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Making more out of pixel-level change information: using a neighbourhood approach to improve land change characterization across large and heterogeneous areas

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ABSTRACT

The paper demonstrates two issues; (i) how a 'moving window approach', that translates pixel level detected changes to landscape level, can be implemented; (ii) how the approach can overcome the limitations of pixel level change information to characterize change over large areas. First we detected changes from two periods (1986 and 2010) of LULC maps. On the pixel-based changes, we ran focal statistics summation operator separately for selected window sizes (1–10 km). Further, we assessed effect of scale in depicting the pattern and amount of change. The approach is found useful to overcome major shortfalls of pixel-based change characterization. However, varying scale of analysis provide varying amount of change and differently represent change patterns. Thus, implementing the approach over complex and large areas requires multi-scale approach. Subdividing complex and large areas into homogeneous zones can help to implement the multi-scale approach and facilitate the selection of appropriate scale of analysis.

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Moving window; Upper Eastern Nile Basin; Landscape-level change; Ethiopian Highlands; land use/cover change

1. Introduction

Understanding and estimating processes of land use and land cover (LULC) change remains a major task on the global research agendas of geographers and geospatial scientists (Turner et al. 2007; Gong et al. 2013; Singh, Laari et al. 2017). Despite the great significance that spatially explicit information about LULC change has for land use decision-making, such information is frequently still lacking for the required periods, at the required level of detail and spatial extent (Herold et al. 2008). As a result, it has been difficult for local, regional and national actors to take proactive decisions on land use. The advent of remote sensing and geospatial science in the 1970s has improved knowledge about land change, and many challenges have been addressed (Usman et al. 2015; Singh, Laari et al. 2017). But there are still constraints to efficient use of the benefits that remote sensing technology has provided, particularly when it comes to characterizing and assessing land change processes at global, continental, national and regional scales (Verburg et al. 2011). In the case of land change assessments based on

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satellite imagery, two categories of challenges still impair proper documentation and characterization of land change across large and complex areas. The first category is related to satellite data and includes (1) quality issues (cloud cover, noise and resolution) and (2) availability and accessibility issues (Herold et al. 2008; Gong et al. 2013). The second category is related to methodology and includes (1) producing multi-temporal LULC maps across large and complex areas (Chen et al. 2015; Kassawmar et al. 2016) and (2) detecting, mapping and characterizing change across large and complex areas (Verburg et al. 2011; Chen et al. 2015). Researchers in the field have been striving to tackle these challenges and harness the advantages of remote sensing technology to document land change processes at the required scales (Verburg et al. 2011).

Since the inception of remote sensing, conventional pixel-based image classification techniques (supervised and unsupervised) have remained indispensable in producing multi-temporal LULC maps (Riggan and Weih 2009). Conventional change detection techniques like post-classification comparison are also still widely used (Pontius and Cheuk 2006). The benefit of such approaches lies in their simplicity and their applicability to any available LULC maps irrespective of differences in spatial and temporal scales (Pontius and Cheuk 2006; Netzel and Stepinski 2015; Lamine et al. 2017). The cross-tabulation matrices resulting from post-classification comparison are particularly helpful in improving our understanding of LULC dynamics (Pontius and Cheuk 2006; Teferi et al. 2013). However, it has been argued that change information generated at pixel level has several limitations when it comes to depicting, characterizing and interpreting land change, especially when the areas of interest are large and complex (Rogerson 2002; Gimona and van der Horst 2007; Netzel and Stepinski 2015). This is mainly because the quality of a change map produced from pixel-level multi-temporal LULC maps will suffer from geometric, atmospheric, topographic and radiometric errors in the basic satellite images used. Unlike vector-based or object-based approaches, change detection approaches based on pixel-level LULC maps and post-classification comparison lead to salt-and-pepper change errors in the resulting change maps (Riggan and Weih 2009). Post-classification comparison, in particular, leads to a compounding salt-and-pepper effect arising from the classification stage (Zhang and Tang 2012). For that reason, these techniques should be used with input data that have undergone standard correction procedures such as geometric, atmospheric, topographic and radiometric correction. Nonetheless, when mapping large and heterogeneous areas, these types of errors in the change map are difficult to avoid completely, as standard correction procedures may sometimes also result in erroneous change information. In sum, pixel-level change maps are not always appropriate to depict and characterize land change across large and heterogeneous areas. They are not sufficiently informative, especially for non-experts; and this means that they are inadequate for land use policy formulation and decision-making. It has been shown that more useful change maps that better explain reality can be generated by analysing several neighbouring pixels (Riitters, Wickham JD et al. 2009). Moreover, when looking at large and heterogeneous areas, it is more appropriate to explain land change in relative than in discrete/absolute terms.

To overcome the limitations of maps showing changes at pixel level, researchers in the field widely use majority filter techniques, which are usually applied separately to each multi-temporal LULC map. However, as it is difficult to apply these techniques selectively, they may cause real changes of small spatial extent to be removed, or small areas with no change to appear changed. Thus, to be sure whether the land represented by a pixel has actually changed, we must also look for possible changes occurring in surrounding pixels (Riitters, Wickham J et al. 2009). Indeed, examining the status of groups of neighbouring changed pixels over time makes it possible to produce change information that is closer to reality than information generated by smoothing the multi-temporal LULC maps using a majority filter (Gagn and Fahrig 2007; Riitters, Wickham JD et al. 2009). Other studies have also found that to obtain more accurate change information, it is necessary to examine groups of changed but neighbouring pixels (Hett et al. 2012). Doing so reduces the risk of reporting erroneous change information, provides flexible options for presenting change on a map, and thereby makes it possible to produce a meaningful change pattern that closely reflects reality and is easily interpreted by non-experts.

In view of the limitations of pixel-level change maps and the benefits of examining several changed pixels within a defined neighbourhood, this study took a neighbourhood approach to mapping and characterizing land change across a large and heterogeneous area. A minimum of two LULC maps showing the area of interest at different points in time is needed to create a new change map based on analysis of pixel-level change information using a neighbourhood approach (Riitters, Wickham J et al. 2009). A neighbourhood approach means categorizing similar values and/or configurations of changed pixels within a 'window' or 'kernel' of a defined size. Technically, this can be done by applying a moving window tool in ESRI's ArcGIS® software, which computes and provides various metrics (Gustafson 1998); the way in which the tool is applied varies depending on the input data and the objective of the study (Griffith 2004; Riitters, Wickham J et al. 2009). The moving window tool analyses clusters of neighbouring pixels, and the size of the moving window represents the extent of the neighbourhood (Riitters, Wickham JD et al. 2009). Important metrics of land dynamics include, among others, amount of change, expressed as the percentage or number of changed pixels per defined neighbourhood, and patterns of change, expressed in terms of the spatial arrangement of changed pixels. Both can be generated by applying a moving window technique to pixel-level change information (Singh, Srivastava et al. 2017). Information about the amount and patterns of change can help to explain land change processes in a more meaningful way than pixel-level information can (Gustafson 1998; Theobald 2010; Lamine et al. 2017). However, outputs produced by means of a neighbourhood approach vary with the size of the moving window (Remmel and Csillag 2003; Wu 2004; Šímová and Gdulová 2012). This means that choosing an appropriate moving window size is crucial. Therefore, proper use of the approach requires close examination of the effect of the moving window size, taking into account the spatial resolution of the input data, the purpose of the analysis and the nature of the change processes observed.

The overall aim of the present study was to explore the potential and limitations of land change information produced at pixel and at neighbourhood level for characterizing land change at regional and national scales. Four specific objectives guided our work. The first was to translate pixel-level change information to the neighbourhood level using various moving window sizes and to compare results obtained with different moving window sizes. The second objective was to examine in detail the effect of the moving window size on amounts and patterns of change obtained at neighbourhood level. Third, we aimed to measure the magnitude of the effect of the moving window size by verifying neighbourhood-level outputs against known changes and identifying factors responsible for the differences. Our fourth objective was to select the optimal moving window size for analysis of a specific area. Our findings and lessons learned will help to assess the potential and limitations of the approach for characterizing land change across large and complex areas.

2. Materials and methods

2.1. Study area

In line with the aims of our study, we chose a large and complex study area: the Ethiopian part of the Upper Eastern Nile Basin (UENB), which covers 370,000 km^2 (Figure 1). The UENB features complex, diverse ecoregions with altitudes ranging between 350 and 4540 m above sea level. In relation to the types, size and density of land changes occurring in our study area, we identified five major ecoregions and nine sub-ecoregions in the UENB, each representing distinct socio-economic and biophysical characteristics (e.g. land cover, rainfall regime, farming systems). We defined the boundaries of these zones based on an overlay analysis of geospatial data-sets on elevation, climate, population density and farming systems. Drivers of landscape transformation, including land administration/land use policy, population pressure, long-term degradation, migration and land rehabilitation activities tend to be homogeneous within these ecoregions and sub-ecoregions. The ecoregions' characteristics and spatial occurrence are indicated in Table 1 and Figure 1, respectively.

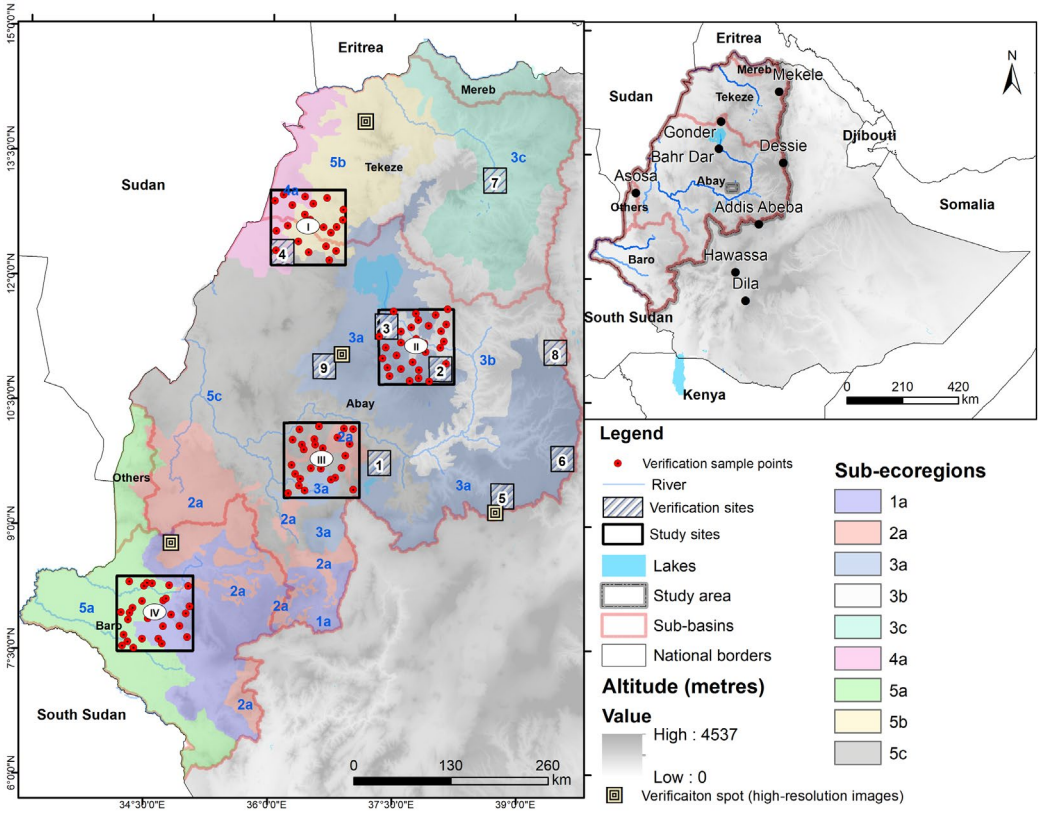

Figure 1. Ecoregions of the Ethiopian portion of the UENB, its sub-basins and the locations of the study sites.

Table 1. Major ecoregions and sub-ecoregions.

Major ecoregions	Sub-ecoregions	Codes	Sub-basins in which they occur	Landscape divides
Forestry- and agroforestry- dominated ecoregions	Natural high forest, agroforestry, and mosaic of croplands with trees and high-rainfall areas	1a	Upper Baro-Akobo	Highlands
Mixed agricultural system (moderately cultivated) landscapes	Disturbed forest, artificial forest, mosaic of crops with high trees, high-potential and high-rainfall areas	2a	Upper Abay	
Mixed agricultural system (intensively cultivated) ecoregions	Intensively cultivated high-potential and high-rainfall areas	3a	Upper Abay	
	Intensively cultivated low-potential and moderate-rainfall areas	3b	Upper Abay	
	Intensively cultivated, low-potential, and low-rainfall areas	3c	Upper Tekeze	
Agro-pastoralist system (lightly cultivated) ecoregions	Lightly cultivated, moderate-potential, and low-rainfall lowland areas	4a	Lower Tekeze	Lowlands
Dominantly pastoralist ecoregions	Wooded and moderate-rainfall lowland areas	5a	Lower Baro-Akobo	
	Wooded and low-rainfall lowland areas	5b	Lower Tekeze	
	Wooded and high-rainfall lowland areas	5c	Lower Abay	

Sub-ecoregions 1a and partly 2a (Figure 1) are dominated by natural high forest and dense woody vegetation. Sub-ecoregion 2a comprises complex mosaics of trees mixed with crops such as cereals, coffee and banana. Sub-ecoregions 3a–c are dominated by intensively cultivated and degraded land comprising scattered shrub and bush vegetation. A conducive agroecological setting has led to very intensive agricultural practices in sub-ecoregions 3a, 3b and 2a (Teferi et al. 2013). Sub-ecoregions 1a, 2a and 5a are considered high-potential areas and comprise disturbed forests. Sub-ecoregions 3b and 3c are most degraded, while the lower reaches of the study area (sub-ecoregions 4a, 5b and 5c), with lower population densities and less cultivation, are largely covered by woody vegetation (Hurni et al. 2005). For the present assessment, we selected four study sites of 100 by 100 km each within the UENB that represent the major ecoregions (Figure 1).

2.2. Data-sets

At least two pixel-level LULC maps were required for our study. We selected two years, 1986 and 2010, taking into account important change processes in the study area that drive LULC change. Each LULC map was produced using 24 scenes of Landsat TM images that partly or fully fell within the boundaries of our study area. Due to the influence of the seasonal monsoon rainfalls on the spectral behaviour of land features and the availability of cloud- and haze-free satellite data, we chose images acquired during the dry months of the year. This also makes it easier to differentiate various land features, as most of the annual crops have been harvested at this time of the year (Hurni et al. 2013; Teferi et al. 2013). Using Google Earth Engine, we downloaded the best quality available Landsat TM products acquired between December and March. Google Earth Engine provides Landsat images that have previously undergone all necessary pre-processing steps such as geometric, atmospheric, topographic and radiometric correction. Using pre-processed images helps to reduce potential errors of image classification and change detection. When producing the two LULC maps, we benefitted from existing national- and local-scale LULC datasets (Muluneh and Arnalds 2010), which we used as a reference to improve our classification. Other data-sets were also integrated in the classification process, including ones on farming systems and livelihood zones produced by FAO, ones on settlement and population distribution provided by Ethiopia's Central Statistical Agency (CSA), and topographic information from the ASTER digital elevation model (http://glovis.usgs.gov). They were used to derive classification segments, while Google Earth images were used to assign unknown classes and validate the classification.

2.3. Classification approach

As the ecoregions in our study area are extremely heterogeneous, we combined classification approaches suggested by Mains et al. (2000) and Crews-Meyer et al. (2004). These approaches aim to reduce the effects of landscape heterogeneity on classification accuracy by dividing the image into smaller, more heterogeneous segments prior to classification. Image classification and class labelling is then performed within these segments. In addition, we opted for a second-level classification scheme. We first defined a set of 10 fairly broad classes, which we refer to as 'Level I' classes (water body, settlement, forest, woodland, shrub/bushland, cropland, grassland, bare land, wetland, Afroalpine vegetation); in a next step, these were differentiated into 40 'Level II' classes. Image classification and class labelling was then performed within the previously produced segments by means of unsupervised clustering and supervised class labelling techniques, in an iterative procedure. This included the integration of several geospatial data-sets and use of local area knowledge. The detailed procedures applied for image segmentation, classification and class labelling are explained in Kassawmar et al. (2016).

The resulting two maps (Figure 2) fulfil three important criteria that made them adequate for use in our neighbourhood-level change assessment. First, they identify and map important classes that essentially represent the complex landscape of the study area with an overall average accuracy >87% for all classes considered in the classification scheme. Given the size and heterogeneity of the study area,

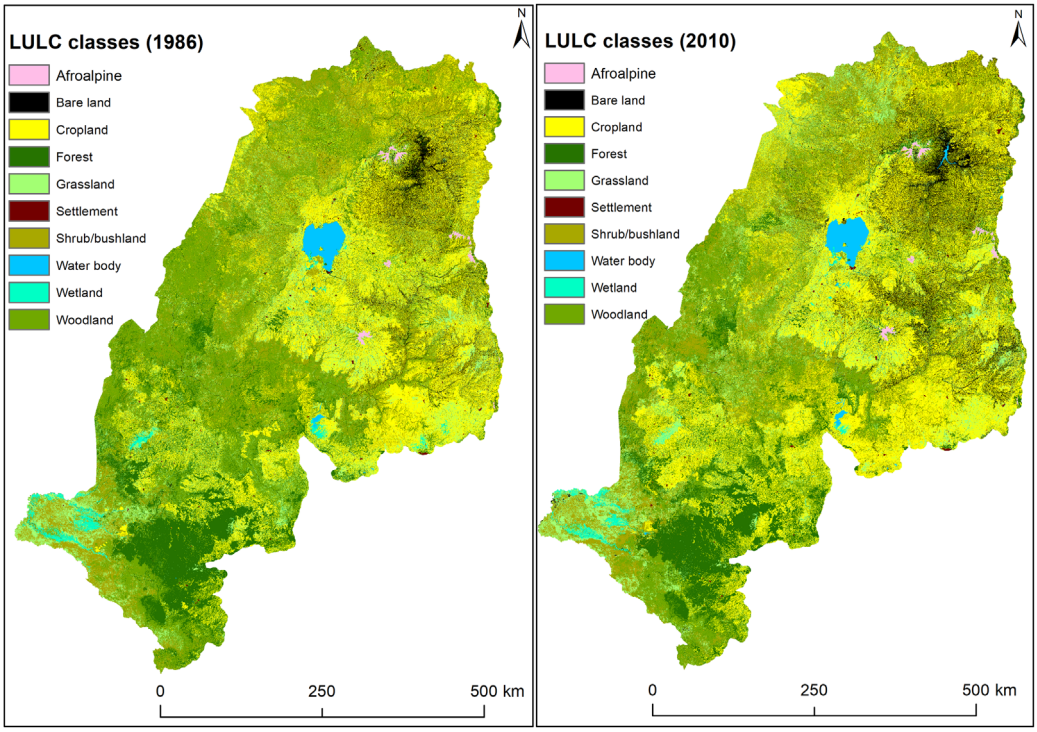

Figure 2. LULC maps used for the present assessment.

this level of accuracy is very good. Second, the two maps were produced from images obtained from the same sensor (Landsat TM) and with the same spatial resolution (30 m). Third, both maps were produced exclusively from images acquired during the dry season, which ensures seasonal consistency. Moreover, as the two LULC maps were produced by the same experts with the aim of using them for change detection, consistency was also maintained in terms of terminology, method of classification and the type as well as the number of classes detected – which is an important issue in using landscape indicators to assess land change (Shao and Wu 2008).

2.4. Change characterization approach

To achieve the overall aim of the study, we pursued the following major steps. (1) First, we detected changes using the two LULC maps and translated the changes detected at pixel level to a more aggregated level using a neighbourhood approach and repeating the procedure with differently sized moving windows. (2) Next, we compared the neighbourhood-level information with the pixel-level information in terms of its potential to characterize land change processes across large and complex areas. (3) Then, we reclassified the full data range on the amount of change into five percentage ranges. (4) After this, we assessed the effect of the moving window size on the resulting amounts and patterns of change. (5) Further, we assessed the effect of the moving window size by comparing the mapping results with known changes on the ground. This helped us to understand how the moving window size affects the results on change processes of varying type, size and density). (6) Finally, based on the findings, we determined a way of selecting an optimal moving window size. Figure 3 shows a schematic representation of these steps. The detailed procedures involved in the approach are described in the following subsections.

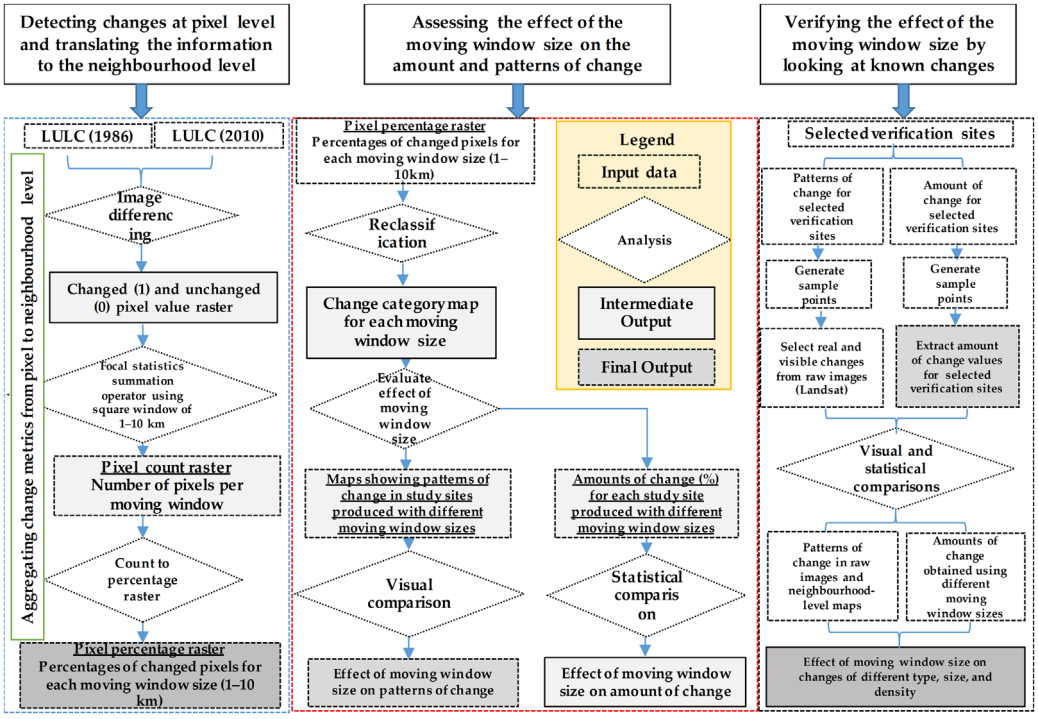

Figure 3. Schematic representation of the workflow.

2.4.1. Detecting changes at pixel level and translating them to the neighbourhood level

As explained in the introduction, this paper strives to establish an improved methodology for characterizing land change at national, supranational and continental scales using LULC maps produced from moderate-resolution satellite images. Use of pixel-level change data to present change at national to continental scales is problematic, as it results in poor visibility of patterns, and metrics are not generated at the required scale (Lamine et al. 2017; Singh Srivastava, et al. 2017). To produce a change map that decision-makers can easily interpret, we aimed to translate pixel-level change information to a more aggregated level. Researchers in the field recommend using a neighbourhood approach to do this (Riitters, Wickham J et al. 2009). Spatial neighbourhood can be analysed with a moving window technique, and the size of the window can be chosen depending on the extent at which changes occurred, the extent of the study area and the objective of change characterization (Messerli et al. 2009; Hett et al. 2012; Hurni et al. 2013). According to Riitters, Wickham J et al. (2009), the size of the moving window must be larger than the spatial resolution of the input LULC map. In our case, this implied that the moving window would have to be larger than 30 by 30 m (1 by 1 pixel).

However, if the goal is to visualize change patterns at regional and national scales, a much larger window is required anyway; initial test runs showed that applying moving window sizes of less than 1 by 1 km (33 by 33 pixels) result in a change map that is not much different in appearance from the original pixel-level change map. Thus, to be able to compare the effect of the moving window size, we applied the following sizes: 1 by 1 km (33 by 33 pixels), 2 by 2 km (67 by 67 pixels), 3 by 3 km (100 by 100 pixels), 4 by 4 km (133 by 133 pixels), 5 by 5 km (167 by 167 pixels), 6 by 6 km (200 by 200 pixels), 7 by 7 km (233 by 233 pixels), 8 by 8 km (267 by 267 pixels), 9 by 9 km (300 by 300 pixels) and 10 by 10 km (333 by 333 pixels).

Initially, we detected changes at the pixel level by combining the two LULC maps (showing the years 1986 and 2010) using the combine tool in ArcGIS® software. This resulted in a single binary raster map with the value '0' representing unchanged pixels and '1' representing changed pixels. To

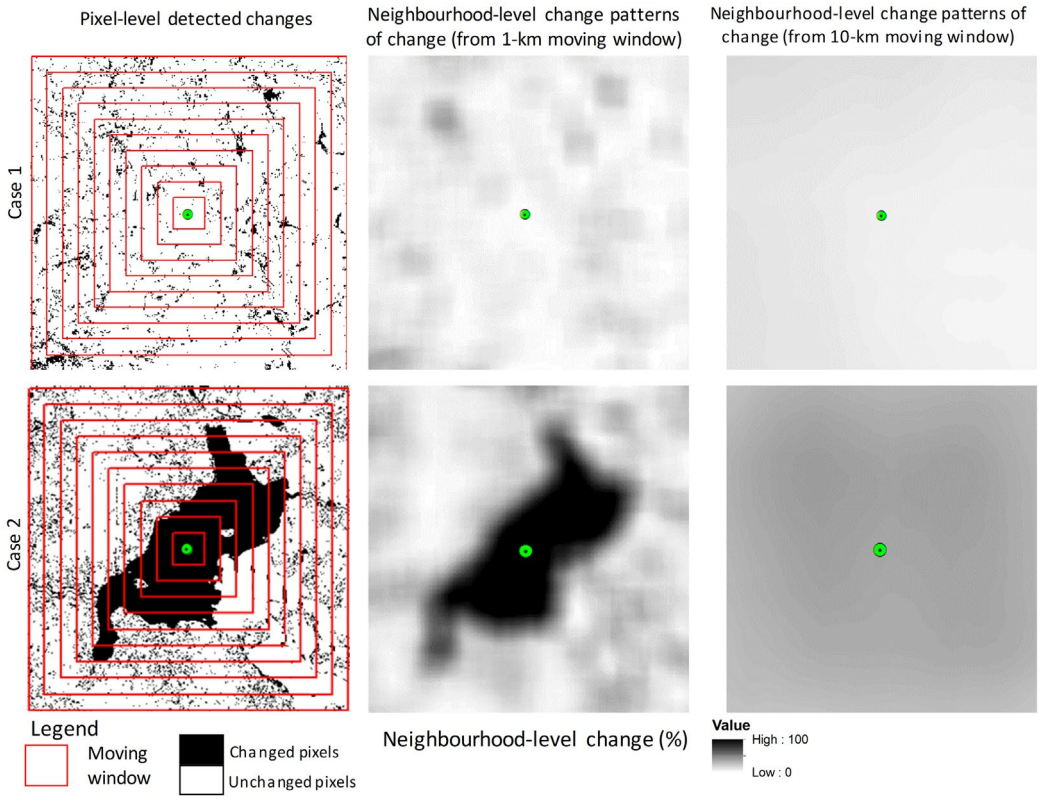

Figure 4. Translating pixel-level change information to the neighbourhood level in order to better characterize change across large and complex areas.

translate the pixel-level change information to the neighbourhood level, using the summation operator we applied the square moving window-based focal statistics analysis available in ArcGIS 10.1®. This was performed using 10 different moving window sizes (1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 km). The focal statistics algorithm produced 10 separate raster files – one for each moving window size – representing LULC changes at the neighbourhood level, with values expressing the number of changed pixels per window (Equation (1)). Further, using Equation (2), we converted the raster values from pixel counts to percentages (ranging from 0 to 100%) in order to better understand the effect of the moving window size (see Section 2.4.2). This resulted in an output representing the percentage of changed pixels per window (Equation (2)). We call this the 'amount of change'. When visualized as a map, this information provides the spatial arrangement of changes estimated by the moving window (Figures 4 and 5). We call this 'patterns of change' (Equation (3)).

$$C_n = \frac{N_p}{MW} \tag{1}$$

$$C_p = \frac{A_{cp}}{MW} \times 100 \tag{2}$$

$$CC = \frac{AC_{cc}}{TA_{ss}} \times 100 \tag{3}$$

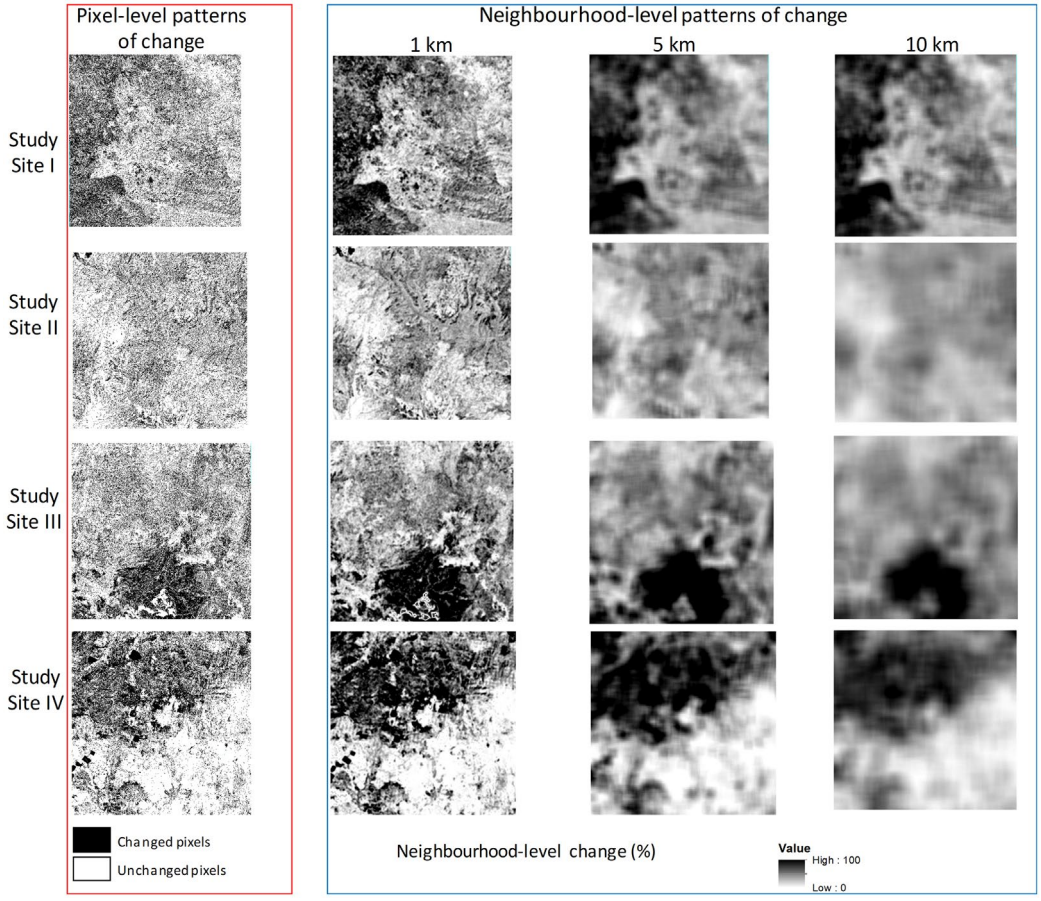

Figure 5. Pixel-level vs. neighbourhood-level spatial representation of LULC change.
Notes: The maps in the first column depict change at the pixel level across each of the four study sites, whereas the other three columns represent patterns of change produced at the neighbourhood level using a 1-, a 5- and a 10-km moving window. The intensity of the shading represents the amount of change in per cent, from low (0) to high (100).

where MW = Moving window size (side length in pixels); N_p = Number of changed pixels per window; A_{cp} = Total area of changed pixels per window; C_n = Change at neighbourhood level (number of pixels); C_p = Change at neighbourhood level (percentage); CC = Change category-based statistics (change in per cent); AC_{cc} = Amount of change per change category in per cent; TA_{ss} = Total area of study site.

2.4.2. Comparing pixel- and neighbourhood-level change information

In view of our overall goal of characterizing change across large and complex areas, we compared pixel- and neighbourhood-level change information based on the following three criteria: (1) ability to illustrate patterns of change in time and space; (2) ability to improve the signal-to-noise ratio or cancel out the unbiased classification error retained in the change map, and thereby to reduce reporting of unrealistic changes; and (3) ability to depict the degree of change in relative terms. We presumed that these criteria are suited to reveal the potential and limitations of the proposed approach. Figure 4 illustrates the visual effects of translating pixel-level change information to a neighbourhood level, using the examples of two patches of 10 by 10 km showing different change characteristics from the study area.

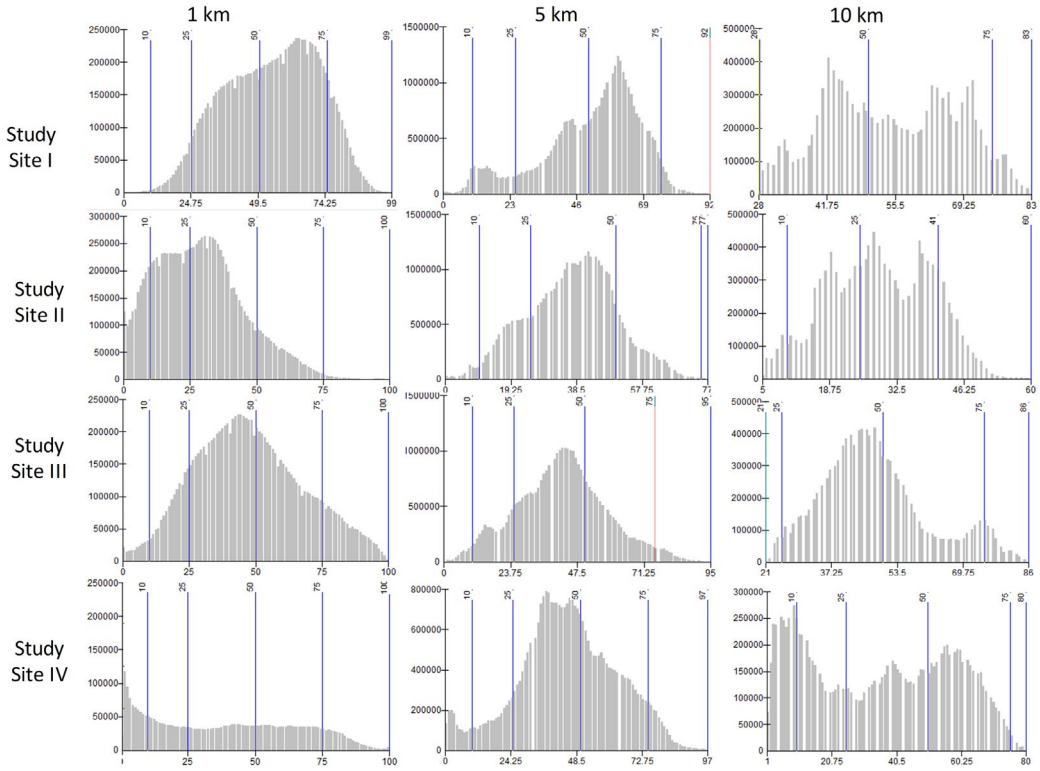

Figure 6. Histogram values of neighbourhood-level amounts of change across each of the four study sites obtained using a 1-, a 5- and a 10-km moving window.

The maps on the left in Figure 4 show changes at the pixel level, overlaid with the different moving window sizes of a 1- and a 10-km side length. Black spots represent changed pixels and white spots unchanged pixels. The maps in the middle and on the right represent changes at the neighbourhood level produced by applying a 1- and a 10-km moving window, respectively, to the pixel-level information. In these maps, the intensity of shading represents the degree of change with a spatial pattern of change. White areas have undergone no or slight change, whereas deep black areas have changed substantially. Below, we compare the information content of neighbourhood-level maps with that of pixel-level maps, as well as that of the various neighbourhood-level maps resulting from different moving window sizes, according to the criteria outlined above.

(1) *Potential for representing spatial patterns of change:* As pixel-level change information is discrete, spatial patterns of change and no change are poorly represented (Figure 4, left). This is particularly problematic in cases where small-sized changes are largely ignored due to the limited spatial resolution of the input data, or where important changes are missed in the change map due to classification errors.

Figures 4 and 5 show visibly that unlike the pixel-level change map, the neighbourhood-level map displays change information in a continuous manner that accounts both for large or small and for sparse or dense changes. In other words, the output change map shows spatial patterns of change based on the density of change within a neighbourhood of pixels, whereas pixel-level maps fail to do so (White 2006). This makes neighbourhood-level change information preferable for visualizing patterns of change across large and complex areas. However, patterns of change risk not being properly represented if changes occur at a small spatial extent and the moving window used is too large.

(2) *Potential for avoiding wrong representation of change:* In the pixel-level change information (Figure 4), a considerable area appears white, signifying 'no change'. However, it is hard to be sure that these areas really remained unchanged. There are three possibilities: Change may have occurred, but the limited resolution of the input data does not allow very small changes to be captured; the classifier did not capture these changes due to unbiased classification error; or there was really no change in these areas and the change detection is accurate. Further, the pixel-level maps show numerous isolated black pixels, signifying change. They might be salt-and-pepper noise due either to the unbiased classification error or to noise in the satellite image retained in the change map; or they might represent real changes affecting only very small areas. This type of change information will affect change statistics if it is removed or considered as is in the change map (Riitters, Wickham JD et al. 2009). As changes at the pixel level are reported in discrete statistics, the above cases will exist in the change map as well as the statistics. In such a situation, a moving window technique can be used to produce a new change map and reduce these potential errors commonly manifested in pixel-level change maps. We hypothesized that translating pixel-level change information to the neighbourhood level will reduce the risk of mapping erroneous changes or ambiguous change information, as the moving window approach produces a new data-set of change information that considers the state of several neighbouring pixels (Riitters, Wickham JD et al. 2009). If, in a given area on the pixel-level map, few pixels have wrong change information, while the majority of the pixels have correct change information, the moving window will prevent the error pixels from being visualized on the new change map, as this map considers both the individual pixel and its neighbouring pixels. In other words, the new data-set consists of continuous information that makes it possible to explain change in relative terms and thereby avoid discretely presenting changes of which we are not sure.

(3) *Potential for describing the amount of change as per users' interest:* The pixel-level change information offers a discrete and lumped statistical change value per a given area, and describing change in relative terms according to users' interest is not possible. Figure 6 shows the histogram values of the amounts of change in the four study sites obtained when using a 1-, a 5- and a 10-km moving window. Using the histogram values of change information, it is possible to compare and describe amounts of change within and across study sites. Moreover, the approach makes it possible to reproduce ranges of change statistics that can be categorized and summarized depending on users' interest (Gagn and Fahrig 2007). It provides the option of expressing change in relative terms, whereas pixel-level change information fails to do so (Netzel and Stepinski 2015). However, this makes it necessary to classify the continuous data into categories as desired by users.

2.4.3. Reclassifying the neighbourhood-level change data

The outputs of our approach, as presented in Figures 4–6, display change information on a continuous scale of 0–100%. We reclassified this continuous change information into categories in order to simplify the interpretation of change across large areas and make the information more usable for planning, and to enable more objective, standardized and comparable assessment of the effect of the moving window size on the output.

To reclassify our continuous data, we defined five categories that describe the degree of change qualitatively as: No change, Slight change, Moderate change, Considerable change and Substantial change. Then, we reclassified the neighbourhood-level change data (with values ranging from 0 to 100) into these five categories. Appropriate break points were identified using the Jenks optimization method or natural breaks available in ArcGIS®. The Jenks method finds points that minimize the sum of squared differences within classes and maximize the sum of squared differences between classes. More specifically, it minimizes within-class variances and maximizes variances between classes. We chose this technique because of its capability to identify meaningful classes in the data. The resulting

classes are: 0–10% representing no change; 10–25% representing slight change; 25–50% representing moderate change, 50–75% representing high change and >75% representing substantial change. Based on these categories, we further assessed the effect of the moving window size by comparing statistics and maps generated with varying window sizes for each of the study sites.

2.4.4. Understanding the effect of the moving window size

The translation of pixel-level change information to the neighbourhood level is scale-dependent (Cain et al. 1997; Saura and Martinez-mlian 2001; Wu 2004). When applying this method across large and complex areas, the main challenge is to find an appropriate moving window size. Applying a single window size across the entire study area can cause important, but small-sized change patterns to be lost, as the method generalizes the information content. However, applying arbitrarily chosen different moving window sizes is no solution either, as it will result in varying amounts and patterns of change, and results will not be easily comparable. Selecting an optimal moving window size requires knowledge about how the moving window size affects the output and about the type and spatial extent of the object or feature to be characterized. For that reason, we assessed the effect of the moving window size on the two main neighbourhood-level outputs, patterns of change and amount of change. The assessment was performed in two ways: considering the whole study sites, and considering systematically selected smaller verification sites where important features to be characterized are clearly observed both in the input image and in the final change map. As explained earlier, the full range of information is difficult to compare; for that reason, we used the reclassified data.

(1) *Looking at the entire study sites:* To understand the effect of the window size on the amount of change, we summarized the overall statistics (amount of change) estimated with each window size using Equation (3). We compared the outputs generated with the different moving window sizes graphically for each change category (see Section 3.1).
(2) *Looking at systematically selected verification sites:* To understand the effect of the moving window size on the spatial arrangement of changes as well as their type, size and density, we visually compared the patterns of change resulting from each moving window size with known real changes having a clear pattern. To do that, we systematically selected nine representative verification sites (Figure 1) showing clearly observable changes. The verification sites cover a minimum of 10 by 10 km each; their sizes vary depending on the size of the feature selected for verification. The type, size and density of changes at the verification sites were identified by means of field visits, Google Earth images and information from locals. Subsequently, we applied all the procedures explained in Sections 2.4.1 and 2.4.3. Further, we investigated in detail the nature of changes in each sub-ecoregion. Reviewing secondary literature on biophysical and socio-economic processes helped us to understand the spatial link between the type, size and density of changes and the amount of change found at the neighbourhood level in each sub-ecoregion. Specifically, to understand the variation in neighbourhood-level estimates produced with differently sized moving windows, we produced false colour composite maps from the Landsat images of 1986 and 2010 for each verification site (see Section 3.2). The neighbourhood-level patterns of change obtained with differently sized moving windows were compared against the spatial arrangement of real changes identified in the false colour composite images. This provided information about the magnitude of over- and underestimation resulting from different moving window sizes (Figure 4), an important criterion for selecting an optimal moving window size.

2.5. Selecting an optimal moving window size

The literature offers no established method for finding the most appropriate moving window size for a given area (Wu 2004). This may be because the optimal moving window size depends on the

purpose of the study and the study area context (Riitters, Wickham JD et al. 2009). In Section 2.4.4, we described our own approach to determining the optimal moving window size, based on comparisons considering the entire study sites and a number of smaller verification sites. In addition, we also applied a selection technique that uses statistical information obtained from sample points. For that purpose, we generated 100 sample points from the selected study sites. Half of them were selected randomly and half systematically, so as to ensure that all sub-ecoregions in each study site were adequately represented. This was important because the types, size and density of changes differ considerably between (sub-)ecoregions, and at the same time these change characteristics are among the factors determining which moving window size is most appropriate. Subsequently, we extracted the percentage values of each point for the 10 neighbourhood-level change raster datasets produced with the differently sized moving windows. We assessed whether a meaningful relationship existed between moving window size and the values of the sample points. We used the standard deviation values of the sample points for each moving window size, so as to understand the degree of over- or underestimation. This analysis was supported by diagrams showing the moving window sizes on the *x*-axis and the sample point values on the *y*-axis (see Section 3.2). On this basis, we determined which moving window size results in the most meaningful representation of change for a given size of the feature or object to be detected and characterized. Finally, from our experience we derived suggestions on how to select the optimal moving window size and a number of issues to consider when applying our approach to characterize land change across large and heterogeneous areas.

3. Results

3.1. Effect of the moving window size

Assessment of how the size of the moving window influences the two main outputs of the presented approach – amount of change and patterns of change – helped us to determine which moving window size is most appropriate. The following subsections present the results of this assessment.

3.1.1. The effect of the moving window size on patterns of change

The maps presented in Figure 7 show how the size of the moving window affects the spatial arrangement of estimated changes. As shown in the maps, different moving window sizes lead to different change patterns.

Figure 7 shows that an increase in the size of the moving window gradually causes changes of small spatial extent to disappear, whereas larger sized changes seem to grow. Further, we can see that patterns of change vary most between moving window sizes in areas where changes are small in size. For instance, in Study Site IV, a fairly large area falls into change category 5 when a 1-km moving window is applied. However, when we applied a 10-km moving window, the majority of the area fell into category 4. When characterizing land changes at the neighbourhood level, such generalization has both advantages and disadvantages: a larger moving window improves the signal-to-noise ratio and reduces classification errors, but at the same time generalizes the change information, and there is a risk of missing changes affecting only very small areas. This implies that the moving window should be set to an optimal size at which accurately detected small-sized changes which are of interest in the given study remain visible on the output map.

3.1.2. The effect of the moving window size on amounts of change

The connection between the effect of the moving window size and patterns or the amount of change looks fairly trivial compared to the effect on the amount of change and for a specific type of change. How the effect of the moving window size changes depending on the type of change that we intend to capture (e.g. deforestation) is more complex and significant. Figure 8 shows how the total amount of change in the change maps of the two cases illustrated in Figure 4. It visualizes how much the total amount of change varies for a particular point of interest when a different window size is applied.

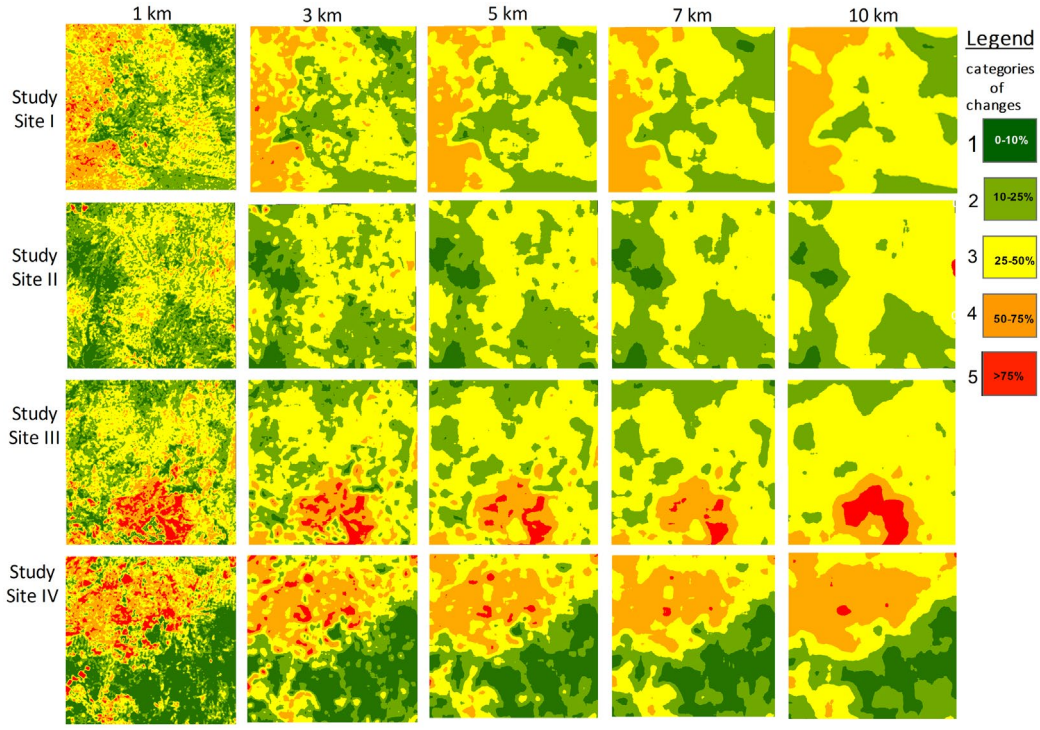

Figure 7. Patterns of change in the four study sites at the neighbourhood level generated with five differently sized moving windows.

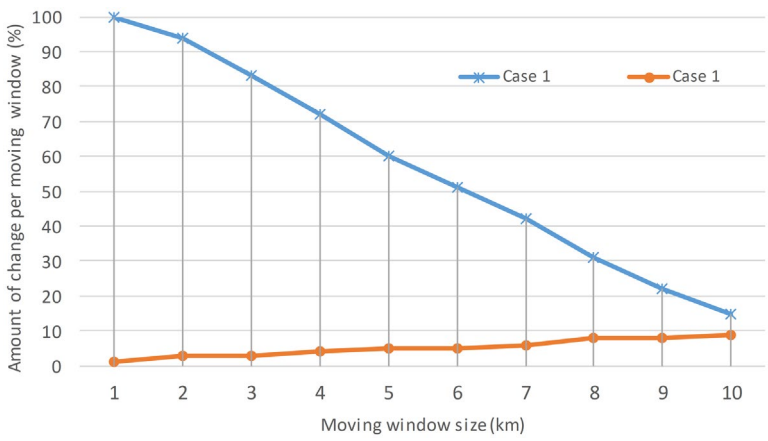

Figure 8. Effect of the moving window size on the estimated amount of change for the two cases mapped in Figure 4.

Figure 9 shows how the size of the moving window affects the total amount of change per study site. The statistics were generated from the maps displayed in Figure 7. The four study sites differ in terms of the type, size and density of changes. The *x*-axis shows the five change categories based on the amount of change (0–10, 10–25, 25–50, 50–75 and >75%). The *y*-axis shows the total area covered by each change category as a percentage of the total area of the study site.

The diagrams in Figure 9 show how the amount of change varies when different moving window sizes are applied. For example, in Study Site I, a 1-km moving window estimated the total area falling

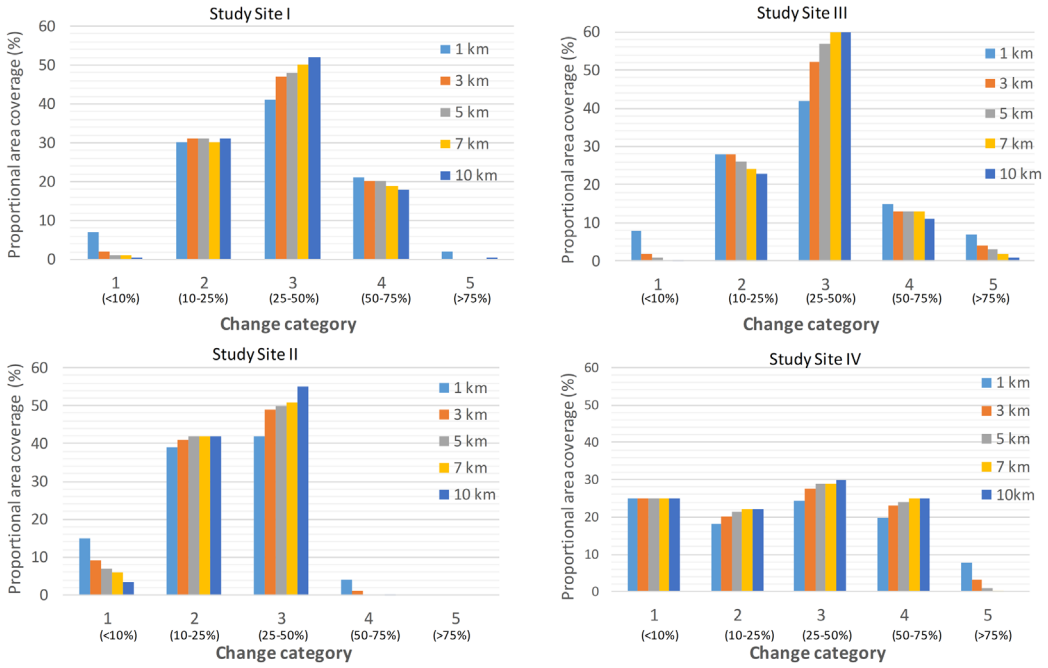

Figure 9. Summary of statistical data on the amount of change estimated with differently sized moving windows for each study site. Note: The *x*-axis represents the five change categories; the *y*-axis represents the proportional area coverage of each change category as estimated using five different moving window sizes.

into change category 3 at about 41% of the study site area. When a 5-km window was applied, the total area falling into the same change category rose to 49%. If we take another case, Study Site III, when a 1-km window was applied, the total area falling into change category 5 was estimated at 8%, whereas it dropped significantly to 0.2% when a 10-km window was applied.

3.1.3. The effect of the moving window size: conclusions from the assessment

In sum, the assessment results presented in Sections 3.1.1 and 3.1.2 revealed the risk of over- or underestimation of change as well as inadequate representation of patterns of change if a single and unrepresentative moving window size is randomly chosen. Table S1 in the Supplemental Material presents a detailed statistical summary on the effect of the moving window size on the output values for selected sample points in each study site. These statistics show that proper characterization of land change requires proper understanding of the effect of the moving window size on the patterns and amount of change, taking into account the type, size and density of the change phenomenon to be characterized. Therefore, it was of paramount importance to verify the effect against reality based on known changes at sample points across all study sites and (sub-)ecoregions.

3.2. Verifying the effect of the moving window size against known changes

The assessment results presented in the above sections demonstrated the overall variation in presenting the amount and patterns using differently sized moving windows for the entire study area. But the variation is not the same in all parts of large and complex areas, as the nature of changes varies considerably. This required us to investigate in which part of the larger study area and for which types of change the variation is significant.

To verify the patterns of change generated with differently sized moving windows, we used raw Landsat TM images with false colour composite (4-3-2). The information mapped in Figure 10 depicts

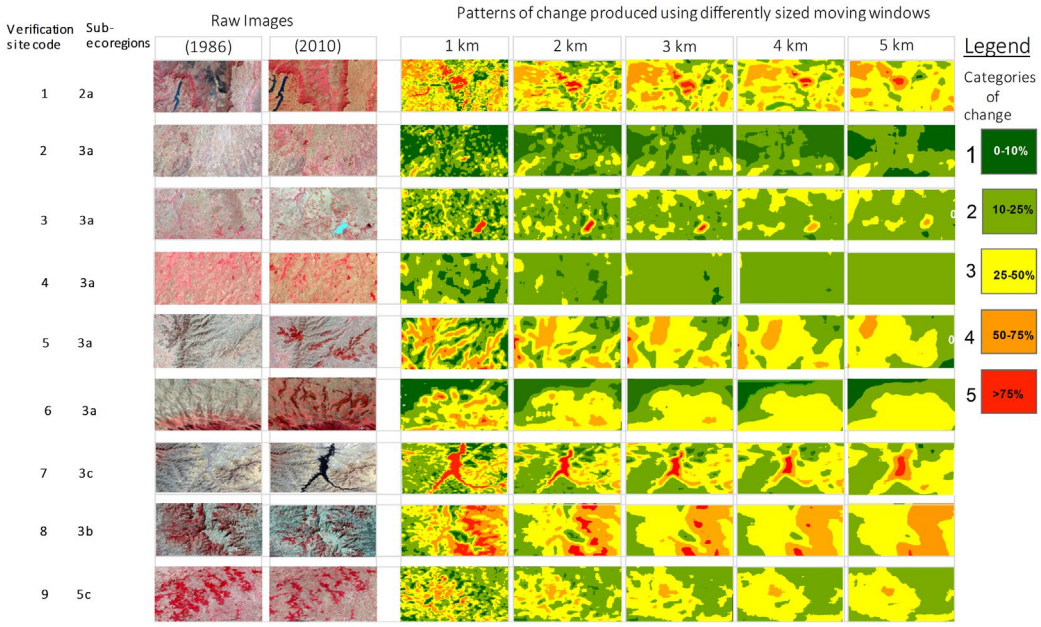

Figure 10. Verification sites that reveal the varying nature of land changes across the UENB.
Note: They were selected based on false colour composites of the Landsat images to verify the effect of the moving window size.

the nature of land changes (in terms of type, size and density) occurring in the different (sub-)ecoregions across the UENB (see Figure 1). From the maps it is possible to understand and compare whether spatially aggregated change patterns are adequately represented, and which moving window size results in the most accurate representation of known patterns of change. The purpose of change characterization is a key factor determining which representation is most meaningful. However, as Figure 10 shows, the spatial representations of the same type of change using differently sized moving windows varies significantly from one site to the next.

For example, in Verification Site 4 (which represents Study Site II), the majority of changes are small in size, indicating smallholder plantations of about 0.25–1 hectare. The patterns of such changes are retained using a smaller moving window (1 km). The larger the moving window, the poorer the visibility of these small patterns of change becomes; they disappear completely when a 5-km moving window is applied. In Verification Site 7 (sub-ecoregion 3c), the spatial arrangement of change arising from the construction of a dam is well represented by moving windows of 1–4 km. But when a 5-km moving window is applied, the pattern of change becomes highly degraded. These examples show that the degree of variance in the spatial representation of changes is linked with the spatial extent of the changed features as well as with the overall spatial distribution and density of changes in a given area. Table 2 summarizes the nature of changes commonly occurring in the five major ecoregions of the UENB (see Table 1). For a better understanding of the effect of the moving window size and the usefulness of the proposed approach, an additional analysis using high-resolution images is provided in Figure S1 (Supplemental Material).

In intensively cultivated ecoregions (represented by Study Site II in sub-ecoregions 3a, 3b and 3c), afforestation practices, communal area closures and rehabilitation of degraded areas are very common. In these parts, of the study area, the majority of changes are as small as 0.25 hectare due to the size of individual landholdings (~10,000 m^2) (see Figure 10, verification sites 3 and 4). In these areas, moving windows larger than 3 km fail to adequately represent patterns of change. By contrast, in the low-lying areas of the UENB, over the last two decades, large-scale mechanized farming as well as smallholder-driven slash-and-burn practices have become common, and as a result, land changes

Table 2. The nature of land changes commonly occurring in the major ecoregions of the UENB.

Ecoregion code	Study sites in this ecoregion	Dominant land cover	Farming system	Important change processes and drivers	Size and density of changes
1	IV	Forest and agroforestry	Mixed farming, but largely forestry	Forest degradation and deforestation	Small and unperceivable
2	II and IV	Intensively cultivated land, high potential	Crop growers and mixed farming	Afforestation and deforestation	Small and dense
3	II	Moderately cultivated land, low potential	Mixed farming	Afforestation, grassland to cropland conversion	Small and sparse
4	I and III	Woodland, grassland	Agro-pastoralist	Deforestation and natural regeneration	Large and dense
5	III	Woodland	Pure pastoralist	Forest degradation, deforestation and natural regeneration	Large and dense

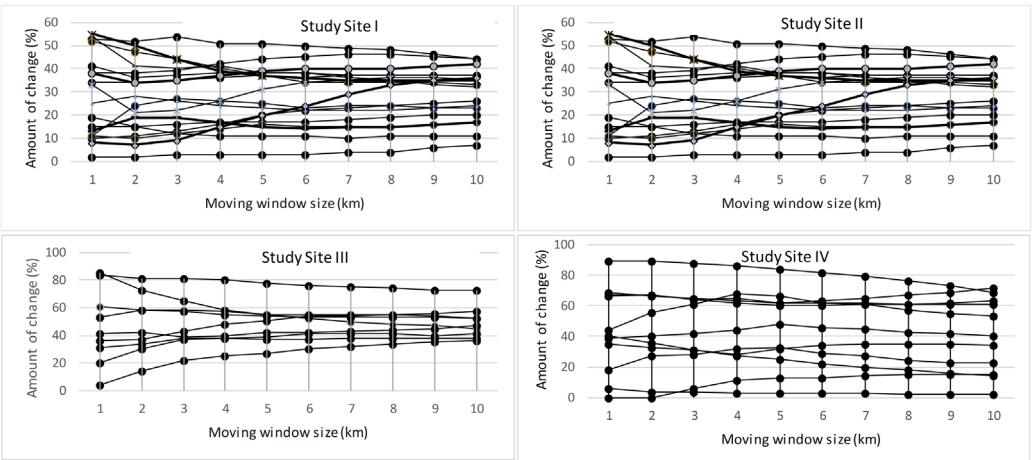

Figure 11. The magnitude of variation in the amount of change observed when applying different moving window sizes (for randomly selected points).

span hundreds of hectares on average. In these areas, moving windows of up to 5 km still adequately retain change patterns (verification site 8, Figure 10). Here too, however, moving window sizes larger than 5 km no longer adequately represent land changes at least for the area we considered.

3.3. Selecting an optimal moving window size

The results of our verification exercise presented in the previous sections enabled us to gain a more comprehensive understanding of how the size of the moving window affects mapping outputs, and provided a basis for determining the optimal moving window size for the purpose of our study. A further analysis based on statistical evaluations of sample points provided further guidance regarding the optimal moving window size. We used two sets of sample points; 50 points were selected randomly, and another 50 were selected systematically.

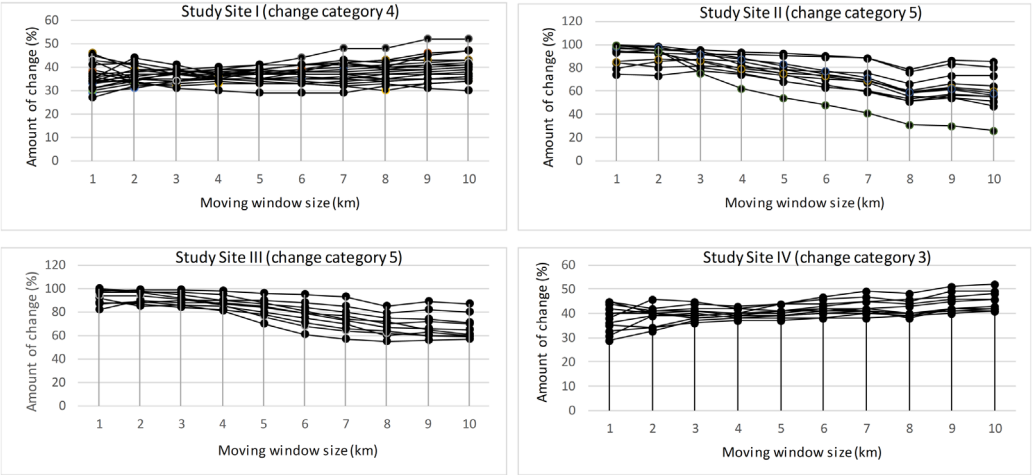

Figure 12. The magnitude of variation in the amount of change observed when applying different moving window sizes (for systematically selected points).

(1) *Randomly selected sample points:* Figure 11 shows the amounts of change generated for randomly selected sample points. Each line represents a sample point, the *x*-axis represents the size of the moving window and the *y*-axis represents the amount of change obtained for each sample point. The diagram shows that the magnitude of variance when applying different moving window sizes varies from study site to study site and depending on the amount of change (Figure 11).

As shown in Figure 11, the amount of change obtained from randomly selected points in each study area shows no predictable trend when the moving window size is increased. This means that both over- and underestimations occur in all study sites. As the variation is unpredictable, we were unable to find an optimal window size for an entire study site falling into several ecoregions. However, we noticed that the variation tends to be similar for sample points representing the same change category and the same sub-ecoregion. Thus, regrouping the sample points based on homogeneity in terms of the nature of changes (within a specific sub-ecoregion) can simplify the selection of an appropriate moving window size.

(2) *Systematically selected sample points:* Figure 12 shows the amount of change generated for systematically selected sample points. The amount of change obtained for systematically selected sample points in the same sub-ecoregion as well as within a defined change category showed predictable relationships with the size of the moving window, at least for the scale ranges we considered.

The sample points were used not only to verify and understand the effect of moving window size on the amount and patterns of change, but also to select the optimal moving window size for each sub-ecoregion. As explained in Section 2.1, each study site falls into several different ecoregions and sub-ecoregions. The identified (sub-)ecoregions differ in terms of the nature of changes occurring in them. As the type, size and density of the changes to be characterized are key factors determining which moving window size is most appropriate, systematically selecting verification sample points within or across the different sub-ecoregions can show the level of variations in terms of adequately depicting change when using larger or smaller window sizes. Such comparison can then be used to determine the most adequate moving window size in relation to the type, size and density of changes occurring in the area of interest. In our case, we defined the optimal moving window size as that which produces the smallest standard deviation across all sample point values. A moving window meeting this criterion

results in minimal over- and underestimation in the sub-ecoregion for which it was deemed optimal. This is shown in Figure 12, where the lines of the sample points are close (asymptotic) to each other.

4. Discussion

Often land change characterization using remotely sensed data is done by measuring the degree of change and locating changes using statistics and maps, respectively. Commonly, this is done using pixel-level change information (statistics and maps) generated at the post-classification stage (Pontius and Cheuk 2006). However, pixel-level change information has several limitations. Among other things, it cannot be used to represent the spatial configuration and composition of changes per a defined area. As our aim was to demonstrate the usefulness of our approach with regard to characterizing land change across large and heterogeneous areas, we used real multi-temporal LULC data covering a large area that are suitable for demonstrating the aforementioned limitation of pixel-level change information. The approach we propose requires translating pixel-level change information to a more aggregated level using an optimally sized moving window. However, based on the results of our assessment, several issues need to be taken into account when applying the approach. These include, first, the detail and accuracy of the LULC input data (Shao and Wu 2008); second, the aim of the analysis (i.e. which change phenomenon is to be characterized); third, the type, size and density of changes; and fourth, the size of the moving window (Homer et al. 2004). Besides, the approach requires detailed verification of detected changes. The main focus of the present study was on the fourth issue that needs to be considered: on how the size of the moving window affects the outputs obtained.

Previous studies have demonstrated that approaches such as ours are sensitive to the spatial resolution of the input data and the size of the moving window applied (Shao and Wu 2008). Therefore, authors suggest that it is vital before applying such an approach to make sure that the spatial resolution of the satellite images used to develop the multi-temporal LULC maps are adequate in view of the features to be characterized (Griffith 2004; Riitters, Wickham J et al. 2009). The composition and visibility of the patterns of change obtained using the moving window approach are primarily determined by the resolution of the input data (Saura 2002). In other words, the quality and resolution of the input data largely determines the size of detectable features. Various authors also suggest that the nature of change processes occurring in the study area is likewise an important factor, making it essential to know the possible spatial extent of the changes and changed features to be characterized (Wu 2004; Riitters, Wickham JD et al. 2009; Hett et al. 2012; Hurni et al. 2013). On the other hand, when translating pixel-level change information to a more aggregated level using a moving window approach, we need to be sure that the size of the moving window is chosen so that the output adequately represents the area in which land cover changes related to land use have been occurring (Messerli et al. 2009; Hurni et al. 2013). According to Riitters, Wickham J et al. (2009), the size of the moving window is determined by the size of the object or feature to be detected. But, at the same time, the size of the moving window cannot be smaller than the pixel size of the LULC maps used for the analysis (Riitters, Wickham JD et al. 2009). In situations where the spatial extent of deforestation and afforestation phenomena varies across the study area – as it does in our study area, the UENB – the size of the moving window needs to be selected considering both the nature of the prevailing changes and their extent of occurrence (Wu 2004). In the present study, we thoroughly assessed all these factors to select the optimal moving window size, keeping in mind the overall aim of characterizing LULC change across a large and heterogeneous study area using the proposed approach.

The overall assessment results regarding the type (deforestation and afforestation) and spatial extent of commonly occurring changes (from 0.25 to 10,000 hectares) enabled us to narrow down the range of potentially suitable moving window sizes (1–10 km). But in order to select the optimal moving window size according to the aim of the study or the common land change processes to be characterized, we had to make a further detailed assessment (Wu 2004; Riitters, Wickham J et al. 2009). We performed a detailed evaluation of the effect of the moving window size by comparing output results with known changes of varying spatial extent in nine selected verification sites. The overall assessment

helped us to understand how the moving window size affects the degree of over- and underestimation of change. The assessment based on the verification sites provided guidance on how the effect of the moving window size varies depending on the spatial extent, amount and patterns of change. A further assessment using 50 randomly selected and 50 systematically selected sample points finally enabled us to determine which moving window size is optimal for which type of change, in which part of the study area. Based on our overall findings, we tried to establish a general procedure for selecting the optimal moving window size for translating pixel-level change information to a more aggregated level for change estimation and characterization across a large and complex area. We concluded that an optimal moving window size can be determined only for partial areas within the study area where changes are similar in nature.

In our case of the UENB, we found moving window sizes larger than 5 km unsuitable for characterizing change, for two main reasons: (1) In most highland parts of the study area, the majority of changes were fairly small in size, causing moving windows larger than 5 km to obscure these changes; and (2) in the lowland parts of the study area, many changes are contiguous, causing moving windows larger than 5 km to exaggerate them. On this basis, we propose optimal moving window sizes for each of the sub-ecoregions in the study area, as follows: In Study Site I and other parts of the UENB with similar landscapes, such as the western part of Study Sites III and IV, 4- and 5-km moving windows are suited to adequately represent patterns of change. The same moving window sizes can be also applied for woodland-dominated areas like sub-ecoregions 4a and 5c, where land cover is rather homogeneous and changes are contiguous and affect larger areas. For ecoregions with a finer mosaic of land cover types, such as in Study Site II, a smaller moving window of 1 or 2 km is more appropriate, as the majority of changes are patchy and affect smaller areas. Forest-dominated ecoregions where change processes affect smaller areas (e.g. deforestation in sub-ecoregion 1a and parts of sub-ecoregion 2a, as well as afforestation in sub-ecoregions 3b and 3c) require a moderate moving window size of 2 or 3 km.

As shown in Figure 12, in areas where changes are commonly patchy and random and occur at a lower density, the amount of change is increasingly underestimated with increasing moving window size. Conversely, in areas where changes are contiguous, the amount of change is increasingly overestimated with increasing moving window size. These predictable relationships were observed for systematically selected sample points in similar ecoregions, and they enabled us to identify the optimal moving window size for each (sub-)ecoregion.

In sum, based on the results obtained from systematically selected sample points, we can derive the following rules of thumb for selecting an optimal moving window size:

(1) The moving window size must be chosen such that changes of interest occurring at a smaller spatial extent are retained and changes of interest occurring at a larger extent are not exaggerated.
(2) An optimal moving window size can only be selected for areas with a homogeneous landscape in terms of the type, size and density of changes.

Uncertainties are common in models developed to represent realities, especially models that use satellite images as input. In the case of the approach presented in this paper, uncertainties can emanate from: (1) errors in the LULC maps; (2) an inappropriate moving window size; (3) reclassification of the neighbourhood-level change information. Although the approach could have been explained using a fictitious change map, in order to better justify the approach, we used real LULC and change maps representing large and complex areas. LULC and change maps covering large and heterogeneous areas are particularly susceptible to uncertainties. However, the LULC maps we used were produced using an approach particularly suited for mapping large and heterogeneous areas and have an overall classification accuracy of more than 87%, which exceeds the recommended minimum accuracy level (Foody 2002). Thus, to account for any uncertainties in the approach and results, it is important that users consider the accuracy of the LULC maps used and the nature of the changes to be characterized. Further uncertainty may arise from the reclassification of the neighbourhood-level change information

into change categories. The number and definition of these categories depends on users' preferences, and the choice of threshold values influences the outputs to some extent. Finally, as discussed in detail in above, uncertainties also exist in the selection of the optimal moving window size.

5. Conclusions

Based on our assessment results, we conclude that even if translation of pixel-level change information to a more aggregated level generalizes the information content, using an optimally sized moving window it can significantly improve the signal-to-noise ratio retained in the pixel-level change information and allows to cancel out unbiased errors. The presented approach makes it possible to express change in relative terms, using ranges of change values. This makes the approach useful for characterizing LULC change at national or regional levels.

However, we recommend that users should consider the following important issues when applying the approach:

(1) Characterizing LULC change across large and heterogeneous areas using the proposed approach requires use of multiple moving window sizes.
(2) Heterogeneous areas need to be subdivided into smaller areas that are homogeneous in terms of the types, size and density of changes occurring in them. The optimal moving window size is then determined separately for each of these subareas.
(3) Prior to characterizing change, the appropriateness of the moving window size must be verified based on known changes.
(4) The optimal moving window size should be determined by considering the spatial extent of the smallest feature to be characterized, as well as the type and direction of change.
(5) The approach produces a generalized output with an improved signal-to-noise ratio compared to the pixel-level change information. However, large moving window sizes will obscure changes of small spatial extent that may be important at the local scale.

In sum, if the approach is applied considering the recommendations presented here, the output change maps have the potential to provide a synoptic view of landscape change processes at regional and national scales. This will support decision-makers and planners in guiding the implementation of sustainable land resources management and rehabilitation endeavours at regional and national scales.

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Disclosure statement

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