Published in final edited form as:
Remote Sens Environ. 2004 October 30; 93(1-2): 42–52. doi:10.1016/j.rse.2004.06.014.

Defining approaches to settlement mapping for public health management in Kenya using medium spatial resolution satellite imagery

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Abstract

This paper presents an appraisal of satellite imagery types and texture measures for identifying and delineating settlements in four Districts of Kenya chosen to represent the variation in human ecology across the country. Landsat Thematic Mapper (TM) and Japanese Earth Resources Satellite-1 (JERS-1) synthetic aperture radar (SAR) imagery of the four districts were obtained and supervised per-pixel classifications of image combinations tested for their efficacy at settlement delineation. Additional data layers including human population census data, land cover, and locations of medical facilities, villages, schools and market centres were used for training site identification and validation. For each district, the most accurate approach was determined through the best correspondence with known settlement and non-settlement pixels. The resulting settlement maps will be used in combination with census data to produce medium spatial resolution population maps for improved public health planning in Kenya.

Keywords

Landsat TM; JERS-1 SAR; texture; settlement mapping; Kenya; public health

Introduction

Ninety percent of projected global urbanization will be concentrated in low-income countries {United-Nations, 2002 #79}. In Africa 38% of the 784 million inhabitants were urban dwellers in 2000. This is estimated to increase to 55% by 2030 as virtually all of this population doubling will be concentrated in urban areas {United-Nations, 2002 #79}. The profound development and epidemiological impacts of these changes are increasingly being realised {Harpham, 1997 #254;McMichael, 2000 #255;Prothero, 2001 #256}. Urban dwellers face a very different set of health risks compared to their rural counterparts {Tatem, 2004 #224}. In Sub-Saharan Africa (SSA) for example, urban residents are more at risk from directly transmitted diseases such as tuberculosis {Banerjee, 1999 #571;Floyd, 2002 #557} and HIV {Mhalu, 1996 #568;Abebe, 2003 #570;Lagarde, 2003 #569} as well as certain vector-borne diseases such as dengue fever {Lines, 1994 #572}, but contrastingly are around ten-times less likely to receive a malaria-infected mosquito bite {Hay, 2000 #190;Robert, 2003 #537} and have significantly better access to health care facilities {Noor, 2003 #235}.

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Planning for the health consequences of urbanization in the countries of sub-Saharan Africa relies on the provision of information and maps of settlement location, size and distribution. Whilst high-income countries often have mapping resources at their disposal to define and delineate settlements for such public health planning and management, this is often not the case for low-income regions of the world.

Satellite remote sensing offers a cheap and effective solution to mapping settlements and monitoring urbanization at a range of spatial scales. From continental scale urban-mapping using AVHRR, MODIS and night-time imagery {Imhoff, 1997 #70;Vogelmann, 1998 #84;Civco, 2002 #1;Schneider, 2003 #223}, to medium-scale regional settlement mapping and classification using Landsat TM, SPOT HRV and ERS-1/2 {Forster, 1983 #77;Baraldi, 2000 #62;Dell'Acqua, 2003 #58}, down to the recent wave of settlement-scale studies using fine spatial resolution {Tatem, 2001 #76;Quartulli, 2003 #193;Roth, 2003 #192;Giada, 2003 #228}, there now exist well documented approaches for settlement delineation, classification and validation at all scales, reviewed in {Tatem, 2004 #224}. Few attempts have been made to use satellite imagery in combination with census data to produce global and continental population maps (Landscan: {Dobson, 2000 #249;Dobson, 2003 #154} UNEP GRID: {Deichmann, 1996 #246} GPW 2.0: {Deichmann, 2001 #248}). However, the administrative level of input census data for SSA is so coarse that population estimates at an administrative level fine enough to facilitate effective public health management can be inaccurate {Hay, 2004 #236;Hay, 2004 #237}. The scarcity of reliable data for map validation and the difficulty in obtaining other data such as census statistics are cited as the main obstacles to settlement mapping in the region (Noor, 2003 pers.comm).

Study Aims

The work detailed in this paper forms part of a larger project aimed at extending the application of GIS and remote sensing technology to the quantification of human population distribution to allow more accurate malaria risk mapping and disease burden estimation across Africa. The findings of this study will therefore form an important input to this work and be used to scale up settlement maps and subsequently population maps to Kenya level. This study therefore has two main aims:

- Assess the utility of both multispectral and radar imagery, along with derived texture layers, in producing settlement maps across four contrasting Kenyan districts at a spatial scale fine enough to facilitate application in public health management.
- Utilise the findings to inform on methods of scaling-up to Kenya-wide settlement maps.

Methodology

The Districts

Four study districts were chosen to represent the full range of land cover types, topography, climate, settlement distribution and public health requirements found in Kenya. Figure 1 shows the location of the four districts both on a geographical map and malaria endemicity map of Kenya {Craig, 1999 #539}, and table 1 lists the features of each.

Data

Orthorectified Landsat 5 Thematic Mapper (TM) 30 metre spatial resolution imagery in seven spectral bands were acquired for each district. Japanese Earth Resources Satellite 1 (JERS-1) Synthetic Aperture Radar (SAR) 12.5 metre spatial resolution imagery (processed to level 2.1) was also acquired. Table 2 shows the number of individual scenes required to

cover each district and the date each were taken on. For each district, the component Landsat TM and JERS-1 SAR images were mosaiced together using Erdas Imagine ™ version 8.6 {ERDAS, 2002 #293} to create single TM and SAR images for each district. The Landsat TM imagery was then radiometrically corrected {Richter, 1990 #577}, but no high resolution DEMs of the districts were available for topographic correction of the imagery sets. Each image was then georegistered using Erdas Imagine™ to vector polygon enumeration area images of their respective district {Noor, 2003 #235}. Within the Landsat TM images, approximately 8% of the Makueni image, and approximately 5% of the Kwale image contained cloud cover. Figures 2(i) and (ii) show the Landsat TM and JERS-1 SAR images of Bondo District respectively.

Data for map validation were a set of vector points and ancillary data for each district collected through ground survey in 2001 and 2002 using a GPS {Noor, 2003 #235}. These included the locations of health facilities, market centres, schools, villages and selected households. In addition, 1999 census data at the enumeration area level were secured for each district {Hay, 2004a #236}. Vector layers of roads, rivers, dams and swamps were also available and are described elsewhere {Noor, 2003 #235;Noor, 2004 #250;Noor, 2004 #251}. For training of the classifier on non-settlement land covers, three different land cover maps of Kenya were obtained, so that specific land covers could be identified. These were the global 1km landcover classification {Hansen, 2000 #561}, the FAO Africover map for Kenya {FAO, 2003 #562} and an Africover-derived spatially aggregated landcover database {FAO, 2003 #562}.

Classifier—A traditional supervised maximum likelihood classification algorithm {Paola, 1995 #51;Chan, 2001 #257;Stefanov, 2001 #12} was used to produce settlement maps for each district. For the district of Bondo, which has areas of distinctly differing landcovers, consequently resulting in differing signature mixing at the edge of settlements, a pre-classification segmentation was also evaluated. This involved firstly the application of an image segmentation algorithm {Ruefenacht, 2003 #226} to all image layers. The algorithm was used to segment the district of Bondo into five spectrally unique and spatially contiguous zones. A map of these zones is shown in figure 2(iii). Separate training and maximum likelihood classification was then carried out within each zone.

Training area selection—For each of the four districts, the point data on market centres, health facilities and schools were utilised in the identification of settlement training sites, and census data was used as a check to ensure a settlement had indeed been identified. As a further test, the spectral signature, radar return and texture statistics of each settlement training site were then compared to those of other known settlements to ensure representative statistics had been extracted. The various land cover maps obtained were then used in combination with the census data and GIS layers to identify representative training samples for all non-settlement areas of the four districts. The histograms of each set of training pixels were also examined to ascertain that each were approximately normally distributed, to fulfil the requirements of the parametric maximum-likelihood classifier.

Texture measures—For each JERS-1 SAR district image, eight texture feature images calculated from the grey level cooccurrence matrix (GLCM) method {Haralick, 1973 #98;Haralick, 1979 #230} were produced, including mean, variance, contrast, homogeneity, dissimilarity, correlation, entropy and angular second moment {Haralick, 1973 #98;Baraldi, 1995 #231} Following work on urban areas using similar spatial resolution imagery and texture, a 7×7 moving window size was used {Zhang, 2003 #225}.

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Band Combinations—To test the utility of each image type, seven combinations were tested for each district (see table 2 for details).

Accuracy Assessment—The ground-collected set of vector points were used as the principal source of settlement mapping assessment. These points were taken to represent locations of settlements to validate the accuracy with which each classification identified settlement pixels. In addition to these, the same points were used in combination with the land cover maps, census data and visible Landsat TM bands to identify an equal set of non-settlement points for each district. Half of these points were located on the edge of known settlements to assess the success by which the settlement maps had delineated the extent of settlements. Buffer areas around known settlements were identified and points were randomly selected from within these. The other half were located in areas clearly at a distance from settlements to assess whether the predicted settlement maps had identified false areas of settlement. Non-settlement areas were identified and again points were randomly selected from within these.

Given the variation in populations and number of settlements in each district, the numbers of validation points for each district, excluding those falling under cloud cover in the Landsat TM imagery, were as follows: Bondo: 606 points; KisiiGucha: 222 points; Makueni: 144 points; Kwale: 94 points. The satellite image-derived settlement maps were binary encoded into settlement/non-settlement pixels and the vector-point validation datasets were used to extract pixels for each district and measures of accuracy were calculated. Health facilities were found to be on average 400 metres from settlement centres, so any pixels predicted as containing a settlement within this distance of a health facility validation point were counted as correct. Accuracy assessment measures included producer's accuracy, consumer's accuracy, overall percentage correct {Campbell, 1996 #573} and Kappa {Ma, 1995 #227}. Finally a visual comparison between 1999 enumeration area census counts and settlement maps was made to check for any obvious inaccuracies.

Results

Supervised maximum likelihood classification was carried out on the band combinations detailed in table 2, both for the entirety of all four districts and within the segmented zones of Bondo shown in figure 2(iii). The results of accuracy assessment of each predicted settlement map are shown in table 4, with the consumer's and producer's accuracy figures for the most accurate classification of each district in table 5. Figure 3 shows an area of each district from JERS-1 SAR imagery and Landsat TM red, green and blue bands, compared to the validation points, census data and derived most accurate settlement map. For Bondo, the Landsat TM, JERS-1 SAR and texture combination of layers using the pre-segmented classification was found to most closely correspond to the validation points, with a Kappa value of 0.964. For Kisii/Gucha, the results differed, with the classification of just the Landsat TM imagery proving most accurate, classifying 86.5% of the verification points correctly. The verification points of both Makueni and Kwale were most accurately mapped using all available image sources, with kappa values of 0.569 and 0.915 respectively.

Discussion

Methodology

The principal aim of the study was to assess the utility of various combinations of satellite imagery in producing accurate settlement maps, so the classifier used was not varied. Initial testing of Mahalanobis distance {ERDAS, 2002 #293}, minimum distance {ERDAS, 2002 #293}, hard and soft feed-forward neural networks {Kavzoglu, 2003 #574} and superresolution {Tatem, 2001 #563} algorithms indicated no significant difference or

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improvement to results however. Supervised classification is not typically the process of choice in large area classifications due to the requirement for significant amounts of training data {Bauer, 1994 #578}, but the comprehensive set of ground-collected data available removed this constraint. Therefore, the sole use of a supervised maximum likelihood classifier, successfully applied in other settlement mapping studies {Mesev, 1998 #91;Giada, 2003 #228} ensured that too many variables were not introduced and that the maps produced using each image combination could be quantitatively compared, thus not detracting from the overall focus of the paper.

Many studies have shown the benefit of applying texture algorithms to SAR imagery in order to extract further land cover information {Marceau, 1990 #232;Gong, 1992 #234;Karathanassi, 2000 #19;Arzandeh, 2002 #233;Dekker, 2003 #213}, an approach currently underutilised in image classification {Franklin, 2002 #575}. The methodology adopted for this study aimed to assess whether the addition of JERS-1 SAR derived textural information could improve settlement mapping accuracy. Several methods for image texture quantification exist {Laine, 1993 #239;Carr, 1998 #238;Dekker, 2003 #213}, but those based on the grey-level co-occurrence matrix (GLCM) have often been found to be most effective for satellite imagery {Haralick, 1973 #98;Baraldi, 1995 #231;Zhang, 2003 #225}. Recent texture studies have also shown that the highest classification accuracies are achieved with the inclusion of the maximum number of texture layers available {Dekker, 2003 #213;Zhang, 2003 #225}, but this was not investigated here.

Findings

The individual benefits of medium-spatial resolution multispectral imagery, SAR imagery and SAR-derived texture measures for settlement mapping have been widely extolled (e.g. {Forster, 1980 #107;Iisaka, 1982 #108;Yuan, 1997 #73;Henderson, 1999 #286;Dell'Acqua, 2003 #58}), but very few studies have attempted to quantify the potential improvements gained from combining each (e.g. {Toll, 1985 #290;Lichtenegger, 1991 #289}), and no studies of note have examined their potential in SSA. The benefits to settlement mapping of combining these different layers are amply demonstrated in figure 4 where the strengths and weaknesses of each are highlighted. Small settlements of grass-roofed houses surrounded by grassland are impossible to identify solely by multispectral imagery, whereas the high radar return from such regularly shaped objects is detectable, a benefit of radar imagery also noted in other studies {Lo, 1984 #287;Lo, 1986 #288;Henderson, 1997 #57}. In contrast, settlements on steep slopes surrounded by forest prove difficult to isolate using SAR imagery alone, but produce enough of a spectral reflectance difference with their surroundings to be clearly delineated by a classifier using multispectral data. On top of all this, texture measures can add further discriminating layers of information.

For Bondo, table 4 demonstrates that while solely Landsat TM imagery produces excellent results in classifying over 90% of the verification points correctly, the addition of extra layers of information in the form of SAR backscatter and SAR-derived texture measures enables the classifier to improve further on these results. Additional improvements are also witnessed when segmenting the imagery and classifying within each segment. The varying land cover zones of Bondo mean that each group of settlements have distinct reflectance and backscatter signatures where mixing with the surrounding land covers occur at the settlement edge. Segmentation by land cover zone therefore allows the classifier to more clearly identify settlement pixels in feature space. Kisii/Gucha by contrast does not exhibit the high levels of accuracy as Bondo does in correctly classifying the verification points. The use of just Landsat TM imagery produces the largest overall percentage correct and Kappa value, probably due to the mountainous nature of the district. The varying topography and lack of a high spatial resolution DEM to correct for the effects this has on the SAR imagery and derived texture layers results in these imagery layers being a hindrance in

settlement mapping, rather than the help they were in relatively flat Bondo. Makueni represented the toughest challenge of the four districts, covering such a wide range of topographies and land covers, in addition to being sparsely populated. Nevertheless, the use of all three types of imagery again proved to be the most accurate in classifying the verification points, with a kappa value of 0.569. Kwale produced a similar result, where combing Landsat TM, SAR and texture successfully mapped 95.74% of the verification points. The settlement producer's accuracy of 100% showed also that all the settlement verification points were classified correctly. Finally, although the low number of validation points for Kwale may have inflated accuracy results, the flat topography of the district is reflected in the large percentage correct and kappa values when using solely SAR or texture layers, an indication of the potential benefits to the other districts of using topographically-corrected SAR imagery.

In sum, the results clearly demonstrate that the combination of medium spatial resolution multispectral satellite imagery with similar scale SAR imagery and derived texture layers is effective in identifying and mapping settlements at medium-scale spatial resolution across the diverse landscapes of Kenya.

Scaling-up to Kenya-wide settlement mapping

The natural continuation of this study is to utilise the findings and recommendations made here to scale up to a settlement map of Kenya. Results indicate that accurate settlement maps can be produced using Landsat TM and JERS-1 SAR imagery, however, certain band combinations appear to be more suited to certain topographies. This fact, and the success of the pre-segmented map of Bondo, suggests that any attempt to map settlements at Kenya level should be based on an initial division of the country into zones of similar topography, land cover and settlement density. This could be achieved for example, by application of the spatial-spectral segmentation algorithm utilised in this paper on countrywide DEM, coarse spatial resolution satellite imagery (e.g. MODIS) and road density layers. Results indicate that unless topographically-corrected SAR imagery can be obtained, its application in Kenya-wide settlement mapping should be restricted to non-mountainous zones.

Scaling-up to a Kenya level settlement map will require expansion from the 13 Landsat TM scenes and 40 JERS-1 SAR scenes used in this study to 35 Landsat and 360 SAR scenes. Although this will be technically challenging, it is well within modern processing and computing capabilities, as recent large-scale studies have shown {Fuller, 1994 #579;De Grandi, 2000 #576;Franklin, 2002 #575;Siqueira, 2003 #229}. Ideally, the application of a combination of very high spatial resolution imagery, such as that from IKONOS {Tanaka, 2001 #292}, Quickbird {Volpe, 2003 #197} or TerraSAR {Roth, 2003 #192}, to settlement mapping across Kenya would increase confidence with which settlements could be identified and delineated, but such an approach is both technically and financially prohibitive.

Future Steps….

This study forms the starting point of a larger project aimed at quantifying human population distribution initially in Kenya, but ultimately across Africa, to facilitate improvements in the accuracy of malaria risk maps and disease burden estimates. This will be achieved by scaling-up findings of this work to produce settlement maps as input, along with other GIS and recent census information, to population mapping models (e.g. {Wright, 1936 #241;Tobler, 1979 #240;Deichmann, 1996 #246;Deichmann, 2001 #248;Eicher, 2001 #269;Langford, 2003 #148}). The high spatial resolution of these efforts will be more appropriate to the scale of human population and disease processes and an order of magnitude finer than previous attempts {Deichmann, 1996 #246;Deichmann, 2001

#248;Dobson, 2000 #249;Dobson, 2003 #154;Sutton, 2001 #41;Sutton, 2003 #156}. Furthermore, high spatial resolution human population distribution maps will help facilitate many of the wider aspirations of those involved in public health research across Africa with respect to commodity needs estimation, health service and intervention equity issues and some basic analyses on the efficacy of delivery mechanisms for control services.

Conclusions

This paper has presented an appraisal of the efficacy of two types of satellite imagery and derived texture layers in identifying and mapping settlements across four contrasting Kenyan districts. Results demonstrate that the combination of medium spatial resolution multispectral satellite imagery with similar scale SAR imagery and derived texture layers is effective in identifying and delineating settlements across the diverse landscapes of Kenya. Such information provides a valuable input to population mapping models designed for public health applications.

Acknowledgments

We thank Scott Goetz and Alastair Graham for comments on earlier drafts of the manuscript. SIH and AJT are funded by a Research Career Development Fellowship (to SIH) from the Wellcome Trust (#069045).

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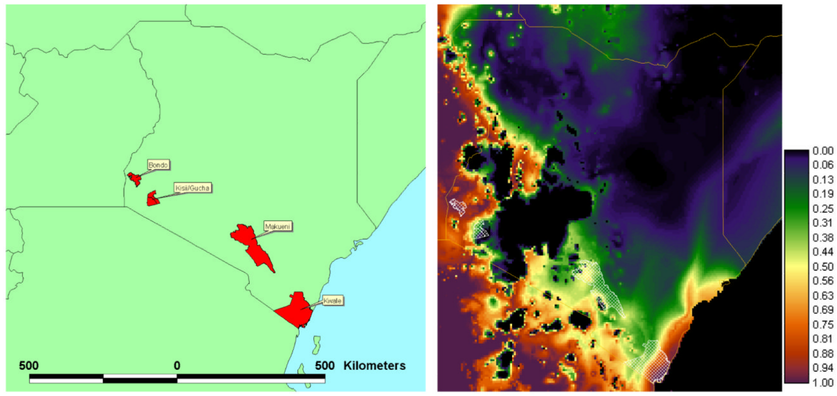

Figure 1.
(i)Map showing location of the four districts (ii) Location of the four districts on an ecozone map of Kenya.

Figure 2.
(i)Landsat RGB image of whole of Bondo (ii) SAR image of whole of Bondo (iii) Segmentation map for per-parcel classification.

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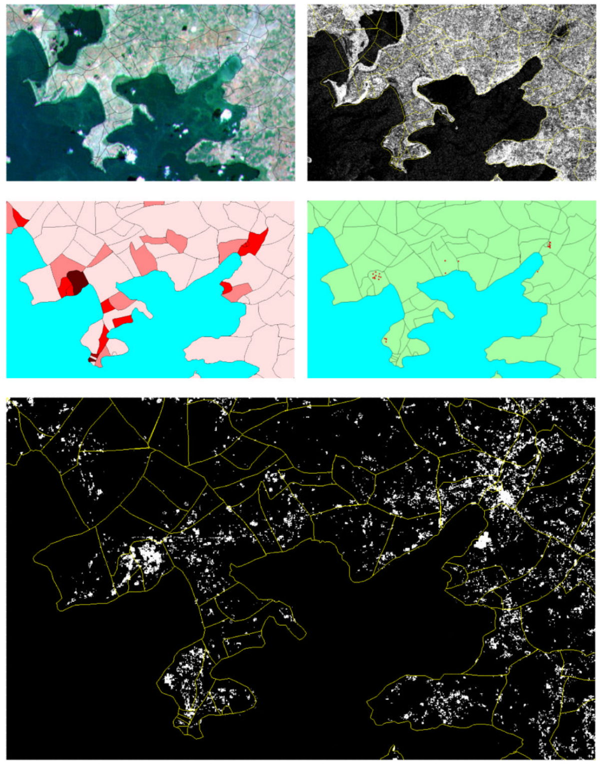

Figure 3.
Closeup of an area of each of the four districts with (i) Landsat RGB image (ii) JERS-1 SAR image (iii) Hosp/Mkt points for same area (iv) 1999 census map of the area (v) Predicted settlement map of the area.

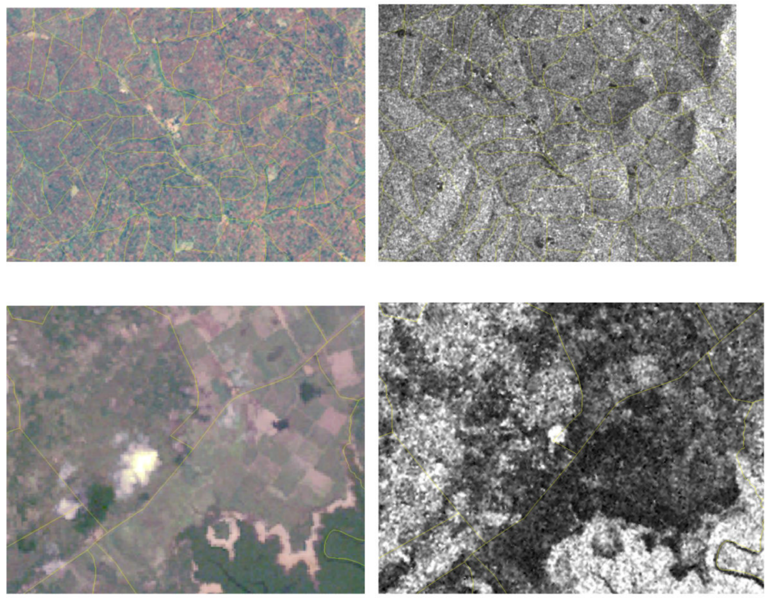

Figure 4.

(i) Closeup of a settlement visible in RGB landsat bands, but invisible in SAR image next to it. (ii) Closeup of a settlement invisible in RGB landsat bands, but visible in SAR image next to it

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Table 1

Features of each of the four study districts

District	Area (km^2)	Population	No of Government of Kenya health facilities	Malaria ecology
Bondo	960	238,780	21	Perennial, intense
Kisii / Gucha	1310	952,725	44	Highland, acutely seasonal
Kwale	8295	496,133	50	Seasonal, intense
Makueni	8266	771,545	59	Semi-arid, acutely seasonal

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Table 2

Satellite imagery specifications and features

District	Number of Landsat TM scenes required	Date of each Landsat TM scene	Number of JERS-1 SAR scenes required	Date of each JERS-1 SAR scene
Bondo	1	Mar 1995	5	Jan 1996
Kisii / Gucha	4	Jan-Mar 1995	4	Jan 1996
Kwale	4	Jan-Feb 1995	15	Jan-Feb 1996
Makueni	4	Jan-Feb 1995	16	Jun 1996

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Table 3

Band combinations assessed for settlement mapping (SAR = JERS-1 SAR; LSAT = Landsat TM; TEXTURE = JERS-1 SAR-derived texture measures)

Band Combination
SAR
LSAT
TEXTURE
SAR + TEXTURE
LSAT + TEXTURE
SAR + LSAT
SAR + LSAT + TEXTURE

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Table 4

Accuracy statistics of each band combination and classification type (OA = Overall Percentage Correct, K = Kappa)

	Bondo		Kisii/Gucha		Makueni		Kwale	
Band Combination	**OA (%)**	**K**	**OA (%)**	**K**	**OA (%)**	**K**	**OA (%)**	**K**
Full Image Classification								
SAR	39.77	−0.205	25.68	−0.486	21.53	−0.569	76.6	0.532
LSAT	90.43	0.809	86.49	0.73	75	0.5	82.98	0.66
TEXTURE	42.57	−0.149	65.77	0.315	52.78	0.056	85.11	0.702
SAR+TEXTURE	51.16	0.023	38.29	−0.234	28.47	−0.431	77.66	0.553
LSAT+TEXTURE	92.57	0.851	80.63	0.613	75	0.5	85.11	0.702
LSAT+SAR	92.9	0.858	74.77	0.495	74.31	0.486	94.68	0.894
SAR+LSAT+TEXTURE	97.52	0.95	79.73	0.595	78.47	0.569	95.74	0.915
Pre-Segmented Classification								
SAR	50.66	0.013	n/a	n/a	n/a	n/a	n/a	n/a
LSAT	90.92	0.818	n/a	n/a	n/a	n/a	n/a	n/a
TEXTURE	55.61	0.112	n/a	n/a	n/a	n/a	n/a	n/a
SAR+TEXTURE	57.92	0.158	n/a	n/a	n/a	n/a	n/a	n/a
LSAT+TEXTURE	91.42	0.828	n/a	n/a	n/a	n/a	n/a	n/a
LSAT+SAR	94.22	0.884	n/a	n/a	n/a	n/a	n/a	n/a
SAR+LSAT+TEXTURE	98.18	0.964	n/a	n/a	n/a	n/a	n/a	n/a

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Table 5

Consumer's accuracies (CA) and Producer's accuracies (PA) for the four settlement maps where the validation points were most accurately classified.

	Settlement		Non-Settlement	
	CA(%)	PA(%)	CA(%)	PA(%)
Bondo	97	99	99	97
Kisii/Gucha	87	86	86	87
Makueni	78	79	79	78
Kwale	92	100	100	91