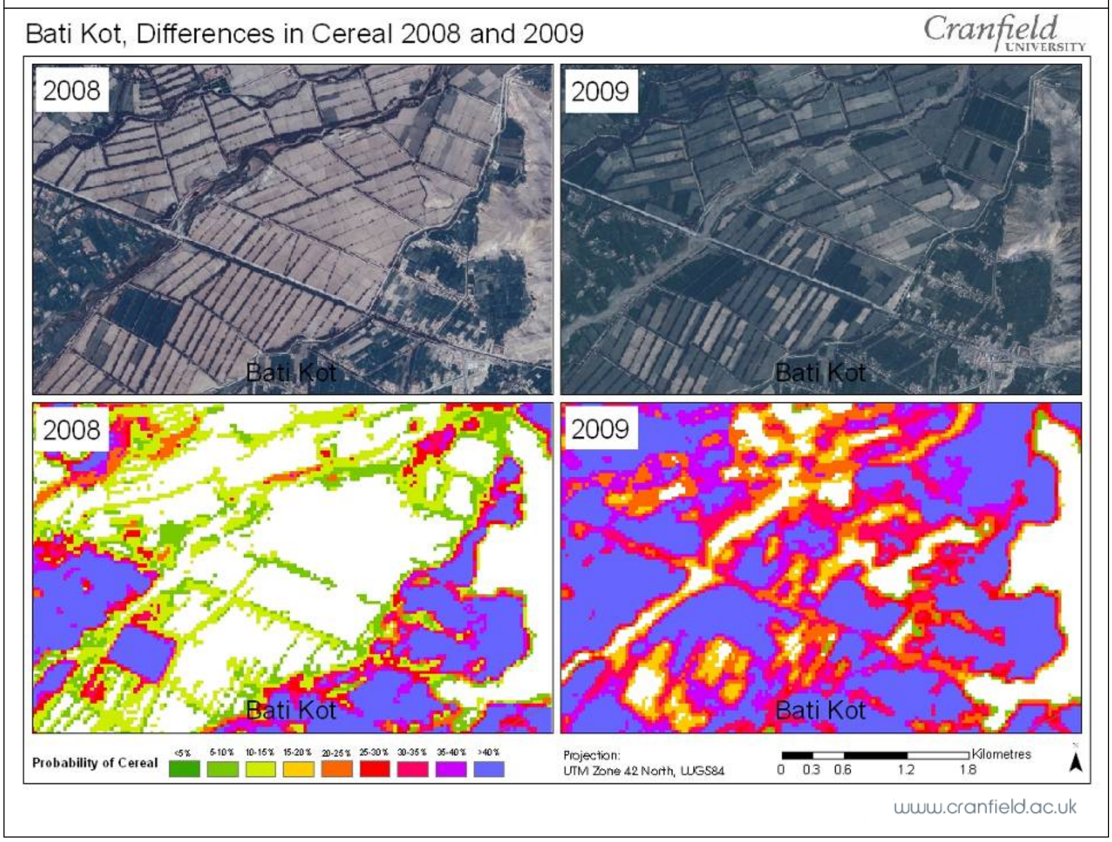

2008 Poppy Distribution in Nangarhar
Darah-i- Noor
Kuzkunar
Behsud
Kama
Goshta
Jalalabad
Surkh Rud
Lalpoor
Hesarak
Chaparhar
Rodat
Bati Kot
Khugyani
Sherzad
Shinwar
Mohmand Dara
Kot
Pachir wagam
Deh Bala
Dur Baba
Nazyan
Achin
Cranfield UNIVERSITY
Probability of Poppy
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
0 5 10 20 30 40 Kilometres
N
Produced by SMTV July 2009, Projection: UTM 42N WGS84, AGCHO District boundaries
www.cranfield.ac.uk

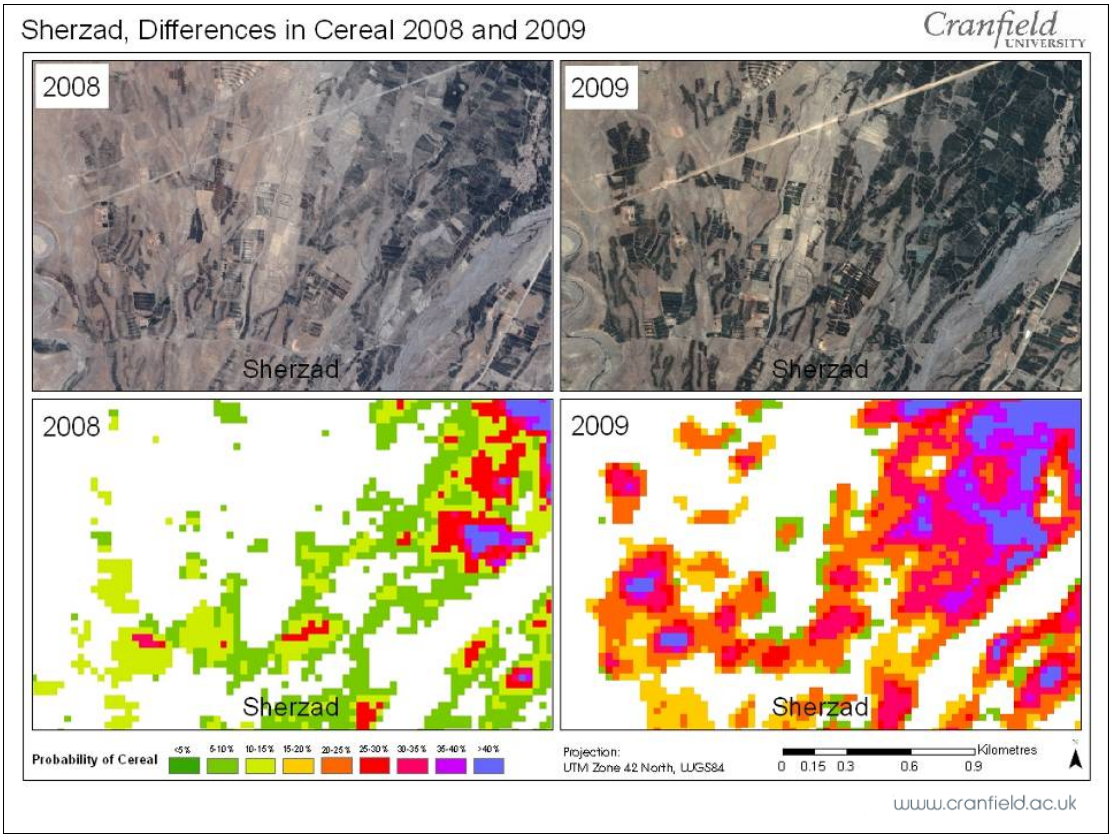

2009 Poppy Distribution in Nangarhar
Darah-i- Noor
Kuzkunar
Behsud
Kama
Goshta
Jalalabad
Surkh Rud
Lalpoor
Hesarak
Chaparhar
Rodat
Bati Kot
Khugyani
Sherzad
Shinwar
Mohmand Dara
Kot
Pachir wagam
Deh Bala
Dur Baba
Nazyan
Achin
Cranfield UNIVERSITY
Probability of Poppy
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
0 5 10 20 30 40 Kilometres
N
Produced by SMTV July 2009, Projection: UTM 42N WGS84, AGCHO District boundaries
www.cranfield.ac.uk


2007 Cereal Distribution in Nangarhar
Darah-i- Noor
Kuzkunar
Behsud
Kama
Goshta
Jalalabad
Surkh Rud
Lalpoor
Hesarak
Chaparhar
Rodat
Bati Kot
Khugyani
Mohmand Dara
Sherzad
Shinwar
Kot
Pachir wagam
Deh Bala
Dur Baba
Nazyan
Achin
Cranfield UNIVERSITY
Probability of Cereal
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Kilometres
0 5 10 20 30 40
N
Produced by SMTV July 2009, Projection: UTM 42N WGS84, AGCHO District boundaries
www.cranfield.ac.uk


2008 Cereal Distribution in Nangarhar
Darah-i- Noor
Kuzkunar
Behsud
Kama
Goshta
Jalalabad
Surkh Rud
Lalpoor
Hesarak
Chaparhar
Rodat
Bati Kot
Khugyani
Mohmand Dara
Sherzad
Shinwar
Kot
Pachir wagam
Deh Bala
Dur Baba
Nazyan
Achin
Cranfield UNIVERSITY
Probability of Cereal
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Kilometres
0 5 10 20 30 40
N
Produced by SMTV July 2009, Projection: UTM 42N WGS84, AGCHO District boundaries
www.cranfield.ac.uk


2009 Cereal Distribution in Nangarhar
Darah-i- Noor
Kuzkunar
Goshta
Behsud
Kama
Jalalabad
Surkh Rud
Lalpoor
Hesarak
Chaparhar
Rodat
Bati Kot
Khugyani
Mohmand Dara
Sherzad
Shinwar
Kot
Dur Baba
Pachir wagam
Deh Bala
Nazyan
Achin
Cranfield UNIVERSITY
Probability of Cereal
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Kilometres
0 5 10 20 30 40
Produced by SMTV July 2009, Projection: UTM 42N WGS84, AGCHO District boundaries
N
www.cranfield.ac.uk


Bati Kot, Differences in Cereal 2008 and 2009
Cranfield UNIVERSITY
2008
2009
Bati Kot
Probability of Cereal
<5% 5-10% 10-15% 15-20% 20-25% 25-30% 30-35% 35-40% >40%
Projection:
UTM Zone 42 North, WGS84
Kilometres
0 0.3 0.6 1.2 1.8
N
www.cranfield.ac.uk


Sherzad, Differences in Cereal 2008 and 2009
Cranfield UNIVERSITY
2008
2009
Sherzad
Sherzad
2008
2009
Sherzad
Sherzad
Probability of Cereal
<5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
>40%
Projection:
UTM Zone 42 North, WGS84
0 0.15 0.3 0.6 0.9
Kilometres
www.cranfield.ac.uk

Appendix D
Project reports 2009

Table D.1. Project reports produced in 2009.

Date	Type	Title
01/08/2009	Presentation	Tri-party (US-UK-UNODC) review Conference Vienna
31/07/2009	Report	Cereal cultivation in Nangarhar (Helmand delivered 15-Jun-09)
15/07/2009	Report	Eradication Verification Summary report
15/07/2009	Report	Poppy cultivation in Kandahar, Uruzgan, Nimorz, Farah, Nangarhar 2007 - 2009
15/06/2009	Presentation	Poppy and Cereal Cultivation in Helmand Province 2007 - 2009 to FCO London and British Embassy Kabul
15/06/2009	Report	Poppy and Cereal Cultivation in Helmand Province 2007 - 2009
31/05/2009	Report	End of May Eradication Verification Report
14/05/2009	Presentation	Briefing on project results and activities in Helmand Food Zone to FCO
11/05/2009	Report	Cereal and Poppy cultivation in the Helmand Food Zone, 2007-2009 Preliminary Results
30/04/2009	Report	End of April Eradication Verification Report
15/04/2009	Bulletin	Mid April Drought Bulletin
07/04/2009	Report	Interim eradication recovery assessment
31/03/2009	Report	End of March Eradication Verification Report
31/03/2009	Bulletin	End of March Drought Bulletin
20/03/2009	Report	Presence of poppy in Helmand target areas
10/03/2009	Report	Eradication Verification Progress Report
10/03/2009	Presentation	Progress report briefing to FCO ADIDU
10/02/2009	Presentation	Tri-Party (US-UK-UNODC) Review Conference in Vienna