Variability in Soft Classification Prediction and its implications for Sub-pixel Scale Change Detection and Super Resolution Mapping

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Abstract

The impact of intra-class spectral variability on the estimation of sub-pixel land-cover class composition with a linear mixture model is explored. It is shown that the nature of intra-class variation present has a marked impact on the accuracy of sub-pixel class composition estimation, as it violates the assumption that a class can be represented by a single spectral endmember. It is suggested that a distribution of possible class compositions can be derived from pixels instead of a single class composition prediction. This distribution provides a richer indication of possible sub-pixel class compositions and highlights a limitation for super-resolution mapping. Moreover, the class composition distribution information may be used to derive different scenarios of changes when used in a post-classification comparison type approach to change detection. This latter issue is illustrated with an example of forest cover change in Brazil from Landsat TM data.

Introduction

Remote sensing has been commonly used as a source of information on land-cover and land-cover change. Unfortunately, the accuracy of both land-cover mapping and monitoring activities is often limited by the presence of mixed pixels. A mixed pixel occurs when the area represented by the pixel encompasses more than one land-cover class (Fisher, 1997). The proportion of image pixels that are mixed can be large and generally increases with a coarsening of the spatial resolution of the sensor used to acquire the imagery. Thus, the mixed pixel problem occurs most severely in coarse spatial resolution data sets. Unfortunately, these data sets are widely used in the mapping and monitoring of large areas, applications where remote sensing has perhaps its greatest potential as a source of basic environmental information. Since a mixed pixel represents an area of more than one land-cover class, a mixed pixel cannot be appropriately represented by a conventional hard approach to image classification, and this can lead to substantial error in land-cover mapping from remotely sensed data. This error may propagate into studies of land-cover dynamics, especially if based on post-classification comparison. The errors arising from mixed pixels can be very large, with, for example, Skole and Tucker (1993) reporting that deforestation may be over-estimated by approximately 50 percent if coarse spatial resolution imagery are used. In order to derive accurate land-cover information researchers need to address the mixed pixel problem. One approach is to use fine spatial resolution imagery, and so reduce the proportion of mixed pixels. This can be a very effective approach but is far from problem-free. The imagery may, for instance, be costly to acquire and considerable pre-processing could be necessary to inter-calibrate and mosaic the set of images required to cover the study area. An alternative approach to addressing the mixed pixel problem is to attempt to derive sub-pixel scale information from the coarse spatial resolution imagery.

Sub-pixel scale land-cover information is typically derived by unmixing the spectral response of mixed pixels to indicate their class composition. A variety of methods for estimating the class composition of mixed pixels have been applied to remotely sensed data, including the linear mixture model and soft or fuzzy classifications (e.g., Foody, 1996; Bateson *et al.*, 2000; Small, 2004). The output of these analyses is typically a set of fraction images, one per-class, that indicate the estimated proportion of the pixel's area covered by a class. These fraction images can yield accurate estimates of class composition. They also open the door to the representation of environmental continua and the detection of land-cover modifications and conversions when used in post-classification analyses (Foody, 2001; Haertel *et al.*, 2004). The sub-pixel information also forms the basis of super-resolution mapping, in which the geographical location of the estimated class fractions is located within each pixel's area to yield a thematic map at a finer spatial resolution than the imagery used in its derivation (Tatem *et al.*, 2001; Mertens *et al.*, 2006; Muslim *et al.*, 2006; Boucher and Kyriakidis, 2006). Although sub-pixel land-cover composition estimation and analyses such as super-resolution

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mapping on which they are based can reduce some of the problems associated with mixed pixels there are still concerns. In particular, the accuracy of sub-pixel land-cover composition estimation may often be low. For example, in many studies there is a very large degree of scatter around the regression line between the actual and predicted class compositions (Carpenter *et al.*, 1999; Jug *et al.*, 2003; Peterson and Stow, 2003; Liu and Wu, 2005; Song, 2005). This is clearly a major limitation to studies seeking to estimate class fractional cover and its change over time or the sub-pixel scale spatial distribution of classes in applications such as super-resolution mapping.

The interpretation and use of sub-pixel scale land-cover information typically places great confidence on the estimated class cover proportions. For example, in using a pair of soft classifications for change detection the estimated class proportions are typically compared directly (Foody, 2001; Haertel *et al.*, 2004). In super-resolution mapping, some approaches strive to maintain the class proportion information output from a soft classification (Tatem *et al.*, 2001; Muslim *et al.*, 2006). This trust in the single set of class proportion predictions may be unwise. In particular, this trust often seems to be based on an implicit assumption that a class can be represented by a single spectral endmember. This is clearly unrealistic as classes typically display a degree of spectral variability. Indeed, it is known that the level of intra-class variation can impact negatively on unmixing analyses (e.g., Petrou and Foschini, 1999; Rogers and Kearney, 2004) and approaches to refine basic unmixing methods to accommodate for this have been developed (Bateson *et al.* 2000; Song, 2005). However, it is still common to see basic approaches to unmixing being used and the sub-pixel class composition estimates derived used in a manner that places great confidence in their accuracy. This paper aims to briefly explore the impacts of class spectral variability on unmixing and highlight its implications for analyses based on soft classification outputs such as the detection of land-cover change and super-resolution mapping.

Data and Methods

Two data sets were used. First, to control the analysis, a simulated data set was used to illustrate and explore the effect of class spectral variability on sub-pixel class composition estimation. The data set comprised three classes and, to accommodate for a dimensionality constraint in unmixing (Settle and Drake, 1993), four simulated spectral wavebands. For simplicity, the spectral response of each class was normally distributed in each waveband. The spectral response of the classes was, however, varied in the experiment to illustrate the impacts of differences in intra-class variation, including co-variation, in spectral feature space on the accuracy of sub-pixel class composition estimation and the key parameters describing the data are summarized in Table 1. Here, the linear mixture model (Settle and Drake, 1993) was used as a convenient tool to derive the sub-pixel scale information on class composition. For illustrative purposes, the data were also subjected to a principal components analyses, and the first two components that explained most of the variation in the data set are used to display the classes in feature space. The accuracy of the sub-pixel class composition predictions was assessed through the correlation with the known class compositions and root mean squared error (RMSE).

A series of analyses were undertaken with the simulated data set. Initially, the class centroids were taken to define the class endmember spectra. Although other means of defining the endmembers exist, and it is well established that endmember definition can be difficult (Theseira *et al.*, 2003; Small, 2004), the precise means of endmember definition is not important. Irrespective of the means of its derivation, the key concern is that a single spectrum is taken to represent the class. Intra-class variation is, therefore, essentially ignored. In later analyses, a multitude of linear mixture models were applied. In this, every pixel in the training set was used to provide the endmember spectrum for the analysis. By unmixing the spectral response of a pixel many times with different endmembers a series of sub-pixel class composition estimates could be derived for a pixel of any given spectral response. As a result of this it was, therefore, possible to form a distribution of sub-pixel estimates for each pixel.

To illustrate the impacts of intra-class spectral variation on sub-pixel class composition estimation and explore its implications some analyses of real remotely sensed data were undertaken. Here attention focused on a common type of analysis in a major environmental science context: the assessment of tropical deforestation. Attention was focused on a small region of Para in Brazil where forest clearance had occurred. Two Landsat TM images of the region, before and after the clearance, were acquired (Figure 1). In these images the region cleared of forest cover is evident. These TM images were classified into forest and non-forest visually and used as the reference data for the analyses. The images were then degraded spatially to 300 m spatial resolution (Figure 2), comparable to the spatial resolution of medium spatial resolution systems such as the Moderate Resolution Imaging Spectroradiometer (MODIS) and Medium Resolution Imaging Spectrometer (MERIS). For each pixel in the spatially degraded imagery, sub-pixel class composition estimates were derived. These were derived using 90 training sites to characterize each of the forest and non-forest

Table 1. Summary of Simulated Data

Class	Mean	Variance-covariance matrix: Small Variability	Medium Variability	Large Variability
A	[380 490 300 320]	$\begin{bmatrix} 4 & 3 & 2 & 3 \\ 3 & 6 & 3 & 4 \\ 2 & 3 & 3 & 3 \\ 3 & 4 & 3 & 6 \end{bmatrix}$	$\begin{bmatrix} 64 & 50 & 40 & 50 \\ 50 & 100 & 45 & 64 \\ 40 & 45 & 49 & 45 \\ 50 & 64 & 45 & 100 \end{bmatrix}$	$\begin{bmatrix} 1024 & 800 & 640 & 800 \\ 800 & 1600 & 720 & 1024 \\ 640 & 720 & 784 & 720 \\ 800 & 1024 & 720 & 1600 \end{bmatrix}$
B	[310 335 235 260]			
C	[250 410 180 390]			

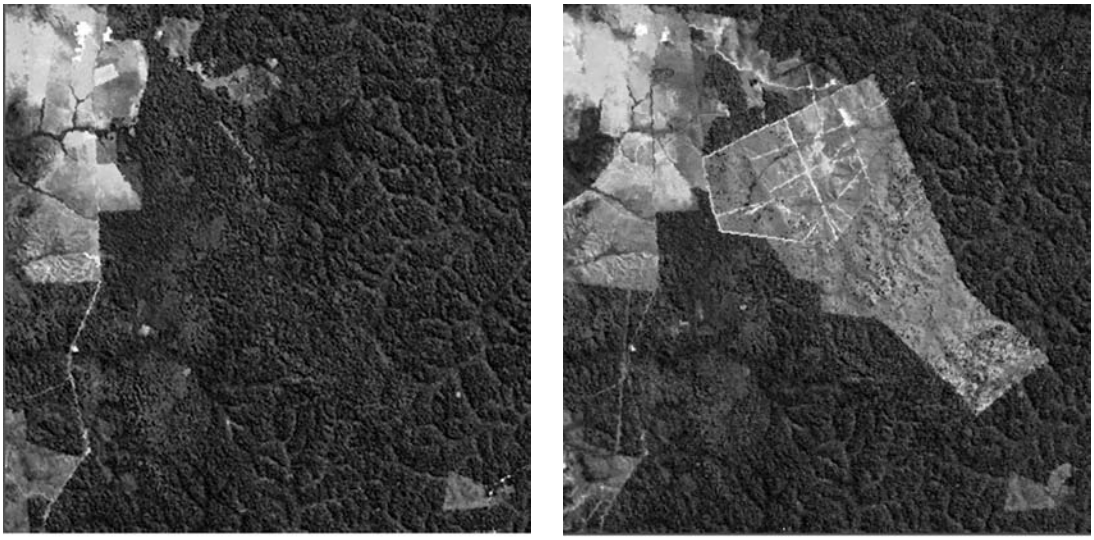

Figure 1. The Landsat TM imagery used: (a) July 1984 and (b) July 1988.

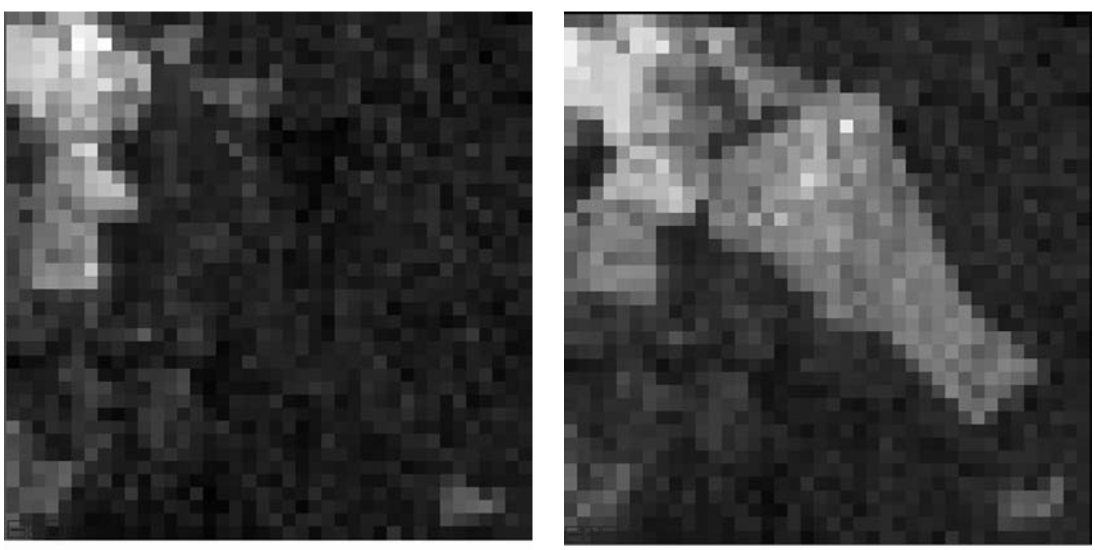

Figure 2. The spatially degraded imagery: (a) 1984, and (b) 1988.

classes, with endmembers defined initially as the class centroids for input to a basic linear mixture model. The centroids, however, do not fully describe the classes spectrally; the spectral response of the classes in the two images are summarized in Tables 2 and 3. The analyses were then repeated many times with the spectral response of the individual training pixels used to define the endmember spectra so that a distribution of possible sub-pixel class composition could be derived for each pixel in the simulated coarse spatial resolution imagery. The distributional information could be used to indicate the variety of possible class compositions with, for example, the interquartile range or deciles used to summarise key characteristics.

Table 2. Class Descriptions for the 1984 Imagery

Class	Mean	Variance-covariance Matrix
Forest	[76.830 51.250 12.715]	$\begin{bmatrix} 11.503 & 6.033 & 1.251 \\ 6.033 & 5.885 & 1.408 \\ 1.251 & 1.408 & 0.362 \end{bmatrix}$
Non-forest	[71.883 96.635 34.554]	$\begin{bmatrix} 37.197 & -24.173 & -11.818 \\ -24.173 & 320.975 & 177.878 \\ -11.818 & 177.878 & 100.546 \end{bmatrix}$

Table 3. Class Descriptions for the 1988 Imagery

Class	Mean	Variance-covariance Matrix
Forest	[72.232 51.792 9.730]	$\begin{bmatrix} 8.534 & 4.070 & 0.614 \\ 4.070 & 5.626 & 1.192 \\ 0.614 & 1.192 & 0.291 \end{bmatrix}$
Non-forest	[62.003 94.035 29.137]	$\begin{bmatrix} 42.327 & -32.492 & -17.513 \\ -32.492 & 159.129 & 80.585 \\ -17.513 & 80.585 & 42.132 \end{bmatrix}$

The outputs of the unmixing analyses were also used to derive super-resolution maps using a Hopfield neural network (Tatem *et al.*, 2001).

Results and Discussion

Figure 3 shows the location of the classes defined by the means and, what is termed here, the medium variability variance co-variance matrix (as defined in Table 1) in the feature space of the simulated data set. As expected, each class occupies an area of the feature space. A class clearly cannot be adequately represented by a single spectral endmember, an implicit assumption in much unmixing research. Note also that as a consequence of the intra-class variation, pixels with a particular class composition would also occupy an area of feature space. The distributions for class composition mixtures shown in Figure 3 were derived by using each training pixel's spectrum as an endmember in a series of linear mixture model analyses. More critically, however, it is apparent from Figure 3 that any one point in feature space could be associated with a variety of class compositions. Note, for example the area of overlap between two class compositions highlighted in Figure 3. Indeed, for any one point in feature space there are a variety of possible class compositions that could be associated with the spectral response linked with that location. The variety of possible compositions will be a function of the degree of intra-class variation and will impact on the accuracy of the sub-pixel estimation using a conventional linear mixture model. This is illustrated in Figure 4 in which the linear mixture model used the classes defined in Table 1 as endmembers. Note, that the scatter in the relationships between predicted and actual class composition increases with an increase in the degree of intra-class spectral variation, reducing the accuracy of the sub-pixel class composition estimates derived (Table 4). The amount of scatter observed in the relationships, even when the spectral intra-class variability was large, is comparable to that reported in other studies (e.g., Carpenter *et al.*, 1999; Jug *et al.*, 2003; Peterson and Stow, 2003; Liu and Wu, 2005; Song, 2005).

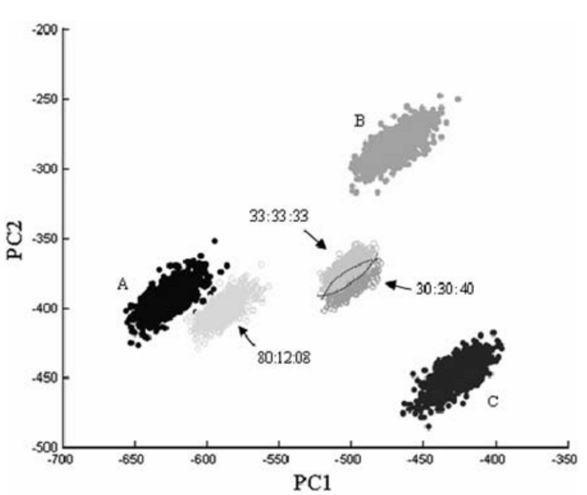

Figure 3. Location of the classes defined by Table 1 and three mixed class composition scenarios in the feature space defined by the first two principal components. The mixed compositions are defined in terms of the percentage cover of class A:B:C. Note the large area of overlap between the 33:33:33 and 30:30:40 mixtures.

From Figure 3 it is apparent that for any pixel extracted from the imagery, a distribution of possible class compositions could be derived. The nature of this distribution will depend on the location of the pixel in feature space and the degree of intra-class variation and class co-variation present. Figure 5 shows the distribution of possible class compositions for a series of pixels located in feature space for three scenarios based on the class descriptions summarised in Table 1. These scenarios were (a) the description represented the means and medium variability variance-covariance matrix in Table 1, (b) the same general set of descriptions but with a four-fold increase in the degree of intra-class variability of class C, and (c) finally, the first scenario repeated but with the distribution of class C rotated, for illustrative purposes, 90° in feature space. Note that for each location in feature space a distribution of possible compositions is derived and that the shape of this distribution is a function of the degree of intra-class variation (compare especially the distributions for transects iii and v highlighted in Figure 5) and the degree of co-variation (compare especially the distributions for transects iii, v, and vi in Figure 5). Given these results and, especially the impacts on sub-pixel class composition estimation accuracy (e.g., Table 4), it seems unwise to place great trust on the single class composition prediction for a pixel that is conventionally derived in unmixing/soft classification studies. Instead it would seem more sensible to recognise that a distribution of compositions is possible and utilise that in subsequent analyses.

To illustrate the impacts of intra-class spectral variation on analyses of remotely sensed data attention turned to the estimation of sub-pixel composition and change over time from the Landsat TM data (Figure 2). The forest class and, in particular, the more heterogeneous non-forest class both exhibited a degree of variation in feature space (Figure 6). Using the centroids of each class as endmembers, the class composition of pixels was estimated using a linear mixture model. The accuracy of the sub-pixel estimation was evaluated and significant relationship between actual and predicted class cover observed, albeit with a large degree of scatter (Figure 7). Comparisons of the class composition estimates derived from the two time periods were also derived to estimate the sub-pixel scale change in class composition in time (Figure 8).

As with the simulated data set, it was possible to derive a distribution of class composition estimates for each pixel. Comparison of the distributions derived at the two time periods may result in a different interpretation to that derived through comparison of the single class composition estimate derived from a standard sub-pixel analysis. This is illustrated for seven pixels in Figure 9. The direct

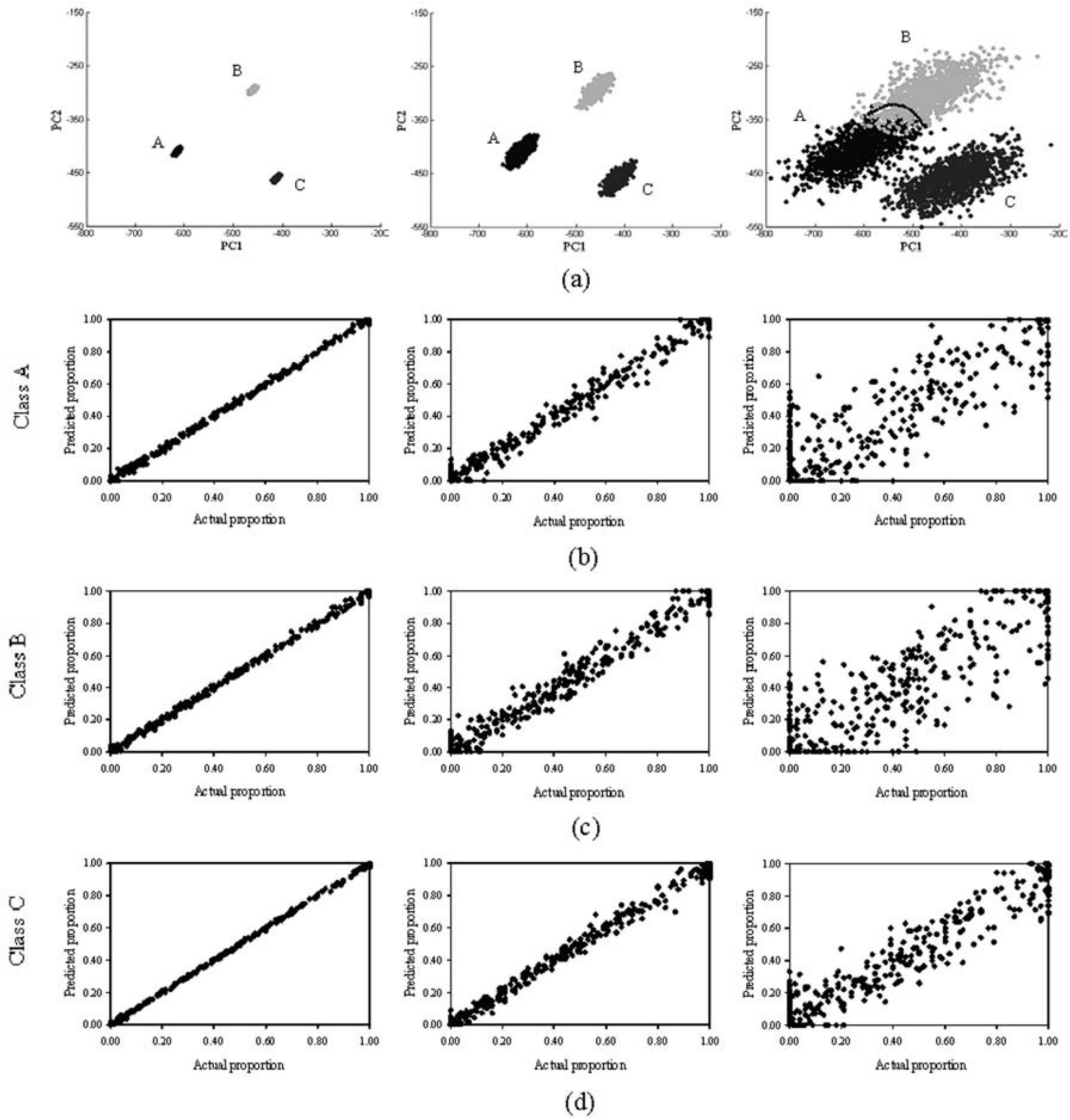

Figure 4. The impact of intra-class variability on the accuracy of unmixing. Note that the spread of the data in the scatterplots increases with the degree of intra-class variation (left to right in the diagram). The classes are defined in Table 1: (a) location of the classes in feature space, (b) relationship between predicted and actual cover for class A, (c) relationship between predicted and actual cover for class B, and (d) relationship between predicted and actual cover for class C.

Table 4. Accuracy of Predictions Depicted in Figure 4 Derived With (a) Low, (b) Medium and (c) Large Variance (Table 1)

	Class	r	RMSE
(a)	A	0.9994	0.0120
	B	0.993	0.0133
	C	0.998	0.0072
(b)	A	0.9930	0.0407
	B	0.9880	0.0533
	C	0.9963	0.0310
(c)	A	0.8723	0.1691
	B	0.8621	0.1766
	C	0.9588	0.1023

comparison of the single predictions from a standard unmixing analysis yields a single estimate of the amount of sub-pixel land-cover change (Table 5). The apparent precision of the estimated amount of change could be problematic, leading potentially to misinterpretation and error. For example, comparison of the class composition distributions derived with a Kolmogorov-Smirnov test highlights an instance in which an apparent 6.6 percent cover change was associated with distributions that did not differ significantly (Table 5). Moreover, the distributions of class composition estimates provided a richer description of the class composition that may allow the change to be viewed from different perspectives. For example, the danger in using the single prediction from a standard

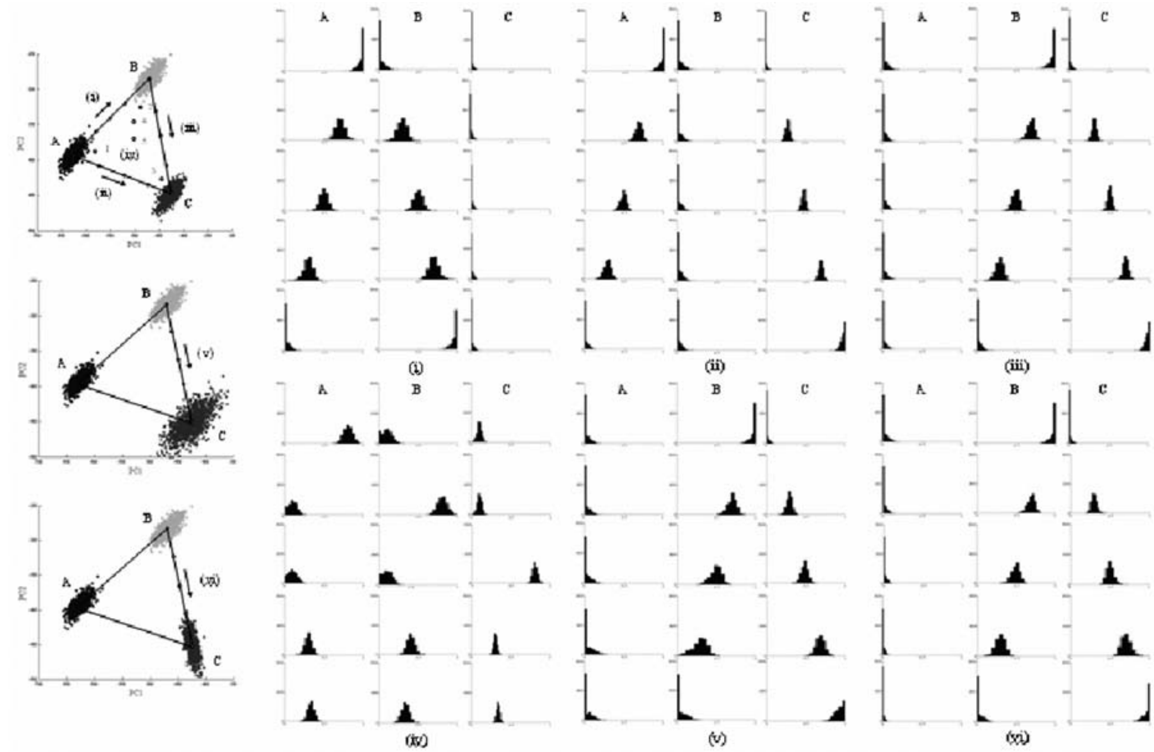

Figure 5. Class composition distributions from the mixing of the classes defined in the text. Histograms show distribution of cover for a class at various locations in feature space and particularly along transects running between the class centroids.

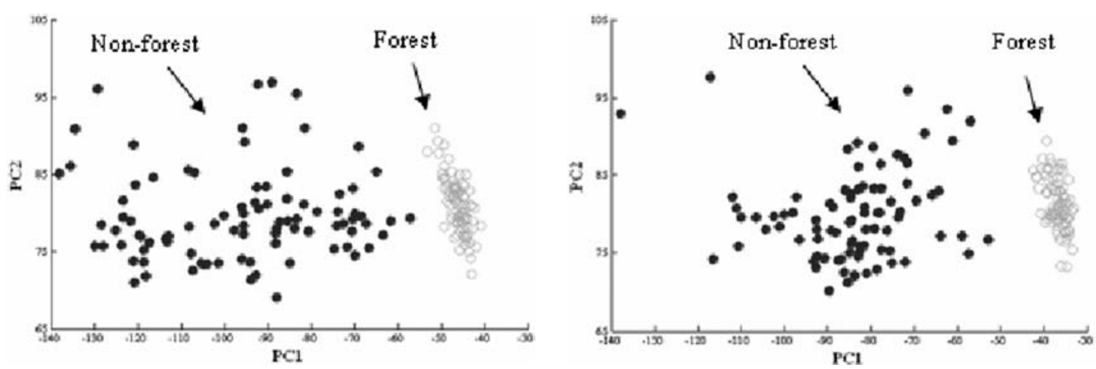

Figure 6. Location of the classes in feature space: (a) 1984, and (b) 1988.

application of the linear mixture model could be recognized and the distributions used to indicate change. This could be taken from a range of perspectives. So rather than directly compare single predictions (Figure 8c), one could, for instance, focus on the upper and lower quartiles of the distributions to derive what could be considered by some to be a relatively optimistic (or *good*) and pessimistic (or *bad*) case scenarios of change (Figure 10). This provides a useful extension and qualification to the standard use of single prediction estimates.

The inappropriateness of placing great confidence on the single class composition prediction typically generated in a soft classification for super-resolution mapping is illustrated in Figure 11. A boundary line to separate the forest from non-forest classes may be defined from a classification output. For a hard classification, this line is

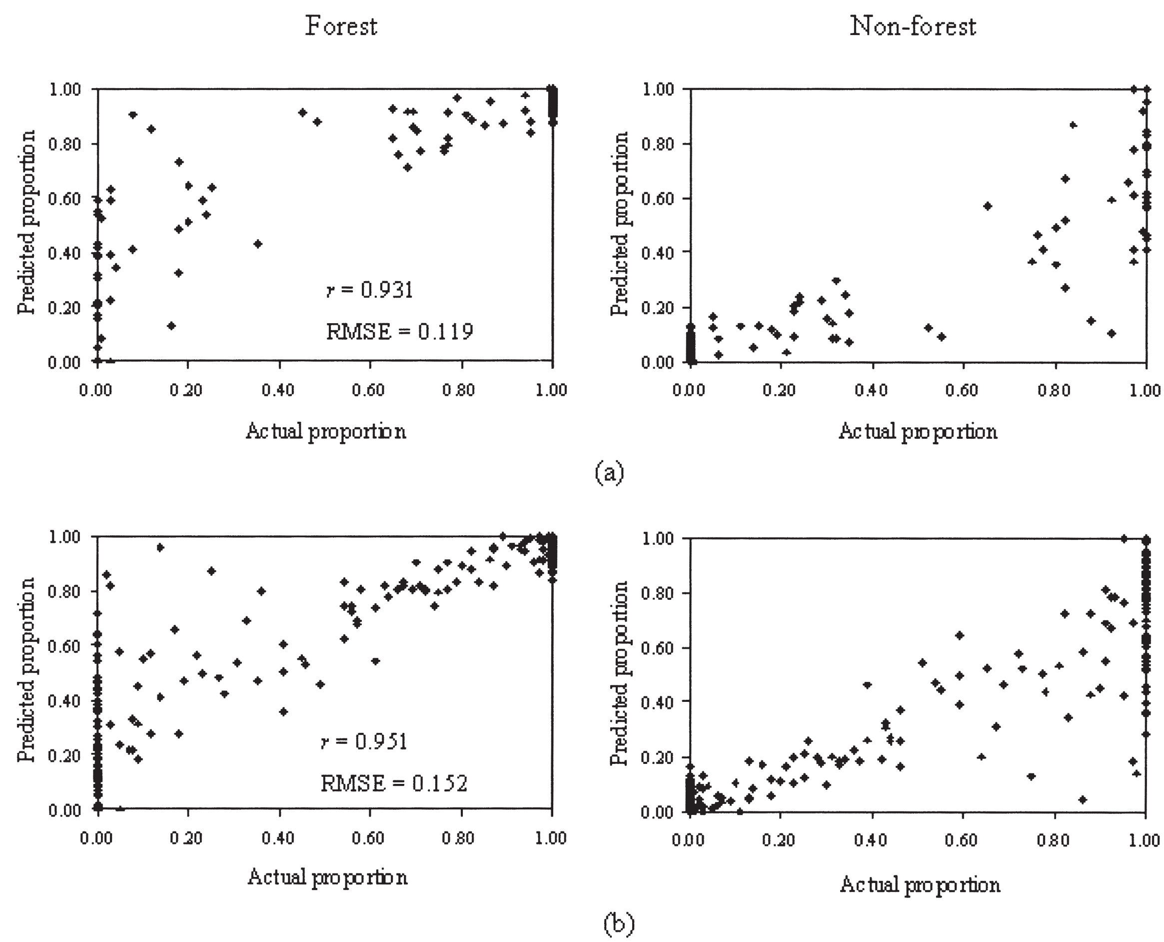

Figure 7. Relationships between predicted and actual class proportional cover: (a) 1984, and (b) 1988.

fitted between pixels allocated to the different classes, resulting in an unrealistically jagged boundary (Figure 11c). A refinement on this representation is to produce a super-resolution map based on the outputs of the soft classification. Here, a Hopfield neural network (Tatem *et al.*, 2001) was used to derive a super-resolution representation (Figure 11d). Although the super-resolution approach yielded a more accurate and appropriate representation, it quite rigidly used the sub-pixel class composition estimates derived from the conventional mixture model. In reality, since a distribution of possible class compositions may be derived for each pixel, it may be preferable to be aware of the range of possible boundary positions. To provide a guide to this, Figure 11e shows the location of the boundary determined using the 10th and 90th deciles of the class composition distributions generated. This type of information could be used to view the boundary from different perspectives (e.g., a conservative or perhaps a pessimistic viewpoint on forest cover). Critically, Figure 11e highlights that a range of possible boundary locations may be defined and that the width of the zone containing its likely location may vary along its length. As well as indicating a degree of uncertainty in boundary location this result also indicates potential problems for the derivation of estimates of class extent and change that are dependent on the defined boundary. Awareness of the distribution of class composition estimates for pixels may, therefore, allow a richer and more qualified assessment of land-cover issues at a sub-pixel scale.

Soft classification analyses have attracted considerable attention as a means of reducing the mixed pixel problem that is often encountered in remote sensing applications. The standard output of a soft classification analysis for an image pixel comprises an estimate of the sub-pixel class composition in which there is a single predicted fractional coverage for each class. The apparently precise estimated coverage for a class may be mis-leading, as a variety of class mixtures could be associated with a particular spectral response. Thus, for each pixel, it may sometimes be more appropriate to recognize that a distribution of possible coverage may be derived for each class. The width of this distribution is a function of the degree of intra-class spectral variation present and will impact on the use of the soft classification output. As illustrated in the example, the nature of the distribution may impact on change detection derived through post-classification analysis or on some super-resolution mapping applications. Although the exact nature of the results derived are a function of the classification

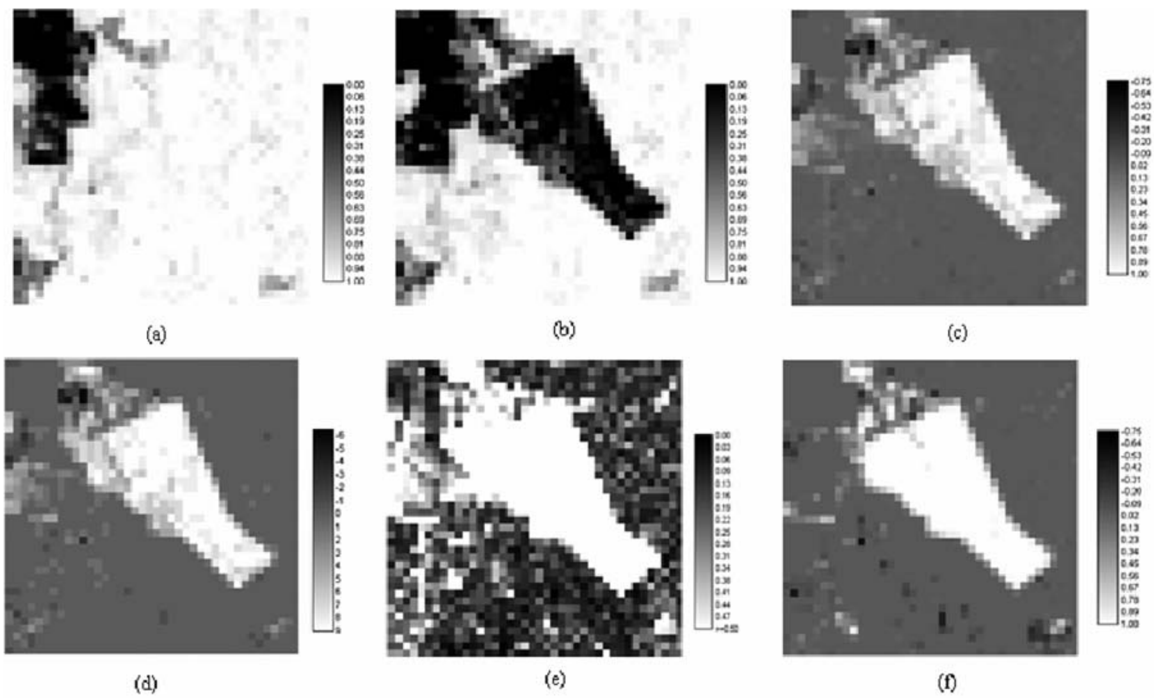

Figure 8. Sub-pixel estimates and change detection: (a) sub-pixel forest cover estimate 1984, (b) sub-pixel forest cover estimate 1988, (c) Difference (1984–1988) in forest cover estimates, (d) change assessed if sub-pixel estimates placed in classes of 0.1 (10 percent) cover width, (e) *D* value from Kolmogorov-Smirnov test, and (f) actual change (1984–1988).

TABLE 5. SUMMARY OF CHANGES BASED ON ACTUAL AND SINGLE SUB-PIXEL CLASS COMPOSITION ESTIMATES FROM A LINEAR MIXTURE MODEL USING CLASS CENTROIDS AS ENDMEMBERS FOR THE CASES ILLUSTRATED IN FIGURE 9. THE *D* VALUE WAS DERIVED FROM A KOLMOGOROV-SMIRNOV TEST, WITH A CRITICAL VALUE OF 0.211 AT 95 PERCENT LEVEL OF CONFIDENCE

	Change Estimated		
Case	Ground Data	Soft Classification	*D*
a	0.00	0.026	0.189
b	0.00	0.046	0.244
c	0.00	0.066	0.211
d	0.05	0.102	0.322
e	0.62	0.371	0.878
f	0.41	0.506	0.856
g	0.84	0.751	0.978

algorithm and endmember definitions used the results highlight a common problem in soft classification and later analyses based upon it such as super-resolution mapping.

Summary and Conclusions

In much sub-pixel scale analysis in remote sensing an assumption made implicitly is that the classes may be described by a single endmember. Following from this assumption, great trust is placed in the single class composition prediction made in spectral unmixing. However, class spectral variability means that no single spectrum can describe a class adequately. A consequence of this is that a distribution of possible class compositions exists for each pixel. It has been shown here that the accuracy of sub-pixel class composition estimation is a function of the degree and nature of intra-class spectral variation present in the data set. In addition some implications of this situation for later analyses such as change detection and super-resolution have been illustrated. It is suggested that the distribution of possible class composition predictions could be used to provide a richer interpretation of sub-pixel land-cover, change, and location.

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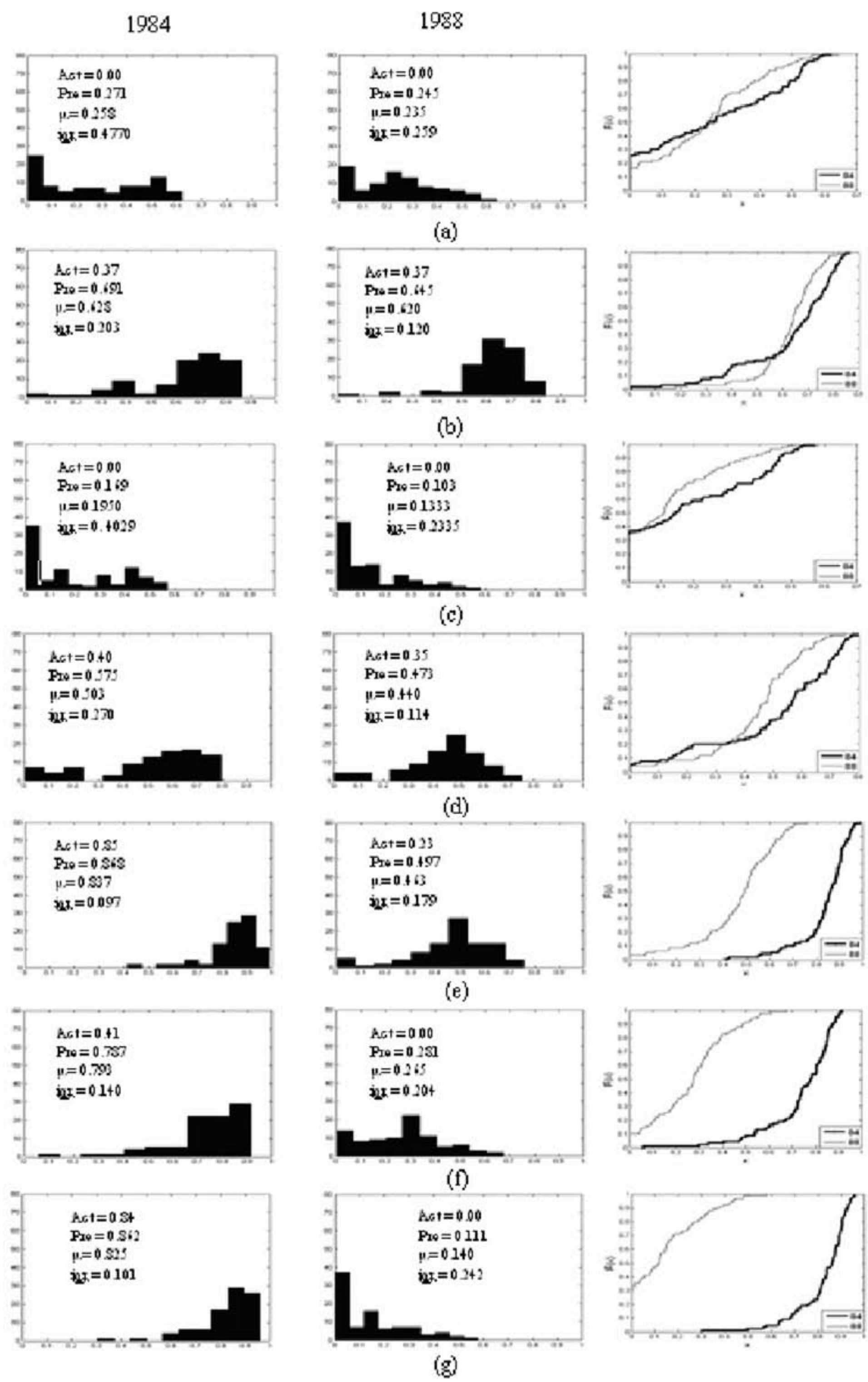

Figure 9. Sub-pixel class composition distributions for seven pixels derived from 1984 and 1988 image together with a graphical comparison of their difference in cumulative distributions. Summary statistics are given for each case in Table 5.

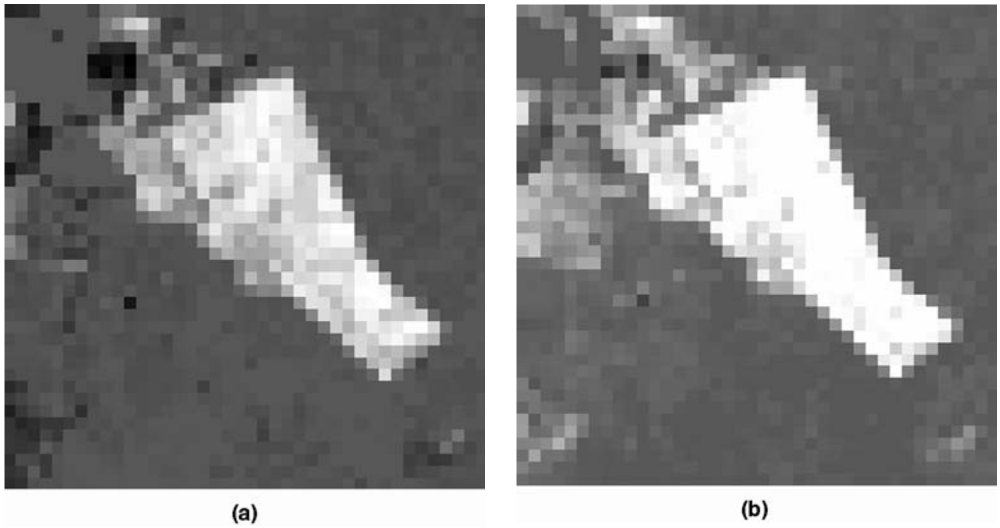

Figure 10. Different scenarios of change derived by comparison of class composition distributions. Assuming that forest clearance is viewed negatively, the images show what might be considered (a) a relatively *good* case scenario (first quartile 1984 – third quartile 1988), and (b) a relatively *bad* case scenario (third quartile 1984 – first quartile 1988).

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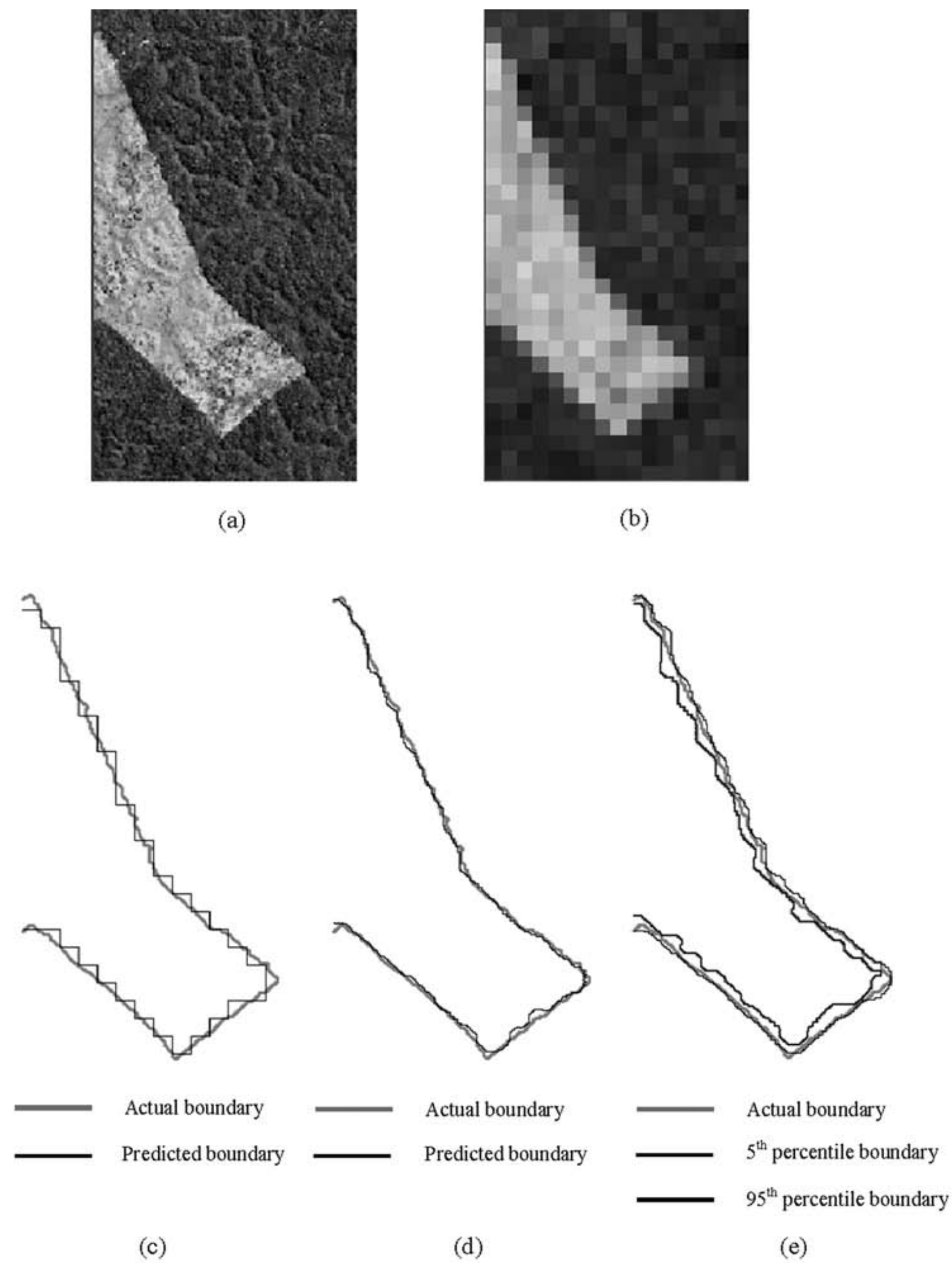

Figure 11. Impacts of intra-class variation on super-resolution mapping: (a) extract of the Landsat TM imagery used, (b) spatially degraded imagery; (c) actual boundary and boundary derived from a conventional hard classification; (d) actual boundary and boundary derived from super-resolution mapping using HNN applied to the soft classification output from the mixture model; and (e) actual boundary and the locations of boundaries defined at the 10th and 90th deciles of the class composition distributions.