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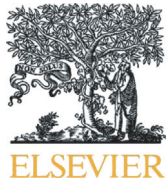
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Review

A critical synthesis of remotely sensed optical image change detection techniques

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ABSTRACT

State of the art reviews of remote sensing change detection are becoming increasingly complicated and disparate due to an ever growing list of techniques, algorithms and methods. To provide a clearer, synoptic view of the field this review has organised the literature by the unit of analysis and the comparison method used to identify change. This significantly reduces the conceptual overlap present in previous reviews giving a succinct nomenclature with which to understand and apply change detection workflows. Under this framework, several decades of research have been summarised to provide an overview of current change detection approaches. Seven units of analysis and six comparison methods were identified and described highlighting the advantages and limitations of each within a change detection workflow. Of these, the pixel and post-classification change methods remain the most popular choices. In this review we extend previous summaries and provide an accessible description of the field. This supports future research by placing a clear separation between the analysis unit and the change classification method. This separation is then discussed, providing guidance for applied change detection research and future benchmarking experiments.

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Contents

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1. Introduction

Remote sensing change detection is a disparate, highly variable and ever-expanding area of research. There are many different methods in use, developed over several decades of satellite remote sensing. These approaches have been consolidated in several reviews (Coppin et al., 2004; Hussain et al., 2013; Lu et al., 2004; Radke et al., 2005; Warner et al., 2009) and even reviews of reviews (İlsever & Ünsalan, 2012), each aiming to better inform applied research and steer future developments. However, most authors agree that a universal change detection technique does not yet exist (Ehlers et al., 2014) leaving end-users of the technology with an increasingly difficult task selecting a suitable approach. For instance Lu et al. (2004) present seven categories divided into 31 techniques, making an overall assessment very difficult. Recent advances in Object Based Image Analysis (OBIA) have also further complicated this picture by presenting two parallel streams of techniques (G. Chen et al., 2012; Hussain et al., 2013) with significant conceptual overlaps. For instance, direct image comparison and direct object comparison (Hussain et al., 2013) could relate to identical operations applied to different analysis units. This review provides a clearer nomenclature with less conceptual overlap by providing a clear separation between the unit of analysis, be it the pixel or image-object, and the comparison method used to highlight change.

Previous reviews (Hussain et al., 2013; Lu et al., 2004) have identified three broad stages in a remote sensing change detection project, namely pre-processing, change detection technique selection and accuracy assessment. This review focuses on the second stage, aiming to bring an improved clarity to a change detection technique selection. A change detection technique can be considered in terms of four components (Fig. 1): the pre-processed input imagery, the unit of analysis, a comparison method and finally the derived change map ready for interpretation and accuracy assessment. To identify change(s), the input images are compared and a decision is made as to the presence or degree of change. Prior to this, the geographical 'support' (Atkinson, 2006) must be defined so that it is understood exactly which spatial analysis units are to be compared over time. At a fundamental level this might be individual image pixels but could also include; systematic groups of pixels, image-objects, vector polygons or a combination of these. With a comparison framework established, analysis units are then compared to highlight change. There are many different methods of achieving this, from simple arithmetic differencing, sequential classifications or statistical analysis. This comparison results in a 'change' map which may depict the apparent magnitude of change, the type of change or a combination of both.

2. Unit of analysis

Modern remote sensing and image processing facilitate the comparison of images under several different frameworks. In the broadest sense image pixels and image-objects are the two main categories of analysis unit presented in the change detection literature (G. Chen et al., 2012; Hussain et al., 2013). When further exploring the possible interactions, there are in fact many more permutations by which a change comparison can be made. For instance, image pixels may be considered individual autonomous units or part of a systematic group such as a kernel filter or moving window. Listner and Niemeyer (2011a) outlined three different scenarios of image-object comparison; those generated independently, those generated from a multi-temporal data stack, and lastly a simple overlay operation. In addition to these one could also consider mapping objects, typically vector polygons derived from field survey, or stereo or mono photogrammetry (Comber, Law, & Lishman, 2004; Sofina et al., 2012; Walter, 2004). Furthermore, a mixture of analysis units may be utilised, with this strategy sometimes referred to as a hybrid approach (G. Chen et al., 2012; Hussain et al., 2013). We discuss these elements in seven categories, namely pixel, kernel, image-object overlay, image-object comparison, multi-temporal image-object, vector polygon and hybrid. These categories are summarised in Table 1 to include a brief description of each, advantages and disadvantages and some examples from the literature. To further clarify these definitions illustrations are given in Fig. 2, where the absolute change magnitude under each unit of analysis is depicted for a bi-temporal pair of images. The review then continues with a more detailed discussion of each unit of analysis.

2.1. Pixel

The pixel is the most fundamental element of an image (Fisher, 1997) and forms a convenient and well used means of comparison. Since the beginning of satellite remote sensing images have been analysed digitally by comparing pixel intensities for changes in a range of applications such as urban development (Deng et al., 2008; Jensen & Toll, 1982; Torres-Vera et al., 2009), land cover and land use
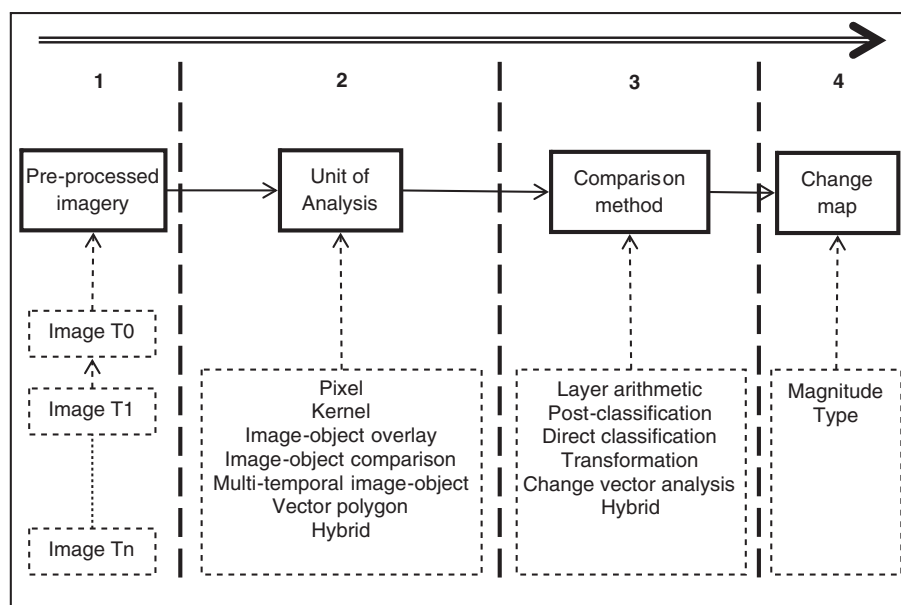

Fig. 1. A schematic showing the four components of a change detection technique.

Table 1
An overview of analysis units commonly used in remote sensing change detection studies. The comparable features are based on Avery & Colwell's fundamental features of image interpretation; as cited by Campbell 1983, p 43.

	Description	Comparable features	Advantages	Limitations	Example studies
Pixel	Single image pixels are compared.	Tone shadow (limited)	Fast and suitable for larger pixel sizes. The unit does not generalise the data.	May be unsuitable for higher resolution imagery. Tone is the only comparable reference point.	Abd El-Kawy et al. (2011), Deng et al. (2008), Green et al. (1994), Hame et al. (1998), Jensen and Toll (1982), Ochoa-Gaona and Gonzalez-Espinosa (2000), Peiman (2011), Rahman et al. (2011), Shalaby and Tateishi (2007), Torres-Vera et al. (2009)
Kernel	Groups of pixels are compared within a kernel filter or moving window.	Tone, Texture, Pattern (limited), Association (limited), Shadow (limited)	Enables measures of statistical correlation and texture. Facilitates basic contextual measures.	Generalises the data. The scale of the comparison is typically limited by a fixed kernel size. Adaptive kernels have been developed but multi-scale analysis remains a challenge. Contextual information is limited.	Bruzzone and Prieto (2000), He et al. (2011), Im and Jensen (2005), Klaric et al. (2013), Volpi et al. (2013)
Image-object overlay	Image-objects are generated by segmenting one of the images in the time series. A comparison against other images is then made by simple overlay.	Tone, Texture, Pattern (limited), Association (limited), Shadow (limited)	Segmentation may provide a more meaningful framework for texture measures and generalisation. Provides a suitable framework for modelling contextual features.	Generalises the data. Object size and shape cannot be compared. Sub-object change may remain undetectable.	Comber, Fisher, & Wadsworth (2004), Listner and Niemeyer (2011a), Tewkesbury and Allitt (2010), Tewkesbury (2011)
Image-object comparison	Image-objects are generated by segmenting each image in the time series independently.	Tone, Texture, Size, Shape, Pattern, Association, Shadow	Shares the advantages of image-object overlay plus an independent spatial framework facilitates rigorous comparisons.	Generalises the data. Linking image-objects over time is a challenge. Inconsistent segmentation leads to object 'slivers'.	Boldt et al. (2012), Dingle Robertson and King (2011), Ehlers et al. (2014), Gamanya et al. (2009), Listner and Niemeyer (2011a), Lizarazo (2012)
Multi-temporal image-object	Image-objects are generated by segmenting the entire time series together.	Tone, Texture, Pattern, Association, Shadow	Shares the advantages of image-object overlay plus the segmentation can honour both static and dynamic boundaries while maintaining a consistent topology.	Generalises the data. Object size and shape cannot be compared.	Bontemps et al. (2012), Chehata et al. (2011), Desclée et al. (2006), Doxani et al. (2011), Teo and Shih (2013)
Vector polygon	Vector polygons extracted from digital mapping or cadastral datasets.	Tone, Texture, Association, Shadow (limited)	Digital mapping databases often provide a cartographically 'clean' basis for analysis with the potential to focus the analysis using attributed thematic information.	Generalises the data. Object size and shape cannot be compared.	Comber, Law, & Lishman (2004), Duro et al. (2013), Gerard et al. (2010), Sofina et al. (2012), Walter (2004)
Hybrid	Segmented image-objects generated from a pixel or kernel level comparison.	Tone, Texture, Pattern, Association, Shadow	The level of generalisation may be chosen with reference to the identified radiometric change. Although size and shape cannot be used in the comparison it may be used in the interpretation of the radiometric change.	Object size and shape cannot be compared.	Aguirre-Gutiérrez et al. (2012), Bazi et al. (2010), Bruzzone and Bovolo (2013)

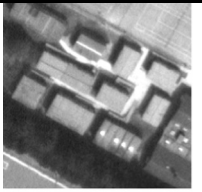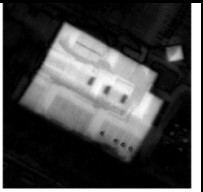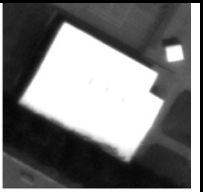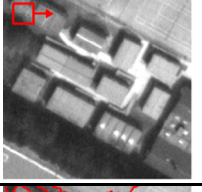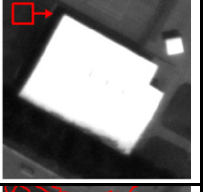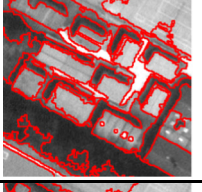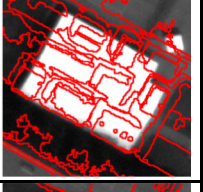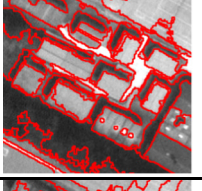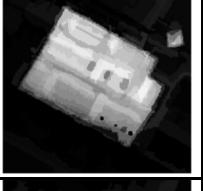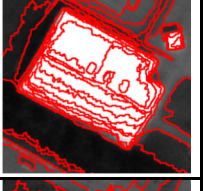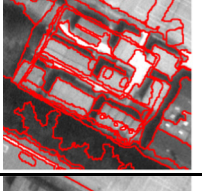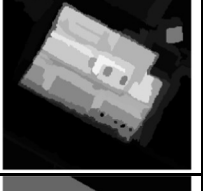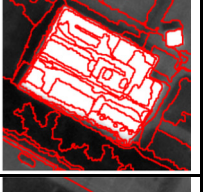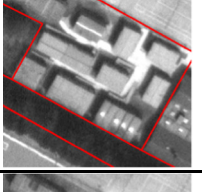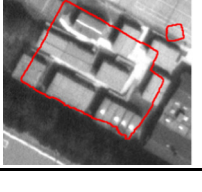|	Image 1	Change magnitude	Image 2
Pixel			
Kernel (moving window)			
Image-object overlay			
Image-object comparison			
Multi-temporal image-object			
Vector polygon			
Hybrid			

Fig. 2. A matrix of analysis units commonly used in remote sensing change detection studies. Image 1 is 25 cm resolution aerial imagery over Norwich, UK from 2006. Image 2 is aerial imagery captured over the same area in 2010, also at 25 cm resolution. The change magnitude is the absolute difference between Image 1 and Image 2 calculated over the respective unit of analysis. All imagery ©Airbus Defence and Space Ltd. 2014.

changes (Green et al., 1994; Ochoa-Gaona & Gonzalez-Espinosa, 2000; Peiman, 2011; Shalaby & Tateishi, 2007) and forestry (Coops et al., 2010; Hame et al., 1998; Wulder, Butson, & White, 2008). The concept of comparing images is very simple, with arithmetic operations such as subtraction or division applied to continuous band radiance or reflectance (Green et al., 1994; Jensen & Toll, 1982), or integer class labels (Abd El-Kawy et al., 2011; Rahman et al., 2011). These examples show that when the pixel spatially represents the anticipated change relatively well it can be a simple and effective focus by which to make change decisions, especially when there is a strong relationship between pixel intensity and the land cover transitions under investigation.

The pixel as a unit for change comparison does have many critics, and is not seen as a suitable approach when considering modern Very High Resolution (VHR) imagery. For instance G. Chen et al. (2012) argue that pixels have limited comparable classification features, typically just tone or radiance and so do not provide an adequate framework to model contextual information. Whereas Hussain et al. (2013) highlight that the pixel may be a source of geometric error, especially

when integrating different data types. The overriding criticism of the pixel as an analysis unit for change detection is the susceptibility of producing spurious, noisy change pixels as a result of within class spectral variability and image registration issues. This issue commonly referred to as classification 'salt and pepper' is widely discussed in the change detection (G. Chen et al., 2012; Hussain et al., 2013; Radke et al., 2005) and general remote sensing literature (Baraldi & Boschetti, 2012; Blaschke, 2010) as a prominent feature of pixel-based classifications, especially when dealing with VHR imagery. In light of these limitations, other means of comparison have been developed and implemented with a focus on groups of pixels.

2.2. Kernel

The use of a pixel kernel filter or moving window is a systematic way of generalising change results and introducing contextual information. By considering a local neighbourhood of image pixels change can be interpreted statistically, aiming to filter noise and identify 'true' change. A neighbourhood of pixels is also a means of modelling local texture and contextual relationships by statistical and knowledge-based means. For instance, Im and Jensen (2005) used a neighbourhood correlation analysis to improve the identification of change information in VHR imagery by considering linear regression parameters instead of pixel radiance alone. The use of kernel-based texture measures has also proved to be a complementary addition to the change detection problem in several studies including those by He et al. (2011) & Klaric et al. (2013). Furthermore, the use of contextual information is an effective method of filtering spurious change pixels (Bruzzone & Prieto, 2000; Volpi et al., 2013). These examples highlight the benefit of kernel filters; as a means of reducing spurious change and as a mechanism of allowing change decisions to be made beyond basic tonal differences. Unfortunately, kernel filters are often operated at a fixed scale and the determination of optimum window sizes is not clearly defined (Warner, 2011). Consequently their use can lead to blurred boundaries and the removal of smaller features.

2.3. Image-object overlay

Objects segmented from one image may simply be overlaid on another forming the spatial framework for comparison (Listner & Niemeyer, 2011a); Fig. 2 illustrates this concept. These objects then form the basis of an arithmetic or statistical comparison of the underlying image pixels. Image-objects have been found to make the modelling of contextual information more accessible. For example Tewkesbury and Allitt (2010) segmented aerial imagery and used mean image ratio differences to assist in the identification of impermeable surface change. In further work a spatial knowledge base was applied to separate the identified change into those associated with existing properties and those that are part of a new development (Tewkesbury, 2011). Research by Listner and Niemeyer (2011a; 2011b) segmented one image and then used a measure of object heterogeneity calculated on bi-temporal imagery to highlight change. Comber, Fisher, and Wadsworth (2004) overlaid classified image-objects on a pixel-based classification and then used expert knowledge to assist in the identification of true change from classification error. Overlaying existing objects onto new images can form a simple basis for change detection while benefiting from object-based contextual measures. The main disadvantage of this approach is that the geometry of the image-objects reflects only one of the images; with change in the opposing image not necessarily conforming to the imposed spatial framework.

2.4. Image-object comparison

The premise of image-object comparison is that two images are segmented independently so that the image-objects and their respective properties may be compared. The theoretical construct here is that corresponding image-objects may be 'linked' across space and time allowing a comparison to be made without the constraint of a geometric union. The distinct advantage here is that all object properties can be compared including size and shape (Listner & Niemeyer, 2011a) or class label (G. Chen et al. 2012). However, due to variations in factors such as illumination, viewing angle, phenology and atmospheric conditions, segmentations may be highly variable even under stable land cover and perfect co-registration.

The process of comparing one object with another is therefore complicated and non-trivial. Listner and Niemeyer (2011a) propose two approaches to comparison namely, *directed object correspondence* whereby an object is given a weighted sum of all overlapping objects and *correspondence via intersection* where object attributes are compared directly, but only over the spatial intersection created between the two time periods. The majority of the literature in this area uses the latter method, especially when applied to post-classification change (Boldt et al., 2012; Dingle Robertson & King, 2011; Gamanya et al., 2009). Image-object comparison by intersection is also illustrated in Fig. 2. The main limitation of a spatial intersection of segmentations, also referred to as *correspondence via intersection*, is that it introduces a widely reported problem of 'sliver' objects under inconsistent segmentations (G. Chen et al., 2012; McDermid et al., 2008). Sliver objects can result in false change being detected and impact the utility of updated land cover maps (Linke et al., 2009a). One method of minimising sliver objects is to simply remove smaller change objects, as demonstrated by Boldt et al. (2012). However, this approach equates to a systematic reduction in the cartographic scale of the change analysis and information loss. Linke et al. (2009b) tackled this problem by using object width to highlight slivers prior to elimination. They showed that this allows the compilation of a dynamic land cover inventory; however, this approach remains insensitive to narrow change objects below the specified width threshold. While the work of Linke et al. (2009b) provides a robust strategy to suppress sliver objects more work is required on the rigorous matching of image objects so that their full properties may be used in a change comparison (Hussain et al., 2013; Listner & Niemeyer, 2011a).

2.5. Multi-temporal image-object

Multi-temporal objects may be created by simply segmenting all available images together in a single data stack as illustrated in Fig. 2. This approach has the distinct advantage of considering all images during object formation therefore minimising sliver errors and potentially honouring key multi-temporal boundaries. For example, Doxani et al. (2011) used this approach to detect detailed urban change, an application that would be prone to widespread sliver errors due to differences in viewing geometry and shading. Teo and Shih (2013) also used multi-temporal image-objects as the basis for urban change detection, this time utilising LiDAR data, where it was found to perform well even in the presence of high magnitude spatial registration noise found at the edge of buildings. This approach has also proved successful in forest change applications at large (Chehata et al., 2011), moderate (Desclée et al., 2006) and small (Bontemps et al., 2012) cartographic scales. These examples show how multi-temporal image-objects are an elegant way of representing an image time-series, especially in applications involving elevated features where extensive viewing geometry differences are expected. However, this analysis unit is limited because object size and shape cannot be easily compared and smaller or indistinct changes may be generalised out during the segmentation process.

2.6. Vector polygon

Vector polygons originating from existing mapping databases can be overlaid over imagery and used as a basis to group image pixels in a change analysis. Groups of pixels across a temporal sequence may then be analysed statistically, the result of which may indicate changes

within the corresponding polygons. This approach is often linked to map updating in which remotely sensed images are used to automatically identify broad scale change in polygons and regions where map updating is required, thereby reducing the manual review process. For instance Walter (2004) calculated spectral means, variances and corresponding pixel class area for a set of land parcel polygons. These features were then used within a supervised classification to identify changed parcels. In a simpler workflow Gerard et al. (2010) overlaid recent CORINE land cover parcels against aerial images to visually assess historical changes over 50 years. These demonstrate how vector polygons can be used to spatially guide a change assessment. However, since the polygons often form part of land informational database this information may also be used to help inform the change detection process. For example, Comber, Law, & Lishman (2004) used soil properties, rainfall and terrain to supplement the satellite spectral information when updating land cover mapping in Scotland.

Existing class labels can provide useful information in change detection workflows, allowing efforts to be focused and acting as a thematic guide for classification algorithms. For instance, Bouziani et al. (2010) & Sofina et al. (2012) used a 'map guided' approach to train a supervised classification algorithm to identify new buildings and Duro et al. (2013) used cross correlation analysis to statistically identify change candidates based on existing land cover map class labels. The use of vector polygons as a framework for change detection has great potential especially in cases where existing, high quality attribution is used to inform the classification process. However, an assumption of this approach is that the scale of the vector polygons matches the scale of the change of interest. If this is not the case then a strategy will need to be considered to adequately represent the change; for instance pixels may be used to delineate smaller change features within a vector polygon.

2.7. Hybrid

A hybrid approach refers to a combination of analysis units to highlight change in a stepwise way. In its most basic form this relates to a change comparison of pixels which are then filtered or segmented as a mechanism to interpret what the change image is showing. For example, Bazi et al. (2010) first derived a pixel-based change image and then used multi-resolution segmentation to logically group the results. Their approach proved successful when experimentally applied to Landsat and Ikonos imagery. Fig. 2 replicates the method employed by Bazi et al. (2010), first calculating the absolute difference between image pixels and then performs a multi-resolution segmentation on the difference image before finally calculating the mean absolute difference of the original images by image-object. Research by Linke et al. (2009b) found that a multi-resolution segmentation of pixel-based Landsat wetness difference images proved an effective method of identifying montane land cover change in Alberta, Canada. Aguirre-Gutiérrez et al. (2012) combined pixel and object-based classifications in a post-classification workflow that sought to retain the most accurate elements of each. Bruzzone and Bovolo (2013) modelled different elements of change at the pixel level to include shadows, registration noise and change magnitude. These pixel-based change indicators were then used to inform a change classification based on overriding multi-temporal image-objects. These examples show that using a hybrid of analysis units may be an intuitive approach whereby change in pixel intensity is logically grouped towards identifying features of interest.

3. Comparison methods

Previous reviews (Coppin et al., 2004; Hussain et al., 2013; Lu et al., 2004) have presented exhaustive lists of change detection techniques containing many comparison methods. Here six broad comparison methods are identified that capture the key features of previous research in a concise and accessible manner. These categories are summarised in Table 2 to include a brief description of each, advantages and disadvantages and some examples from the literature. This is followed by a more detailed discussion of each comparison method.

3.1. Layer arithmetic

Arithmetic operations such as subtraction or division applied to bi-temporal imagery are simple methods of change detection. These operations give an image depicting radiance differences, which is hoped reflects the magnitude of change on the ground (Singh, 1989). This technique has long been used to highlight areas of image change quickly with minimal supervision (Green et al., 1994; Jensen & Toll, 1982) and is still in use today, typically applied to image-objects (Desclée et al., 2006; Tewkesbury & Allitt, 2010). To add thematic meaning to a difference image, the image radiance may be transformed into a vegetation index or fractional cover image prior to the layer arithmetic. For example Coulter et al. (2011) differenced regionally normalised measures of NDVI to identify vegetative land cover change while Tewkesbury and Allitt (2010) used image ratios to identify vegetation removal in aerial imagery. It is also common to monitor urban expansion by subtracting multi-temporal impermeable surface fractional cover images obtained by sub-pixel analysis (Dams et al., 2013; Gangkofner et al., 2010; Lu et al., 2010). A highly evolved system of layer differencing is presented by Jin et al. (2013), whereby change is assessed based upon combining difference images of image spectral indices and biophysical transformations. These examples demonstrate how simple arithmetic operations of image radiance, or derivative features can be used to highlight changed areas, target specific features based upon an expected spectral response or quantify fractional, sub-pixel changes.

Layer arithmetic comparisons may go beyond simple radiometric differencing by leveraging different units of analysis. This empowers the comparison by considering texture, context and morphology; therefore reducing the dependency on a target's spectral characteristics as an indicator of change. For instance Im and Jensen (2005) found that measures of kernel similarity –namely correlation coefficient, slope and offset– proved to be more effective indicators of change than simple pixel differencing. Further work showed that this same comparison method may also be applied to multi-temporal image-objects (Im et al., 2008); although no significant improvement was found when compared to the kernel based approach. When working with VHR imagery several researchers have incorporated measures of texture and morphology into the arithmetic comparison as a means of reducing the dependence on image tone. For instance, Klaric et al. (2013) present a change detection system based on a weighted combination of neighbourhood spectral, textural and morphological features. The authors argue that this approach is not entirely dependent on spectral change and is applicable to multi-spectral and panchromatic imagery. The idea of reducing the dependence on spectral information is further developed by Falco et al. (2013) in research using Quickbird panchromatic imagery alone, as a basis for change detection, by comparing measures of morphology and spatial autocorrelation. Image change isn't necessarily associated with a strong spectral difference, and these examples have shown how researchers have tackled this problem by using contextual information. However, there is still much research to be done in this area to improve classification accuracies over complex targets.

3.2. Post-classification change

Post-classification change or map-to-map change detection is the process of overlaying coincident thematic maps from different time periods to identify changes between them. The distinct advantage of this technique is that the baseline classification and the change transitions are explicitly known. Furthermore, since the maps may be produced independently, a radiometric normalisation is not necessary (Coppin et al., 2004; Warner et al., 2009). The direct comparison of satellite derived land cover maps is one of the most established and widely used

Table 2
An overview of commonly used comparison methods.

	Description	Advantages	Limitations	Example studies
Layer arithmetic	Image radiance or derivative features are numerically compared to identify change.	Can be simple to implement.	Usually gives little insight into the type of change.	Coulter et al. (2011), Dams et al. (2013), Desclée et al. (2006), Falco et al. (2013), Green et al. (1994), Homer and Xian (2011), Im et al. (2008), Im and Jensen (2005), Jensen and Toll (1982), Klaric et al. (2013), Lu et al. (2010), Tewkesbury and Allitt (2010)
Post-classification change	The comparison of multiple maps to identify class transitions.	Produces a labelled change map. Prior radiometric calibration may not be required.	Errors in any of the input maps are directly translated to the change map.	Abd El-Kawy et al. (2011), Boldt et al. (2012), Chou et al. (2005), Comber, Fisher, & Wadsworth (2004), Dingle Robertson and King (2011), Gamanya et al. (2009), Hester et al. (2010), Li et al. (2012), Teo and Shih (2013), Torres-Vera et al. (2009), X. Chen et al. (2012)
Direct classification	A multi-temporal data stack is classified directly identifying both static and dynamic land covers.	Only one classification stage is required. Provides an effective framework to mine a complicated time series. Produces a labelled change map.	Classification training datasets can be difficult to construct, especially for a time series of images.	Chehata et al. (2011), Gao et al. (2012), Ghosh et al. (2014), Hame et al. (1998), Hayes and Sader (2001), Schneider (2012)
Transformation	A mathematical transformation to highlight variance between images.	Provides an elegant way to handle high dimensional data.	There is no defined thematic meaning to the results. Change may be difficult to locate and interpret.	Deng et al. (2008), Doxani et al. (2011), Listner and Niemeyer (2011a)
CVA	The computation of difference vectors between analysis units giving both the magnitude and direction of change.	Gives insight into the type of change occurring.	In its raw form the change direction and magnitude may be ambiguous.	Bovolo et al. (2012), Bovolo and Bruzzone (2007), Bruzzone and Prieto (2000), Carvalho Júnior et al. (2011), Cohen and Fiorella (1998), Johnson and Kasischke (1998)
Hybrid change detection	The use of multiple comparison methods within a workflow. The most commonly used strategy is a combination of layer arithmetic to identify change and direct classification to label it.	Training data does not have to be collected over radiometrically stable areas.	No specific limitations.	Bruzzone and Bovolo (2013), Doxani et al. (2011), Seto et al. (2002), Xian and Homer (2010)

change detection methods, applicable to Landsat class imagery (Abd El-Kawy et al., 2011; Dingle Robertson & King, 2011; Gamanya et al., 2009; Torres-Vera et al., 2009) and VHR imagery (Boldt et al., 2012; Demir et al., 2013; Hester et al., 2010). The approach may also be used to locate changes of a specific thematic target. For instance, Boldt et al. (2012) and Teo and Shih (2013) both used post-classification change to uniquely identify building changes. These examples show that post-classification change is a thematically rich technique able to answer specific change questions, making it suitable for a range of different applications.

Post-classification change is limited by map production issues and compounded errors making it a costly and difficult method to adopt. The comparison method requires the production of two entire maps which may be an expensive (Lu et al., 2004) and an operationally complex task. Furthermore, input maps may be produced using differing data and algorithms. In this case, a distinction must be made between classification inconsistencies and real change as explored by Comber, Fisher, & Wadsworth (2004). The biggest issue with post-classification change is that it is entirely dependent on the quality of the input maps (Coppin et al., 2004; Lu et al., 2004) with individual errors compounding in the change map (Serra et al., 2003). Therefore, it is difficult and expensive to produce a time series of maps with sufficient quality to obtain meaningful change results.

There have been significant efforts to improve post-classification change results by accounting for classification uncertainty and by modelling anticipated change scenarios. Classification uncertainty may be spatial, thematic or a combination of both and accounted for by assigning confidences to these criteria. For instance, X. Chen et al. (2012) compared fuzzy class probability, rather than crisp labels, to highlight uncertain land cover transitions. Hester et al. (2010) used spatial and thematic fuzziness in the classification of urban change using Quickbird imagery accounting for increased pixel level mis-registration in VHR imagery. Specific change scenarios can also be modelled in an attempt to identify and remove unlikely land cover transitions. For instance Chou et al. (2005) developed a spatial knowledge base, implemented as pixel kernel filters to remove change pixels not conforming to pre-determined change scenarios. This approach has also been extended to include full urban simulations as a means of identifying unlikely transitions (Li et al., 2012). These examples demonstrate that post-classification change has been extended from a simple map label arithmetic operation to one that considers the confidence of a particular label and the likelihood of its indicated change.

3.3. Direct classification

A multi-temporal stack of images can be directly classified to give a land cover inventory over stable areas and land cover transitions where change has occurred. The data stack consists of multiple sets of *n* band images which may be treated by a classifier as one set of classification features. This is then classified with a supervised or unsupervised

technique aiming to give a set of stable land cover classes and changed land cover transitions. The technique is advantageous, since only one classification stage is required and identified changes are thematically labelled. Several researchers investigating forest change have used this approach as a means of directly identifying their target of interest. For instance, Hayes and Sader (2001), Hame et al. (1998) and Chehata et al. (2011) all implemented forest change detection systems based an unsupervised classification of multi-temporal imagery, facilitated by a good understanding of the nature of the change. These examples from forestry applications show how the direct classification technique can be used to solve a relatively well constrained problem. However, direct classification is a powerful tool in the context of a data mining problem such as the interpretation of a dense time series of images. Such a scenario is very difficult to conceptualise or model with expert knowledge, and is an ideal scenario for machine learning algorithms. For example, Schneider (2012) was able to successfully mine a time series of 50 Landsat images from 1988 to 2010 for changes in urban extent using supervised support vector machine (SVM) and decision tree classifiers. The dense time series and machine learning approach allowed the extraction of meaningful change under complicated phenological patterns without explicitly modelling them. Gao et al. (2012) also used this strategy, applying a supervised decision tree classifier to extract impermeable surface change over 33 years using nine Landsat images. These examples demonstrate that the direct classification of a time series of images can be an effective way of deciphering change that may be buried within complex patterns. However, deriving training datasets for such a classification can be very challenging (Lu et al., 2004) and unsupervised approaches can prove unresponsive to small magnitude change patterns (Warner et al., 2009). In light of these limitations, recent work by Ghosh et al. (2014) into semi-supervised change classification is extremely interesting with more research needed in this area.

3.4. Transformation

Data transformations such as principle component analysis (PCA) and multivariate alteration detection (MAD) are methods of data reduction by suppressing correlated information and highlighting variance. When applied to a multi-temporal stack of remotely sensed images there is the potential to highlight image change, since it should be uncorrelated between the respective datasets. For instance, Deng et al. (2008) applied PCA to a multi-temporal data stack of Landsat and SPOT 5 imagery in order to identify changed areas for a subsequent supervised change classification. The PCA image was classified into 'change' and

'no change' domains by labelling unsupervised clusters. In this case, 60 clusters were required to identify the change present, indicating that the change signal was relatively well 'hidden' within the principle components. Doxani et al. (2011) found that applying the MAD transformation to image-objects was an effective method of highlighting change objects in VHR imagery. Listner and Niemeyer (2011a) also applied a MAD transformation to image-objects to highlight change. However, they highlighted that the MAD transformation may become mathematically unstable when applied to highly correlated features. This is particularly relevant when considering the large number of classification features available under OBIA. In order to ensure a robust change detection strategy, they proposed a prior PCA, with the first three principle components acting as the inputs to the MAD transformation. Although this strategy worked in their application, it does highlight an issue with transformations, namely that the first 2 or 3 components may not necessarily contain the desired change information (Bovolo et al., 2012). Therefore, change features may either be missed or buried within a high number of transformation components. Furthermore, PCA and MAD transformations are scene dependant and may prove difficult to interpret (Carvalho Júnior et al., 2013; Lu et al., 2004; Warner et al., 2009). Transformations can be a useful way of assessing change within a complex time series of images. However, they usually only serve to highlight change and therefore should form part of a hybrid change detection workflow to provide change labels. Lastly, due to the scene dependence, it may prove a difficult task to locate change within the multiple components, if the change is represented at all.

3.5. Change vector analysis (CVA)

Change vector analysis is a method of interpreting change based on its magnitude and direction. To facilitate this, bi-temporal datasets are described in three components; namely the feature vector at time 1, the feature vector at time 2 and an interconnecting vector. The interconnecting vector is called the change vector and its magnitude and direction can give us an insight into the type of change occurring. The geometry of a CVA is given in Fig. 3a (in 2D for simplicity). Calculating the magnitude is very simple (see Cohen & Fiorella, 1998, p 91), easily extended to high dimensional feature space. For instance, the change magnitude of all six Landsat spectral bands (excluding the thermal) is often calculated to assess the apparent extent of change (Bruzzone & Prieto, 2000; Xian & Homer, 2010). In theory the magnitude gives the degree to which the image radiance has changed, containing limited thematic content, while the direction indicates the type of change.
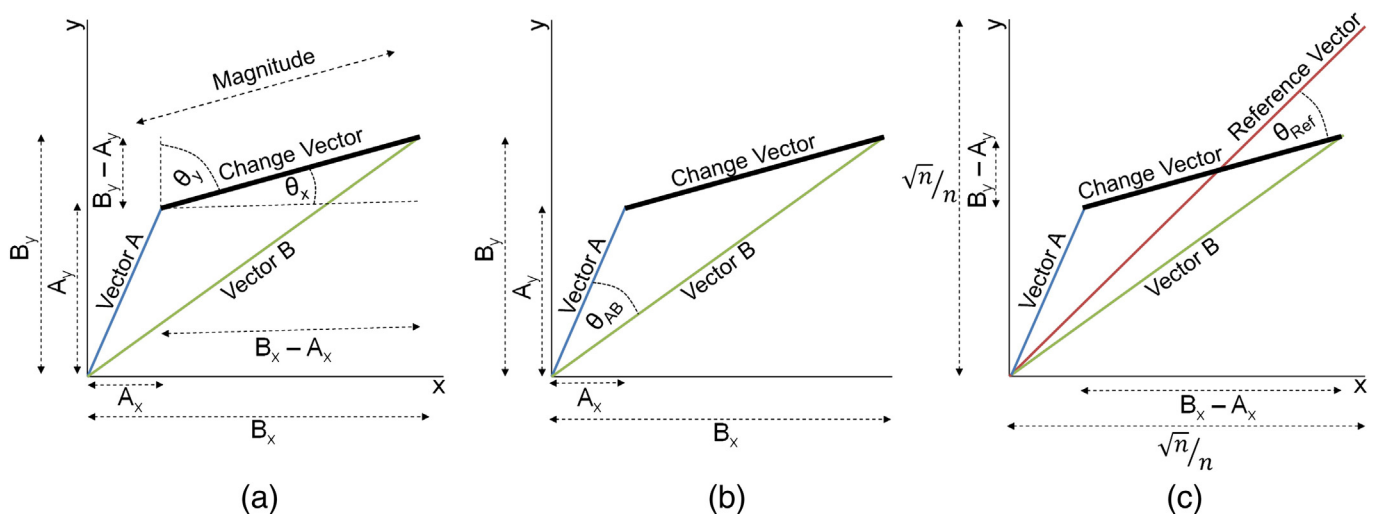
Fig. 3. An illustration in 2 dimensions of the geometry of three formulations of CVA. For each, the x and y axes represent the input features under analysis, typically spectral bands. Vector A and Vector B represent the value of a given analysis unit for a bi-temporal pair of images. (a) The 'standard' formulation of CVA describing the change vector by magnitude and a series of angular directions relative to each axis. (b) Spectral Angle Mapper (SAM) for CVA, after Carvalho Júnior et al. (2011). (c) n dimensional CVA, after Bovolo et al. (2012).

Therefore, the combination of magnitude and direction can be a means of labelling change and minimising false positives (Bovolo & Bruzzone, 2007). In the standard formulation of CVA (Fig. 3a) the direction is described by a directional cosine for each axis of the feature space. Therefore, $n - 1$ directional cosines are required to describe the change direction in n dimensional feature space, leading to a complicated output data array which may be difficult to interpret (Carvalho Júnior et al., 2011). In light of this, many researchers simplify the input feature space to two bands only. For example, Bovolo and Bruzzone (2007) defined a 2D feature space based on Landsat bands 3 and 4 allowing burnt area change to be uniquely identified from magnitude, and a single angular direction. Another method used to simplify CVA direction is by applying a prior transformation to the input multi-dimensional data and performing the analysis on two of the components alone. Cohen and Fiorella (1998) and Johnson and Kasischke (1998) used this approach, transforming the six available Landsat bands into tasselled cap components as input into a 2D CVA. These examples highlight how CVA has the potential to be used as both a change identification and labelling tool. However, a complicated description of n dimensional change limits its application. This point is discussed in detail by Bovolo et al. (2012), who note that limiting CVA to 2 dimensional feature space requires prior knowledge of the nature of the change occurring and may lead to a poor analysis through an ill-informed band selection. This highlights a clear need to more elegantly describe change direction in n dimensional feature space.

More recently, there has been some interesting research describing how n dimensional change directional information can be conveyed in a CVA. These have sought to use several image channels while retaining a simple description of the change direction. For instance, Carvalho Júnior et al. (2011) proposed the use of the Spectral Angle Mapper (SAM) and its statistically normalised derivative, spectral correlation mapper (SCM), both well-established techniques, common in hyperspectral remote sensing. Such techniques are used to describe how similar any two n dimensional vectors are to each other, and so has clear applicability to change detection. SAM, mathematically based on the inner product of two vectors (Yuan et al., 1998) is the single angle between two n dimensional vectors (Fig. 3b). It is worth reiterating that SAM and SCM are both measures of *similarity* and do not give change direction or type per-se. However, they can be highly informative and complementary to a change vector analysis (Carvalho Júnior et al., 2011).

The principle behind SAM was further explored by Bovolo et al. (2012) in order to relate the single angle back to change direction. This work used the same theoretical basis as Carvalho Júnior et al. (2011) but instead evaluated the angle between the change vector itself and an arbitrary reference vector (Fig. 3c), and Bovolo et al. (2012) normalised the reference vector by setting all elements equal to $\sqrt{n}/n$. The rationale for this approach is that the use of an arbitrary reference vector gives a consistent baseline for the change direction, allowing thematic changes to be consistently grouped throughout a scene. Bovolo et al. (2012) argue with reference to experimental examples, that this formulation of CVA does not require any prior knowledge of the anticipated change or its remote sensing response. Moreover, the technique can identify more types of change since all of the available information is considered. These developments could go some way towards establishing CVA as a universal framework for change detection as suggested by Johnson and Kasischke (1998). Due to the recent nature of this research there are few published examples however the underlying philosophy has great potential, particularly when considering future super spectral satellite missions and the wide variety of object-based features available. At the time of writing there is no published research integrating the work of Carvalho Júnior et al. (2011) and Bovolo et al. (2012), despite the complementary nature of these descriptors of multi-dimensional change.

A little-reported limitation of CVA is that both the magnitude and direction can be ambiguous (Johnson & Kasischke, 1998). Consider the

three identified formulations of CVA displayed in Fig. 3a, b & c. It is evident that the change vector itself can be translated within the feature space, while retaining the same measures of magnitude and direction. There is the possibility that multiple thematic changes may be described by identical measures of magnitude and direction, limiting the power of CVA as a change labelling tool. In appraising this limitation, Cohen and Fiorella (1998) concluded that a baseline reference vector, typically from the first time period, should be used when attempting to further classify CVA results. This limitation of CVA is easily surmountable but clearly increases the burden of the interpretation task, especially in the case of high dimensional datasets.

3.6. Hybrid change detection

A hybrid approach uses more than one comparison method in order to increase the understanding of identified change. At an elementary level it could be thought of in two stages: locating change and identifying change. This approach identifies change candidates, minimising reference data collection (Lu et al., 2004). Hybrid change detection is often expressed as a layer arithmetic operation to identify changed elements, followed by a supervised or unsupervised direct classification of the changed features giving them meaning (Lu et al., 2004). For example, Seto et al. (2002) first established a CVA depicting the radiometric change magnitude and direction, and then used a supervised classification to label into specific land cover transitions. While Doxani et al. (2011) tackled urban change detection in VHR imagery by first applying a MAD transform to highlight changed areas, and then applied a knowledge-based classification to filter and classify the results. An interesting formulation of hybrid change detection has recently been presented by Bruzzone and Bovolo (2013). They argue that functional change detection must distinguish semantic change, relating to specific features from radiometric, or image change. This theory was experimentally implemented by combining pixel-based measures of shadow, radiometric change and noise within an object-based classification. These examples highlight a trend amongst research that seeks to use multiple stages of change comparison to solve particular problems, a trend which is likely to continue as workflows become ever more complex.

4. Discussion

Here, we consider some of the specific issues which underlie this review, and make some practical suggestions which may be adopted in future experimental and applied research. The organisation and nomenclature developed is a response to the burgeoning change detection literature, proliferated by the addition of object-based methods. While OBCD has undoubted merits, the pixel as an analysis unit and allied comparison methods is still very relevant. Therefore, remotely sensed optical image change detection should be considered as a whole. We further discuss this rationale starting with the recent rise of OBCD and why its use should be carefully considered on merit and better-organised in experimental research. We then discuss an application-driven framework to identify requirements, and inform the selection of an appropriate unit of analysis and comparison method based on scale and thematic objectives. We argue that a unit of analysis should be selected based on its representation of the application scale with respect to the available image resolution, and its ability to deliver the required comparison features. On the other hand the comparison method must fit the application's thematic objectives.

There is currently a debate in the remote sensing literature over the merits of object-based change detection (OBCD) versus traditional pixel-based methods. Some believe that OBCD is a more advanced solution, capable of producing more accurate estimates of change particularly when VHR imagery is used. For instance G. Chen et al. (2012) and Hussain et al. (2013) argue that OBCD is an advancement beyond pixel-based change detection that generates fewer spurious results

with an enhanced capability to model contextual information. Moreover, Boldt et al. (2012) describe pixel-based change detection of VHR imagery as inappropriate. Kuntz et al. (2011) comment that objects are less sensitive to geometric errors due to a greater potential for a majority overlap and Im et al. (2008) point to the fact that OBIA may be a more efficient means of making change comparisons. Crucially, objects are described as an intuitive vehicle to apply expert knowledge (Blaschke, 2010; Vieira et al., 2012) which if operationalised would represent an opportunity to model specific change features.

There is a significant technical overlap between object and pixel-based approaches. It is becoming increasingly common in the literature to subdivide change detection methods into either pixel or object-based approaches followed by a range of sub-methods (Boldt et al., 2012; G. Chen et al., 2012; Hussain et al., 2013). This results in a very disparate and complicated set of change detection methods, making evaluation and selection extremely difficult. However, many of the sub-methods are very similar, if not identical, varying only by the analysis unit used for the comparison. For instance, post-classification change remains conceptually the same under pixel and object-based implementations as shown in a comparative analysis by Walter (2004). Simple arithmetic change operations such as differencing and ratios (Green et al., 1994; Jensen & Toll, 1982) –arguably the foundation of remote sensing change detection– may be applied equally to pixels or image-objects. More complicated procedures such as a multivariate correlation analysis may also be applied to pixels or objects (Im et al., 2008). Warner et al. (2009) suggest that any change detection technique that can be applied to pixels can also be applied to objects. While there are obvious merits to working with objects, it is not always useful to make a hard distinction between object and pixel-based change detection. This can result in an overly complicated and disparate presentation of the available techniques.

Focusing on OBCD may unnecessarily narrow the focus of a literature review or method selection because of a bias towards the unit of analysis, at the detriment of the comparison methodology. Although using image-objects for change analysis has its undoubted merits and is a 'hot topic' for research (Blaschke, 2010), it is important to consider remote sensing change detection as a whole and be aware of advancements in both pixel and object-based methods since they are usually interchangeable. For instance, two recent reviews of change detection focusing on OBIA methods (G. Chen et al., 2012; Hussain et al., 2013) bypass recent important advancements in CVA (Bovolo & Bruzzone, 2007; Bovolo et al., 2012; Carvalho Júnior et al., 2011). CVA and the vast majority of comparison methodologies are not constrained to image pixels with a change analysis executable on pixels, primitive image-objects or meaningful image-objects (Bruzzone & Bovolo, 2013). In essence, change detection workflows are more often than not transferable between analysis units regardless of their initial conception. Ultimately, it is more useful to make a technique selection considering the merits of both the comparison methodology and analysis unit in relation to the task in hand.

OBIA and by association OBCD is a means of generalising image pixels, with the segmentation scale directly controlling the size of detectable features. When segmenting at a particular scale the resultant objects are conveying statistical summaries of the underlying pixels. As highlighted by Walter (2004), regions of change must occupy a significant proportion of an object or exhibit extraordinary magnitude in order to be detectable. Therefore, the segmentation scale and image resolution must be carefully chosen so as to adequately define change features of interest (Hall & Hay, 2003). Dingle Robertson and King (2011) highlight that the selection of an appropriate segmentation scale is not straightforward. In their workflow they qualitatively identified a suitable segmentation scale but nonetheless found that smaller, less abundant classes were not retained in their post-classification change analysis. The generalising properties of OBIA are however actively used as a means of removing spurious, 'salt and pepper' features (Boldt et al., 2012; Im et al., 2008). This point would be of particular

concern when seeking change at large cartographic scales. Clearly then, when considering an object-based unit of analysis, the size of the target change must be known prior to performing the analysis so that a suitable segmentation scale may be applied.

Experimental methods aiming to test object-based methods against pixel-based counterparts are often flawed because several variables are under comparison. Research aiming to compare pixel-based classifications against object-based ones should then be designed with the analysis unit as the sole variable. Under the framework presented in this review, change detection analysis units could then be meaningfully compared while maintaining identical comparison methodologies. However, it is often the case that experiments are undertaken varying both the analysis unit and comparison or classification method. For instance, Dingle Robertson and King (2011) compared a maximum likelihood classification of pixels to a nearest neighbour classification of image-objects; While Myint et al. (2011) compared nearest neighbour and knowledge based classifications of image-objects to a maximum likelihood pixel classification. These experiments provide conclusions based on compounded variables with the effect of an analysis unit change confused with a change of classification algorithm. Conversely, interesting research by Duro et al. (2012) found that the differences in accuracy of pixel and object-based classifications were not statistically significant when executed with the same machine learning algorithm. There is then a case for caution before declaring object-based methods as superior. In the case of change detection it is hoped that the clearer demarcation between the analysis unit and comparison methodology presented in this review can help to steer research in this area, providing more reliable information as to the relative merits of each component.

The nomenclature presented here may be used to help guide method selection in applied research. While this is an extremely complicated and non-prescriptive task, we believe that the breakdown of change detection into two discrete components does help to focus selection decisions more meaningfully. An application-driven framework is provided by which to build criteria for a technique selection. This framework, along with the key decisions and considerations is illustrated in Fig. 4. A given change detection application will always start with thematic and scale objectives, which may be summarised by the required types of change and the spatial scale at which they must be identified and depicted. These objectives inform the selection of the unit of analysis and comparison method directly, but are also used in the selection of suitable imagery and the identification of classification features required to satisfy the thematic objectives. Comparison features are typically identified by expert knowledge and understanding of the anticipated change, which may develop into full ontological descriptions as explored by Arvor et al. (2013). Although not a scientific consideration, costs will inevitably constrain most change detection projects to some degree. Therefore, sensible substitutions must be made in lieu of techniques and data requirements that prove too resource intensive.

The application scale with respect to the resolution of the available imagery contributes to the selection of an appropriate unit of analysis. If we consider change targets as geo-objects — abstractions of the reality on the ground at a particular scale (Castilla & Hay, 2008), then the unit of analysis will seek to approximate geo-objects to varying levels of spatial, morphological and contextual fidelity. Single pixels are still routinely used as the unit of analysis for change at moderate scales based on medium resolution imagery (Abd El-Kawy et al., 2011; Schneider, 2012). Moreover, urban change detection has been demonstrated at relatively large cartographic scales using sub-pixel analysis of medium resolution images (Lu et al., 2010; Xian & Homer, 2010). It is argued by Blaschke et al. (2014) that geo-objects are best represented by many pixels aggregated to image objects, irrespective of the image resolution. This is clearly present in the object-based change detection literature, with projects conducted using imagery at high (Chehata et al., 2011; Doxani et al., 2011; Ehlers et al., 2014), medium (Desclée et al., 2006; Dingle Robertson & King, 2011; Gamanya et al., 2009; Lizarazo, 2012)
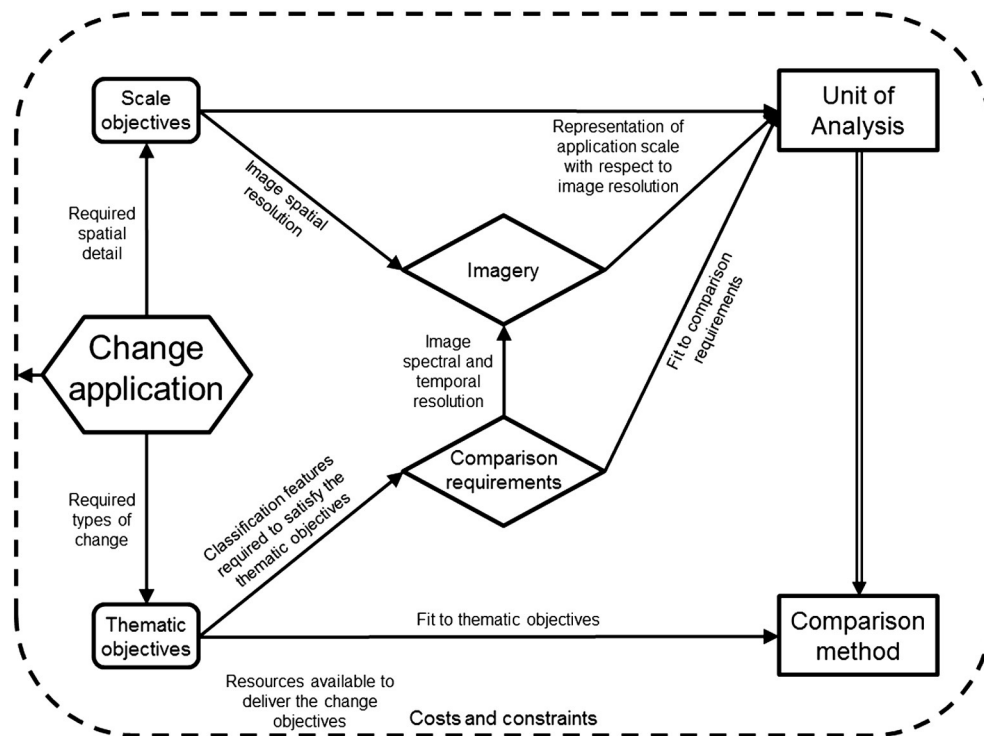
Fig. 4. An application driven framework for the selection of an appropriate change detection unit of analysis and comparison method.

and even low (Bontemps et al., 2012) resolutions. Based on imagery licensing, storage and processing it is a fair assumption that the cost to conduct a change analysis will be related to the number of pixels under investigation. Therefore, the use of aggregated image-object units of analysis may represent a higher cost solution for a given application scale. For example, the sub-pixel detection of change at a relatively large cartographic scale employed by Xian and Homer (2010) presents a solution with 'reasonable costs and production times' (Xian & Homer, 2010, p 1685). Given the huge variability present in the literature, it is not possible to recommend an appropriate unit of analysis based on the application scale and image resolution alone. Clearly, cost has influenced previous projects but the required comparable features, driven by an application's thematic objectives is a crucial factor that completes the decision.

The classification features required to make a meaningful change comparison are pivotal when selecting an appropriate unit of analysis. To illustrate this point, we consider the comparison requirements for a specific change application (the comparison of impervious surfaces) and then refer to instances in the literature that have addressed this problem. The comprehensive identification of impervious surfaces, and the monitoring of their change over time using remotely sensed data, would require the comparison of multi-spectral image tone, supplemented by texture and context. More specifically, this task might involve the analysis of: (1) key absorption and reflection features present in the visible, near-infrared and especially short-wave infrared regions (Weng, 2012), (2) fine scale textures (Perry & Nawaz, 2008), and lastly (3) the image scene's contextual and 3D parameters (Herold, 2008). Interpreting these may imply an image-object comparison of hyperspectral imagery; which may be beyond the resources of most applications. Therefore, it is common to sensibly reduce the scope of a change analysis to meet the available resources. For example, while Landsat imagery does not have the spectral fidelity to model impervious spectral responses precisely, Landsat's broad short wave infrared band is useful in the task. For example, Xian and Homer (2010) developed a sub-pixel method of estimating relatively large-scale impervious surface change derived from the spectral information of 30 m Landsat pixels alone. If there is an exploitable spectral signature associated

with the change of interest, which may be identified in the available data, then a tonal comparison only is required. This opens up all available units of analysis. For instance, forest change has been detected by comparing image tone by pixel (Cohen & Fiorella, 1998; Hayes & Sader, 2001; Tan et al., 2013), image-object overlay (Tian et al., 2013) or multi-temporal image-objects (Bontemps et al., 2012). Returning to the impervious surface change theme, Zhou et al. (2008) found that their available VHR colour infrared images were insufficient to detect impervious surfaces spectrally. Therefore, 3D LiDAR information and auxiliary mapping were utilised to assist with the detection. Research by X. Chen et al. (2012) also found spectral confusion in change detection, this time between forest and cropland change. In these circumstances, the inclusion of additional classification features –facilitated by units of analysis other than the pixel– may be used to improve change detection results. For example, kernel based texture (He et al., 2011), multi-temporal image-object texture (Desclée et al., 2006), image-object shape comparison (Boldt et al., 2012), local image correlation from kernel (Im & Jensen, 2005) and multi-temporal image-objects (Im et al., 2008) and lastly, context modelled with kernels (Volpi et al., 2013) and image-object comparison (Hazel, 2001). To summarise, if the target of interest is associated with a measurable spectral signature then the separation may be 'trivial' (Blaschke et al., 2014, p 182), opening up all available units of analysis. In this case selection may be based on the application's scale objectives and the available imagery. For more complex situations, the ability of the unit of analysis to model textural, morphological and contextual features over time should be used in the selection. Image-object comparison presents the most comprehensive framework, but the technical complications may limit its application. Therefore in such circumstances, image-object comparison and hybrid approaches offer simplified, albeit more limited frameworks.

The thematic objectives of an application must be carefully considered when evaluating a comparison method. Consequently, it is important to distinguish between the two broad outcomes of a change analysis, namely the identification of radiometric change and semantic change (Bruzzone & Bovolo, 2013). Radiometric change relates to spectral or image change (Warner et al., 2009) and is simply an observed difference in image tone. Radiometric change relates to all changes

indiscriminately to include actual changes on the ground and those associated with illumination, phenology or viewing geometry. Semantic change on the other hand is thematically subdivided into meaningful categories — be they differences in scene shading or specific land cover transitions. Clearly, semantic change is of greater value, directly informing the end user. Unfortunately, these two very different outcomes are normally presented jointly as 'change detection' (Johnson & Kasischke, 1998) making comparisons between different research projects very difficult. Generally, simple layer arithmetic comparisons resulting in a difference image depict radiometric change only, leaving the end user to review all radiometric change prior to identifying features of interest. Bruzzone and Bovolo (2013) have argued strongly that change detection should identify different types of change in order to effectively remove noise and isolate targets of interest. The default choice of identifying semantic change for applications requiring meaningful, quantitative information is post-classification change (Abd El-Kawy et al., 2011; Rahman et al., 2011; Torres-Vera et al., 2009) but this may be prohibitively expensive in some cases. In applications such as impervious surface change (Lu et al., 2010), layer arithmetic may be used to directly inform the thematic objectives. For more complicated requirements, a direct classification of a multi-temporal data stack shows great potential, especially when applied to a dense time series with suitable training data.

5. Conclusions

This review has presented optical image change detection techniques to a clear, succinct nomenclature based on the unit of analysis and the comparison methodology. This nomenclature significantly reduces conceptual overlap in modern change detection making a synoptic view of the field far more accessible. Furthermore, this approach will help to guide technique comparison research by placing a clear separation of variables between the analysis unit and classification method.

The summary of analysis units shows that more research is required to identify optimum approaches for change detection. While image-object comparison is theoretically the most powerful unit, in light of inconsistent segmentations, matching image-objects over space and time requires far more sophisticated map conflation technology. Therefore, multi-temporal image-objects or a hybrid approach is likely the most robust analysis units, while the pixel is still suitable for many applications. It is recommended that future research in this area ensures a strict separation of analysis unit and comparison method variables in order to provide clearer information on the relative merits of each.

Post-classification change is the most popular comparison method due to the descriptive nature of the results allowing specific thematic questions to be answered. A direct classification of a complicated data stack is also an effective method of identifying semantic changes. However, the required training data is extremely difficult to obtain since the location of change is usually not known prior to an analysis. As highlighted by Lu et al. (2004) a hybrid approach may inherit the benefits of a direct classification while simplifying training data collection. Recent developments in CVA provide a powerful framework to compare multi-dimensional data but remain largely untested in the literature. Therefore, more research is required exploring recent formulations of CVA, in particularly the effect of integrating object-based features and other contextual measures.

The use of image-objects as the unit of analysis in a change detection workflow should be a carefully considered decision based on the application at hand rather than adopted as a default choice. The main factor in this decision should be the requirement to compare features inherent to image-objects such as morphology and context. This decision must also include the scale of the analysis and acceptable levels of generalisation to be applied with respect to the pixel size of the images under analysis.

Remote sensing change detection is a vast subject that has evolved significantly in the last 30 years but more research is required to tackle persistent problems. These include: scene illumination effects (Hussain et al., 2013; Singh, 1989), changes in viewing geometry (Listner & Niemeyer, 2011a; Lu et al., 2004), scale and the identification of small, 'sub-area' change (G. Chen et al., 2012), objects based feature utilisation (G. Chen et al., 2012; Hussain et al., 2013) and segmentation consistency and comparison (Hussain et al., 2013; Listner & Niemeyer, 2011a). This review makes a contribution by offering a clearer organisation by which to conduct research in this field.

Acknowledgements

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