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Abstract

Thematic mapping via a classification analysis is one of the most common applications of remote sensing. The accuracy of image classifications is, however, often viewed negatively. Here, it is suggested that the approach to the evaluation of image classification accuracy typically adopted in remote sensing may often be unfair, commonly being rather harsh and mis-leading. It is stressed that the widely used target accuracy of 85% can be inappropriate and that the approach to accuracy assessment adopted commonly in remote sensing is pessimistically biased. Moreover, the maps produced by other communities, which are often used unquestioningly, may have a low accuracy if evaluated from the standard perspective adopted in remote sensing. A greater awareness of the problems encountered in accuracy assessment may help ensure that perceptions of classification accuracy are realistic and reduce unfair criticism of thematic maps derived from remote sensing.

1. Introduction

Image classification is one of the most commonly undertaken analyses of remotely sensed data. In even a cursory sweep of the subject's main journals it will be apparent that classification analyses occur in a significant and often dominant proportion of papers published in many issues. Despite the importance of classification analysis within the subject, the evaluation of classifications is, however, a problematic issue.

The main reason for undertaking an image classification is, in effect, to convert the image's information on the spectral response of the Earth's surface into a thematic map depicting classes of interest such as land cover. Given the importance of classification analysis to the subject area, it is not surprising that considerable research has focused on a wide range of issues of relevance to its various components. This research has, for example, addressed the potential of various classification algorithms and the influence of image properties such as the spatial and spectral resolution as well as of various pre- and post-classification manipulations on aspects of the analysis. Throughout this research, a major focus has typically been on the accuracy of the classification.

Classification accuracy has been a focus of attention for a considerable period of time and is a topic that has developed considerably in recent years (Congalton, 1991, 1994; Congalton and Green, 1999; Pontius, 2000, 2002; Foody, 2002; Pontius and Cheuk, 2006). Classification accuracy is the main measure of the quality of thematic maps produced and required by users, typically to help evaluate the fitness of a map for a particular purpose. The accuracy of image classifications has also been central to studies that have sought to evaluate different classification approaches and a suite of issues connected with class discrimination. Although seemingly a simple concept, classification accuracy is a very difficult variable to assess and is associated with many problems (Foody, 2002).

The accuracy of image classifications is often perceived as being inadequate for many users (Townshend, 1992; Wilkinson, 1996; Gallego, 2004). Considerable research has, therefore, sought to increase the accuracy of thematic mapping through image classification analyses. However, from a survey of papers published over the 15 year period 1989-2003, Wilkinson (2005) notes no upward trend in accuracy arising from this effort. Indeed, Wilkinson (2005) reports no observable trend in classification accuracy over time with a mean accuracy, expressed as a kappa coefficient of agreement, of ~0.66. It is, therefore, unsurprising that the accuracy of thematic maps derived from remote sensing is often questioned. Sometimes, however, this questioning arises from situations in which a map is used for applications other than those for which it was designed. For example, this problem may occur when a map developed for specific small cartographic scale applications is used at much larger scales than it was intended for (Brown *et al*., 1999). There is also considerable anecdotal evidence of users questioning the accuracy of maps, often on the basis of very localized assessments (e.g. arguments like ‘that pixel is misclassified’). These and other criticisms of thematic maps derived from remote sensing may sometimes be unfair. Here, it is suggested that the assessment and interpretation of classification accuracy in remote sensing may often be made from an overly harsh perspective. This view is discussed with reference to key widely accepted issues in accuracy assessment such as the targets used as well as in relation to the assessment of the accuracy of maps produced by other mapping communities.

2. Accuracy target

The evaluation of the quality of a thematic map derived by an image classification should ideally be based on a set of criteria defined in advance of its production. As concern is typically focused on the accuracy of the classification, commonly its overall accuracy, the definition of a minimum level of accuracy required provides a simple criterion on which to base the evaluation of classification quality. Thus, classifications are often evaluated in relation to the magnitude of their estimated accuracy. A target accuracy value should be stated prior to undertaking the classification, not least because this reduces the potential for very subjective post-classification evaluations undertaken on a poorly justified *ad hoc* basis. Although a target accuracy is often not stated explicitly, one value that has been widely used as a target in thematic mapping via an image classification is to achieve an accuracy of ≥85% correct allocation (e.g. McCormick, 1999; Scepan, 1999; Wulder *et al*., 2006); it is very rare to see any other target value specified in the literature. Sometimes this 85% target is qualified further to indicate that the component classes of the classification should be classified to comparable levels of accuracy. However, it is against this 85% target that the acceptability of thematic maps derived from remote sensing is commonly assessed. Indeed, the 85% target is often viewed explicitly by some as the standard of acceptability for thematic mapping from remotely sensed imagery (e.g. Wright and Morrice, 1997; Abeyta and Franklin, 1998; Brown *et al*., 2000; Treitz and Rogan, 2004).

The 85% target accuracy often seems to be used without question of its suitability and simply because there is some historical tradition associated with it. This target is sometimes stated without apparent need for justification or provision of supporting evidence from the literature, it is essentially seen by many as a universal standard for thematic mapping in remote sensing (e.g. Fisher and Langford, 1996; Weng, 2002; Rogan *et al*., 2003; Bektas and Goksel, 2004). It is not surprising, therefore, that the 85% target has been used in studies spanning a vast range of applications including the mapping of broad land cover classes at a global scale from 1 km spatial resolution NOAA AVHRR imagery (Scepan, 1999), mapping of very detailed classes such as those depicting variations in forest species cover at a very local or large cartographic scale such as ~1:5,000 from aerial photography (McCormick, 1999) and assessments of change detection with 30 m spatial resolution Landsat TM imagery (Sader *et al*., 2001). The studies reported in these three examples differ greatly in terms of the nature of the classes, the scale of the study and the characteristics of the remotely sensed data used, yet all adopted the same 85% accuracy target.

In many cases the origin of this 85% target accuracy can be traced back to the influential work of Anderson *et al*. (1976). Indeed this work is often cited explicitly in relation to the specification of the target accuracy in many projects (e.g. Fisher and Langford, 1996; Kaminsky *et al*., 1997; Rogers *et al*., 1997; Wright and Morrice, 1997; Brown *et al*., 2000; Franklin *et al*., 2001; Lewis and Brown, 2001; Carranza and Hale, 2002; Yang and Lo, 2002; Weng, 2002; Rogan *et al*., 2003; Shao *et al*., 2003; Kerr and Cihlar, 2004; Treitz and Rogan, 2004; Mundia and Aniya, 2005; Yang and Liu, 2005). However, Anderson *et al.* (1976) do not discuss the matter in great detail or set out to propose a universally adoptable set of map evaluation criteria. For example, in the 28 pages of the article there is little discussion of the map accuracy criteria as the main focus was on the classification system. Indeed, within the article there are actually only two references to the magical 85% figure in the report (both p5), with the reader directed to an earlier publication by Anderson (1971) for further information. Anderson (1971) also only briefly discusses the map evaluation criteria. The main focus of both the Anderson (1971) and Anderson *et al.* (1976) articles was on the classification schemes that could be used with remotely sensed data and not on the evaluation of the accuracy of the derived classifications, although that was clearly an important issue. Both of the articles were explicitly tentative in their proposals, aware that the sensing technology was rapidly developing (the articles were written around the time of the launch of the first Earth resources satellite system, Landsat 1) and that it is unlikely that there is one ideal approach to promote. Furthermore, both Anderson (1971) and Anderson *et al*. (1976) were explicit in relation to the nature of the thematic map under study and have a reason for the 85% figure, which is specified for a particular application scenario. That scenario was the mapping of broad land cover classes, such as those at Anderson level I (e.g. urban, agriculture, forest, water *etc*.), at small cartographic scales in the range of 1:250,000 to 1:2,500,000. Moreover, the suggestion made was that

> “The minimum level of interpretation accuracy in the identification of land use and land cover categories from remote sensor data should be at least 85%” and that the “accuracy interpretation for the several classes be about equal” (Anderson *et al*., 1976; p5).

Thus, at the possible risk of misinterpreting the intended meaning, the focus was also not on overall classification accuracy but on what would be referred to today as a producer’s accuracy.

This is not the emphasis used in some studies that quote the 85% target accuracy. Additionally, the basis of the 85% target was because this would be comparable to the accuracy of land cover maps derived from aerial photograph interpretation undertaken previously in work associated with the USDA's Census of Agriculture. That is, an aim was to emulate the accuracy that could be achieved for a specific task through the application of conventional approaches such as aerial photograph interpretation. Additionally, it must be recognised that the minimum mapping unit for mapping at the specified small cartographic scales is several hundred pixels in size. If, for example, it is assumed that the smallest unit to be depicted on a thematic map is 2.5 x 2.5 mm in size, the minimum area mapped at a scale of 1:500,000, which is appropriate for mapping at Anderson level I, is 150 ha (Lillesand and Kiefer, 2000). Thus, in mapping from 80 m spatial resolution Landsat MSS imagery, the type of data considered by Anderson *et al*. (1976), the smallest mapped area would comprise at least 234 pixels. Although the component pixels of the unit mapped might differ in terms of class of allocation the unit would be given a single label (e.g. dominant class). This is entirely sensible as the map is a generalization of reality but also highlights the inappropriateness of some pixel based evaluations of image classifications derived from remote sensing.

The map evaluation criteria put forward by Anderson *et al.* (1976) were not proposed as being universally applicable. In the context of satellite remote sensing, the 85% target accuracy was, essentially, specified by Anderson *et al*. (1976) for mapping broad land cover classes (Anderson level I, 9 broad classes) from Landsat 1 sensor data (e.g. MSS with 80 m spatial resolution in 4 spectral wavebands). The criteria proposed were not, for example, suggested for detailed class mapping of local regions from imagery of the type available from contemporary satellite sensing systems. It is also questionable whether the 85% target is appropriate for other small scale mapping applications. For example, the 85% target was used in relation to the IGBP DISCover global land cover map (Scepan, 1999) yet this map contains 17 classes and was derived mainly from NOAA AVHRR data with a 1 km spatial resolution (Loveland *et al*., 1999). Direct comparison between the IGBP DISCover mapping programme and that envisaged by Anderson *et al*. (1976) is difficult (e.g. the generation of the IGBP DISCover map used multi-temporal data and some ancillary information). However, it is evident that the Anderson *et al.* (1976) proposal was made in relation to mapping a small number of classes from, what may be considered in this context to be, fine spatial resolution multispectral data with a relatively large minimum mapping unit which is very different to the scenario used in the production of the IGBP DISCover map, the assessment of which was also based on pixel level evaluations (Scepan, 1999). Although generalization is difficult, particularly because of inter-linkages between spatial and categorical scale (Ju *et al*., 2005) as well as a high degree of context dependency, classification accuracy commonly, but by no means always, declines with an increase in the number of classes (e.g. Foody and Embashi, 1995; Joria and Jorgenson, 1996) and/or a coarsening of the spatial resolution of the data (e.g. Irons *et al*., 1985). An increase in the detail of the classes is, therefore, generally associated with a reduction in classification accuracy (e.g Stehman *et al*., 2003). Note, for example, Vogelmann *et al.* (2001) report a 21% decrease in the accuracy for part of the US National Land Cover Data set when moving from the very general Anderson level I to the more detailed Anderson level II. It, therefore, seems reasonable to expect that achieving the 85% target would be more of a challenge for the IGBP DISCover map than the scenario presented by Anderson *et al*. (1976), from which the target value stems. Indeed, in direct comparative studies of mapping at

Anderson level I, Landsat MSS data have been used to derive more accurate classifications than NOAA AVHRR data, especially if the landscape mosaic is heterogeneous (Gervin *et al*., 1983). In many contemporary mapping applications, the challenge encountered may also be more difficult than that presented by Anderson *et al*. (1976), commonly a result of trying to map a large number of relatively detailed classes and often at a relatively local, large cartographic, scale. Consequently, in such applications the use of the 85% target suggested by Anderson *et al*. (1976) may be inappropriate as it may be unrealistically high for the application. Moreover, as mapping scenarios vary enormously in terms of key variables (e.g. scale and legend detail) and the difficulty of mapping is an interactive function of the classes (e.g. their number, detail, spatial arrangement *etc.*) and the remote sensor data used (e.g. spatial resolution, time of acquisition *etc*.), there probably is no single accuracy value that could be adopted universally as a target. Critically, the widely used target of 85% should not automatically be used as a criterion for the evaluation image classifications (Laba *et al*., 2002). It may be that 85% is often a perfectly reasonable target to adopt but it should not simply be accepted for use without question as for many mapping applications it may be unrealistically high.

It should be clear, therefore, that the main application scenario of Anderson *et al*. (1976), from which the widely used 85% target accuracy appears to have arisen, is very different to many image classification analyses that have adopted the 85% target. Many studies seek to map detailed classes at a large cartographic scale (Wilkinson, 2005). Such classes and scales were *explicitly* outside the scope of discussion of Anderson *et al*. (1976) who suggested that substantial amounts of ancillary information would be required for this type of mapping scenario. Yet much of the remote sensing community appears to have latched on to the 85% target accuracy as some general criterion to apply, irrespective of the specific nature of the analysis in-hand. Additionally, the community of map users seems to have followed suit and appear to have adopted the 85% target too. It is unclear why the 85% target has been used so widely, especially as it may not be realistic. If, for example, the aim is to map a small number of very spectrally separable classes then the target should perhaps be set at a higher value. Alternatively, and perhaps more commonly, if there are many classes that are only subtly different it seems reasonable to ask if the target accuracy is too high and unachievable. To be of value, a target should really be specified for the particular application in-hand and be realistic.

Instead of seeking a single universally applicable target value, it would often seem to be more appropriate to set a target for the specific application in-hand; for general purpose maps, producer's can provide accuracy information to enable user's to determine the data set's suitability for their specific needs. The target value to adopt may be expected to vary as a function of variables such as the nature of the remotely sensed data set used (e.g. spatial and spectral resolution), the classes defined (e.g. number and detail of classes) and user needs (e.g. tolerance to error and impacts of variation in error severity). There are, therefore, no universally defined accuracy standards for thematic mapping from remote sensing (e.g. Loveland *et al*., 1999; Kerr and Cihlar, 2004). However, since accuracy relates fundamentally to the fitness for purpose, it should be possible to define the level of accuracy required for the application in-hand. This accuracy value represents the minimum required for the application, it may be less than the accuracy level wanted by users but is sufficient to meet their needs. The required degree of accuracy may also be relatively low. For example, in testing scientific hypotheses about tree species diversity and co-existence, Atkinson *et al.* (2007) required maps showing the spatial distribution of ash and sycamore trees in a mixed woodland. Although tree species may be considered to form very specific classes, more detailed than those at Anderson levels I and II, trees can sometimes be identified to species level with a high accuracy from remotely sensed data. However, a high accuracy may not actually be required. Indeed, for the seemingly complex application of mapping detailed classes, each representing an individual tree species, such that the degree of species aggregation in space can be determined required an image classification in which omission errors of 50% and commission errors of 5% for the species of interest could be tolerated (Atkinson *et al*., 2007). In such circumstances, especially as there was a large number of other species in the woodland, the overall accuracy of an image classification that provided the necessary information could be very low, perhaps in the order of ~10%. Clearly one would normally want and should strive for a higher accuracy but a classification of apparently low accuracy can still yield the information required for the application in-hand.

One issue on which the remote sensing community could, however, adopt a harsher approach is in deciding whether a thematic map produced by an image classification satisfies the target specified. Commonly, the basis of assessing the acceptability of a map is to calculate a measure of the map's accuracy and compare the derived value directly against the target value (e.g. Hayes and Sader, 2001). The map is typically judged to be sufficiently accurate if the calculated accuracy value equals or exceeds the target. However, the accuracy statement derived in most studies is just an estimate of the accuracy of the classification. In many instances it would be more appropriate to fit confidence limits to the estimate and consider these when evaluating the map and deciding if the target accuracy has been achieved.

Although the estimation of confidence limits is relatively simple and the literature encourages the community to use them (Thomas and Allcock, 1984; Morisette and Khorram, 1998; Mas, 2004) they are rarely defined and provided. In many applications, the accuracy statement for an image classification should, however, really take the form of the estimated value ± the half width of the confidence interval at some specified level of statistical confidence. Assuming that the analysis is based on a sufficiently large sample of data acquired by simple random sampling and that the data are normally distributed, the half width of the confidence interval may be derived from $t\sqrt{\frac{p(1-p)}{n-1}}$ where p is the proportion of correctly allocated cases, n the number of cases used to assess classification accuracy and the value of t is derived from the t-distribution at the desired level of confidence (for large sample sizes the value of t approaches that for the appropriate z-score).

The fitting of confidence limits around the estimate of classification accuracy may have a marked impact on the evaluation of a classification. Sometimes the estimated accuracy of a classification may exceed the 85% target value but the confidence limits may suggest that it would be unwise to assume that this means the classification has achieved the target level desired. However, a classification with an estimated accuracy that barely exceeds the target value specified is often viewed as being of acceptable quality (e.g. Hayes and Sader, 2001). For example, and so as to not appear critical of others, Foody *et al*. (2004) accept a thematic map derived from a classification as being satisfactory as its estimated accuracy, 89.5%, exceeded the commonly stated target of 85%. Fitting, the albeit wide, confidence limits at the 98% level to the accuracy estimate, it may be stated that with 0.98 probability that the map's accuracy lies within the range 84.7 - 94.2%. The lower limit of this confidence interval lies below the 85% target and so, at this level of assessment, the map might not be viewed as being sufficiently accurate. At the more widely used 95% level of confidence, the map just passes the threshold as its accuracy may be expressed as 89.5 ± 4.00%, with the lower limit on the confidence interval just over the target accuracy at 85.5%. Note, however, that with just 1 more misclassification in the testing set used to estimate accuracy the resulting classification would have had an accuracy of 89.0 ± 4.08% at the 95% level of confidence, failing to achieve the target as the lower confidence limit again lies below 85%. The casual comparison of the accuracy estimate directly against the target may, therefore, give an inappropriate basis for evaluating a classification. The confidence limits fitted around the estimated value provide important information that should influence the evaluation of the accuracy of the classification and its suitability for later application. The confidence limits are also useful in the comparison of classification accuracy statements. In such applications it is, however, also necessary to recognise the nature of the testing set used in the estimation of accuracy, particularly if the same testing set is used in the evaluation of different classifications (Foody, 2004). Critically, however, the remote sensing community should be encouraged to fit confidence limits to classification accuracy statements and promote their use in evaluating the classification's fitness for its intended application.

3. Accuracy assessment methods

The most widely used approaches for image classification accuracy assessment are site-specific methods based on the analysis of the entries in a confusion or error matrix (Congalton and Green, 1999; Foody, 2002). In principal, this matrix provides a simple summary of classification accuracy and highlights the two types of thematic error that may occur, omission and commission. This not only summarises the accuracy of the classification but may also convey useful information to enhance analyses based on the classification (e.g. Prisley and Smith, 1987; Fang *et al*., 2006). In reality, however, the use of the confusion matrix and interpretation of the accuracy measures derived from it can be distinctly non-trivial activities. For example, the meaning of basic summary measures of accuracy such as the proportion of correctly allocated cases, the most widely used index of classification accuracy, is a function of the sample design used in acquiring the testing set (Stehman, 1995). Thus, the estimates of classification accuracy derived from confusion matrices constructed from testing sets drawn by simple random and stratified random sampling from the same map, without any allowance for the difference in the sample design, may differ substantially if the classes vary in abundance and spectral separability. Additionally, the use of the confusion matrix is based implicitly on the assumption that the pixels are pure and the ground data set is perfectly co-located with the image classification. Both of these assumptions are rarely satisfied. The proportion of mixed pixels in an image is a function of the spatial resolution of the imagery and the land cover mosaic but is often very large. These pixels cannot be accommodated directly in the basic confusion matrix resulting in error. Similarly, much error depicted in a confusion matrix is associated with mis-location of data points in the thematic map and in the ground or reference data. Moreover, there is also a tendency to treat the ground data set as being error-free. The ground data may, however, contain significant uncertainty and error (Joria and Jorgenson, 1996; Khorram, 1999; Mas, 2004) and the direct comparability of the data sets may be limited by the use of different ontologies such that the two data sets may appear to have the same set of classes but their meaning may differ (Comber *et al*., 2005). There are other major sources of error to be considered. For example, geometric pre-processing operations can introduce very large errors in the representation of classes and this can greatly impact on studies such as change detection (Rocchini *et al*., 2004). Despite the various problems with the confusion matrix, *all* of the disagreements between class labels in the thematic map derived from remotely sensed data and the ground data are typically interpreted, unfairly, as errors in the classification used to produce the thematic map (Fitzgerald and Lees, 1994; Foody, 2002). This perspective provides a pessimistically biased starting point for the quantification of classification accuracy.

A key concern in the evaluation of a classification is that the confusion matrix, which is fundamental to contemporary accuracy assessment (Congalton, 1994; Congalton and Green, 1999), is associated with considerable uncertainty and error, including non-thematic error. The problems associated with the use of the confusion matrix are often ignored in accuracy assessment yet will generally act to reduce the magnitude of the estimate of classification accuracy. Thus, not only may the target accuracy be unrealistically high, the approach to assess accuracy may act to give an unfairly negative view of the quality of the thematic map. However, this site-specific and typically pixel-based approach to accuracy assessment is commonly used, even if the various sources of error and uncertainty such as those arising from mis-registration are recognised (e.g. Zhu *et al*., 2000). The standard approach to accuracy assessment, may, however, be adjusted to help reduce some of the problems. For example, rather than rigidly adopt the site-specific comparison the accuracy assessment could perhaps be based on the modal class in, say, a 3x3 pixel window (Vogelmann *et al*., 2001; Stehman *et al*., 2003) or use made of modified accuracy measures that attempt to provide a degree of tolerance for mis-location (Hagen, 2003). It is important, however, to avoid the potential to optimistically bias the accuracy assessment. Similarly, it is important to be aware that some promoted manipulations of the confusion matrix, such as normalization, can be undesirable (Foody, 2002; Stehman, 2004). Normalizing the matix has the effect of equalizing what may actually be very different user's and producer's accuracies and the normalized matrix needs to be used and interpreted with care.

The problems in constructing a meaningful confusion matrix, sometimes the one of the hardest parts of accuracy assessment (Smits *et al*., 1999), and interpreting its contents are often compounded by the use of inappropriate measures to quantify classification accuracy. There are, for example, many calls for the remote sensing community to adopt measures such as the kappa coefficient of agreement in the assessment of classification accuracy (Congalton *et al*., 1983; Congalton and Green, 1999; Smits *et al*., 1999; Wilkinson, 2005). The arguments made for the adoption of the kappa coefficient are typically based on statements such as its calculation corrects for chance agreement and utilizes the entire confusion matrix as well as that a variance term can be calculated for it which facilitates statistical comparisons and because scales exist to aid interpretation (e.g. Congalton *et al*., 1983; Monserud and Leemans, 1992; Janssen and van der Wel, 1994; Smits *et al*., 1999; Wheeler and Alan, 2002). The use of the kappa coefficient for accuracy assessment has, however, often been questioned (Stehman, 1997; Turk, 2002; Jung, 2003). Indeed, each of the commonly argued reasons for using the kappa coefficient as a measure of classification accuracy can be readily criticised. Some of the arguments made for the adoption of the kappa coefficient are incorrect. For example, the kappa coefficient is not calculated from the entire matrix but on the basis of its main diagonal and marginals (Stehman, 1997; Nishii and Tanaka, 1999). Some of the arguments for the adoption of the kappa coefficient fail to recognise that they apply equally to other measures of accuracy. For example, a variance term can be derived for many other measures of accuracy that are widely used, including standard statements based on the percentage of correctly allocated cases, and be used in evaluating the statistical significance of differences in classification accuracy (Foody, 2004). In addition, widely used scales to interpret the kappa coefficient are problematic and arbitrary (Manel *et al*., 2001; Di Eugenio and Glass, 2004). Most critically of all, the allowance for chance agreement, probably the most widely cited reason for the adoption of the kappa coefficient as a measure of classification accuracy, has been criticised in several ways. In particular, it is evident that the degree of chance agreement may be overestimated, leading to an underestimation of classification accuracy (Foody, 1992), and, more fundamentally, that chance correction is completely unnecessary (Turk, 2002). The fact that some of the class allocations in the classification are correct by chance and not by design is a lucky break or windfall gain, it is not necessarily something the users or producers of thematic maps should worry about. Essentially, if the aim is to state the accuracy of a thematic map derived from an image classification then the source of error is unimportant. What is required in such circumstances is an index of map accuracy and not of the map producing technology. One such index that may commonly be appropriate is the percentage of correctly allocated cases. If, however, the aim is to indicate the ability of the classifier to correctly identify the classes then a more appropriate approach for that application might be to calculate a measure of diagnostic ability (e.g. Turk, 1979) rather than classification accuracy.

Despite its limitations, the use of the kappa coefficient and related approaches over the last ~20 years has encouraged an increasingly rigorous and quantitative evaluation of classification accuracy which should be regarded as a useful, if somewhat incorrect, step in the direction towards an appropriate evaluation method. The key concern here, however, is that the use of measures such as the kappa coefficient may have the effect of suggesting on naïve inspection that classification accuracy is lower than it really is. In particular, the removal of chance agreement compounds the common problem of adopting a pessimistically biased perspective in accuracy assessment by adding a pessimistic bias to the quantification of accuracy.

4. Comparison with other mapping communities

While the remote sensing community is gradually moving toward a position in which an accuracy assessment is seen as an essential component of a mapping exercise (Cihlar, 2000; Strahler *et al*., 2006) this is not always the situation with other mapping communities. The remote sensing community may be being rather harsh on itself by setting high standards and using techniques that commonly act to reduce the apparent accuracy of a classification while the producers of other maps use very different approaches and criteria. Typically other mapping bodies, while concerned about map quality, provide little or no information on map accuracy or have relatively loosely defined and tolerant criteria of acceptability. This is not a criticism of these communities or their maps as there is often good reason for the situation. It is apparent, however, that the remote sensing community may be harsher in the evaluation of its products than other mapping communities are of theirs. The user community also appear harsher in their assessments of thematic maps produced by remote sensing than other widely used maps. To illustrate this variation in the harshness of evaluations, the approaches adopted by parts of three other communities, those concerned with geological, soil and topographic mapping, will be briefly discussed.

4.1 Geological maps

The British Geological Survey claims that its maps are amongst the most accurate geological maps in the world (Smith, 2004). This may well be true but the maps are not accompanied by accuracy statements of the type commonly provided with thematic maps derived from remote sensing. Indeed the accuracy information provided generally available relate predominantly to the spatial and cartographic components of the map rather than the thematic, geological, information contained. There may, however, be an increase in attention to the accuracy of the geological information content in the future.

A geological map is simply an interpretation of the geology, a difficult and subjective task as much of the geology is, of course, concealed. Critically, however, the accuracy statement generally provided with geological map data explicitly does not address the quality of the geological linework or data in general as much of this is a matter of interpretation. As all geological units are either represented by a line or contained within a set of lines, the linework of the map is of fundamental importance yet its meaning is very uncertain. Plotted boundaries are recognised explicitly as being no more than approximations which indicate roughly where an actual boundary may occur. Moreover, the linework does not distinguish between the different types of boundary that may occur and the vast majority of the boundaries plotted are inferred with many being little more than best guesses. The geological community is no doubt aware of the general nature of the maps, including their limitations, and appears to simply factor this information into its work when using them. Such maps are, however, clearly likely to contain error when viewed from the overly harsh site-specific approach to accuracy assessment used in remote sensing. Given that the boundaries depicted on a geological map are clearly a simplified generalisation, rigidly accepting them and using testing sites in their vicinity in an assessment of accuracy is likely to be a major source of error. Indeed misclassification in boundary regions has commonly been noted as a major source of error in thematic maps derived from classifications of remotely sensed data. For example, the accuracy of a land cover map of Great Britain increased by ~25% to ~71% when boundary regions were excluded from the evaluation (Fuller *et al*., 1994).

4.2 Soil maps

As with geological mapping, there has been a long history of mapping soils and there is considerable dependence on interpretation. Generally, soil maps show the spatial distribution of soil type classes over a region. These classes are often rather uncertainly defined. For example, in the UK a soil map may show the dominant soil series (Curtis *et al*., 1976). Thus, a mapped polygon might be dominated by one class but some of its area may comprise a number of other soil classes. Moreover, the amount of inclusion is not always evident. Some polygons may contain substantial mixtures of soil types and simply be represented in the map as mixtures. More precise mapping is avoided as probably unnecessary and impractical and many boundaries are located on the basis of surveyor's judgements. In the USDA's soil maps, up to 25% (occasionally >50%) of a mapped polygon may actually be of a type other than that labelled (Soil Survey Division Staff, 1993). Clearly a large proportion of the total mapped area may, therefore, be mis-labeled. Thus, as a simplistic example, a soil map deemed to be completely accurate (100% correct) in which every mapped unit had a 25% inclusion rate would have an accuracy of 75% if evaluated from the perspective adopted in remote sensing. Additionally, a further concern is that the degree of correspondence between the soil map description and field observation may be variable and this has important implications to using the soil data for modelling in a GIS (Drohan *et al*., 2003). As with geological maps, relatively little information on thematic accuracy is provided and there is considerable potential for error when viewed from the harsh site-specific perspective adopted in remote sensing. The evaluation of soil map accuracy is, however, seen as a research topic and, as recognised in other mapping communities (Maling, 1989), one that could benefit from reference to accuracy assessment methods used in remote sensing (McBratney *et al*., 2003).

4.3 Topographic maps

Topographic maps are perhaps the most widely used form of mapped information and the main alternative form of map to thematic maps. The quality of such maps is typically evaluated in terms of a range of variables such as positional accuracy, completeness and attribute accuracy (Maling, 1989; Thapa and Bossler, 1992). A major concern with topographic mapping is typically to correctly represent the relief and key physical features of the landscape. Accuracy statements, therefore, typically focus on the vertical and horizontal errors present in the data set. In common practice, a map would be considered accurate if it satisfied a conventional set of map accuracy standards. For example, in relation to positional accuracy, topographic maps are normally considered accurate if the horizontal and vertical errors contained are below some specified threshold levels. Although positional and thematic accuracy are different variables they are the fundamental properties of topographic and thematic maps respectively. The differences between these two types of accuracy make direct comparison of the approaches to evaluate accuracy difficult. However, in relation to the evaluation of the accuracy of a map, it seems likely that the assessment of a topographic map is less harsh than that applied to thematic maps derived from remote sensing. This may be illustrated with an example in which errors in a topographic data set were treated as if thematic errors in a thematic map derived from a classification analysis.

4.3.1 Topographic map accuracy

A simple experiment may be used to provide a rough guide to the accuracy of topographic maps when assessed from the standard accuracy assessment perspective used in remote sensing. A key issue in topographic mapping is the accurate representation of height. Here, the accuracy of height information in a topographic data set that satisfied conventional topographic mapping standards was assessed using the site-specific accuracy assessment approach widely adopted in remote sensing.

A small extract of a digital elevation model (DEM) for a region of hilly terrain in north Wales, UK, was acquired. The DEM provided information on location (X and Y) and terrain height (Z) for the region with a spatial resolution of 25 m. Within this region, the range in terrain height was 282 m. To help allow the effect of horizontal error to be assessed, this DEM was used to generate a finer spatial resolution surface of the region. For this, the raster DEM data was converted to vector (point) format and a new DEM with a spatial resolution of 1 m derived via a basic interpolation algorithm. This provided a fine spatial resolution terrain surface for the region that was assumed here to be the actual (error-free) terrain surface (Figure 1a).

A further surface that could be taken to be the mapped or modelled representation of the actual situation was produced (Figure 1b). This was designed to satisfy the standard type of horizontal and vertical tolerances allowed in topographic mapping (Maling, 1989). Here, a widely used US standard for mapping at 1:24,000 scale was adopted. As the mapped representation was designed to satisfy the map standard it would be considered an accurate representation of the actual surface.

The mapped surface was derived by adding distortions to the actual surface. With the widely used US map accuracy standards for 1:24,000 scale mapping, a horizontal accuracy such that a sample of 90% of points lie within 40 feet (~12.2 m) of their actual location and a vertical accuracy such that 90% of points lie within a half-width of the contour interval is required for the map to be considered accurate (Maling, 1989). Using the vector file derived from the actual surface, horizontal errors that satisfied the horizontal map standards were introduced into the data set. This was achieved by adding random values with a uniform distribution within the range -7 to +7m to X and to Y for 90% of the points in the actual surface data set. The remaining data were divided into two equally sized data sets and given larger errors. For these data sets, random values with a uniform distribution between -8 to -14 m and 8 to 14 m were added to the data respectively. After the addition of these distortions to the X and Y coordinates of the data set their effect on the horizontal accuracy was assessed. This revealed that 90% of the points lay within 11.7 m of their actual location, satisfying the requirement for an accurate map.

A similar approach was taken to distort the actual height (Z) data. Assuming that the mapped data would have a 10 m contour interval, typical of many maps, distortions were added to the actual Z values. Specifically, for 90% of the points selected at random from the data set, random values with a uniform distribution from -5 to +5 m were added to the data. The remaining data were divided into two equally sized data sets and given larger distortions. Here, the values applied to these data sets were in the range -6 to -10 m and 6 to 10 m. Given that the mapped representation had a contour interval of 10 m, the data set derived in this manner also satisfied the vertical mapping standard for a map to be considered accurate.

The derived data set used to form the mapped representation, therefore, satisfied both the horizontal and vertical mapping standard specified. Consequently, the mapped representation would be considered accurate. Indeed the mapped and actual representations were very highly correlated, r=0.997 (significant at the 99.9% level), and the RMSE was estimated to be 5.8 m, indicating a quality of broadly similar magnitude to digital elevation models reported in the literature (e.g. Bolstad and Stowe, 1994; Giles and Franklin, 1996).

The accuracy of the map was, however, also assessed from the standard remote sensing perspective. For this, height information in the actual and mapped representations were grouped into classes which, to match the specified contour interval, were 10 m wide. For a sample of 1678 locations, the height value depicted in the actual and mapped representations was extracted from the data set. Cross tabulating the height class in the actual and mapped representations yielded a confusion matrix from which basic measures of classification accuracy could be derived. From this confusion matrix, it was estimated that the accuracy of the height information depicted in the mapped representation was 65.5%. Thus the mapped representation, which satisfied the basic map accuracy standards, would appear to be of relatively low accuracy when evaluated from the harsh perspective used in remote sensing. It should be noted, however, that much of the error was, as expected, associated with neighbouring classes. Since the height classes defined lie on an ordered scale, the severity of misclassification error varies as a function of the dissimilarity of the classes and this is not accommodated in the basic approach to accuracy assessment used in remote sensing which treats all errors as being of equal magnitude. Thus, the derived estimate of accuracy could be considered to under-represent the map's actual quality. It is also important to note, however, that many classifications of remotely sensed data include related or ordered classes but are evaluated in the standard way with all errors weighted equally (e.g. Joria and Jorgenson, 1996; Rogan *et al*., 2003). For example, 5 of the 17 classes depicted in the IGBP DISCover map are of forest and for some users mis-allocations amongst these classes may be of no consequence. Indeed for some user's the accuracy of the IGBP DISCover map rises from a stated accuracy of ~78% to ~90% after the aggregation of appropriate classes (DeFries and Los, 1999).

Clearly, the scenario presented above is limited. It is not meant to be taken as a rigorous and thorough example but merely one that indicates the general trend using reasonable values for error magnitudes. It would be trivially easy to adjust the approach to yield a mapped representation that was more erroneous (e.g. there is no upper limit to the error magnitude for the 10% of cases that can lie beyond the target level specified). Similarly, the analysis could as easily be adjusted to show less error (e.g. use of a test site with little variation in height). The key concern is that, using reasonable error values on a data set of moderate relief, the accuracy of the topographic information was low when viewed from the perspective often used in remote sensing. To further illustrate this, it would be necessary for the class width to be increased three times, to 30 m, for the accuracy to rise above the 85% accuracy standard widely promoted in remote sensing. Specifically, with a 30 m class width the accuracy was 86.3 ± 1.6 % at the 95% level of confidence. Note, however, that the lower confidence limit on this accuracy statement lies below the 85% target and so even this classification should perhaps perhaps be viewed as failing to reach the target commonly used in remote sensing.

5. Use of other community's maps by the remote sensing community

Despite the problems with maps produced by other communities (e.g. those concerned with soils and geology), especially their limitations in terms of accuracy assessment and reporting, the remote sensing community often appears to readily use such maps unquestioningly. For example, geological, soil and topographic maps are often used in support of the production of a thematic map from remotely sensed data. It is common, for example, for topographic maps to be used in pre-processing imagery, especially for geometric and topographic corrections (e.g. Hale and Rock, 2003). Error in the topographic map used to geometrically 'correct' an image could be a major source of non-thematic error in a classification of that image. Various types of map and other data sources may also be used as ancillary information to help increase class separability and thereby classification accuracy (e.g. Loveland *et al*., 1991; Maselli *et al*., 1996;

Bruzzone *et al*., 1997; Homer *et al*., 1997; Vogelmann *et al*., 1998; Rogan *et al*., 2003). Although information on the quality of such data can sometimes be incorporated directly in the classification analysis (e.g. Peddle, 1995) ancillary data are commonly used directly, as if error-free, even if the analyst is aware of some possible limitations (Mas, 2004). It, therefore, seems that the remote sensing community is often prepared to accept other maps as being of acceptable quality yet is unduly harsh in the assessment of its own thematic maps.

6. Conclusions

Accuracy assessment is fundamental to thematic mapping from remotely sensed data. The research and user communities, including the remote sensing community, often seems to be unfairly harsh in the assessment of thematic maps derived from remote sensing. This is apparent in relation to the target accuracy commonly specified, the methods of accuracy assessment that are widely promoted and in relative comparison to accuracy assessment in other mapping communities.

The 85% target accuracy that is often adopted in thematic mapping from remotely sensed data appears to stem from early research on mapping broad land cover classes at a small cartographic scale and may be inappropriate for some current mapping applications. The 85% target is, however, widely used in a diverse range of thematic mapping application scenarios. In working to this target accuracy, site-specific accuracy assessment methods based on the confusion matrix are also commonly used although often based on assumptions that are untenable (e.g. that pixels are pure and there is no mis-location error) and unfair (e.g. that the ground data are error-free). Furthermore, commonly promoted measures of accuracy may unnecessarily remove chance agreement leading to an apparent reduction in map accuracy. Commonly, therefore, what may be an ambitiously high target accuracy of 85% is set and an approach to accuracy assessment that is geared to provide a pessimistically biased estimate is used.

Although it may be good practice to set high and ambitious targets, the remote sensing community may, however, often be chasing an unrealistic and inappropriate target and compounding the problem by using pessimistically biased techniques. From this perspective it is not surprising that many thematic maps derived from remote sensing fail to meet the widely specified target accuracy. Other types of map that are widely used without question of their accuracy may also fail to satisfy a similar target if evaluated from the harsh perspective used in remote sensing. However, such maps are often used without question. Thus, it seems that the remote sensing community appears to have a somewhat masochistic tendency in accuracy assessment, subjecting its thematic maps to an overly harsh and critical appraisal using pessimistically biased techniques yet accepting other maps with little question to their accuracy. With this double standard, the remote sensing community may be doing itself and the broader research and user communities a dis-service as it may, effectively, be underestimating its own products while contributing to the accepted belief that other maps are more accurate than they actually are and useable without question.

In no way should the arguments made above be interpreted as suggesting that classifications of a low accuracy should be accepted or that there is no room for targets. Rather the discussion above should be seen as a call for a critical appraisal of fundamental issues such as the aims in mapping and an awareness of how realistic they are within their context. This may help to reduce unfair criticism of thematic maps derived from remote sensing associated with false perceptions of map quality inferred from classification accuracy statements. A realistic target should be defined for each particular mapping exercise. The specification of the target value should recognise the particular features of the specific mapping task (e.g. the nature of the remotely sensed data used and level of class detail). This is very similar to what Anderson *et al*. (1976) proposed for their land cover mapping activities, in which a well-justified case for a target was specified. There is, however, no reason to believe that the target they suggested for their particular mapping scenario should be universally applicable. There is also a need to recognise that problems in accuracy assessment can be a source of pessimistic bias. In particular, the rigid use of site-specific accuracy assessment methods in which all error is seen a arising from the image classification and the inappropriate quantification of accuracy can lead to a mis-representation of classification quality.

Classification accuracy assessment is still very much a topic for further research (Rindfuss *et al*., 2004; Strahler *et al*., 2006). Issues only briefly discussed here such as the minimum mapping unit and the unit for accuracy assessment and reporting as well as a suite of issues such as those associated with variation in error severity and the assessment of soft classifications require further attention. Similarly it must be recognised that other approaches to accuracy assessment may be adopted. Accuracy assessment could, for instance, be viewed as a map comparison activity, for which a varied range of methods exist (e.g. Boots and Csillag, 2006; Dungan, 2006; Foody, 2006; Hagen-Zanker, 2006). For example, instead of the widely used site-specific approach discussed above attention may focus on the use of pattern based indices. With such approaches the focus is on the configuration of the landscape, which typically has an advantageous feature of providing a degree of tolerance to spatial mis-registration error. These techniques are, however, also not problem-free, with, for example, thematic error impacting on the estimation of pattern indices in a complex manner and limitless ways to characterise patterns complicating index selection (Langford *et al*., 2006; White, 2006) but have potential in providing an alternative approach to accuracy assessment. Irrespective of the approach adopted, there is additionally, a need to recognise that there are sources of optimistic bias in accuracy assessment (e.g. Hammond and Verbyla, 1996) in order to ensure that maps of low quality are not viewed acceptable. Given the importance of classification analysis within the subject, it is important that the remote sensing community develops appropriate and practically sound approaches for accuracy assessment to meet its own needs and for the benefit of those in other communities that appear follow its lead on accuracy assessment.

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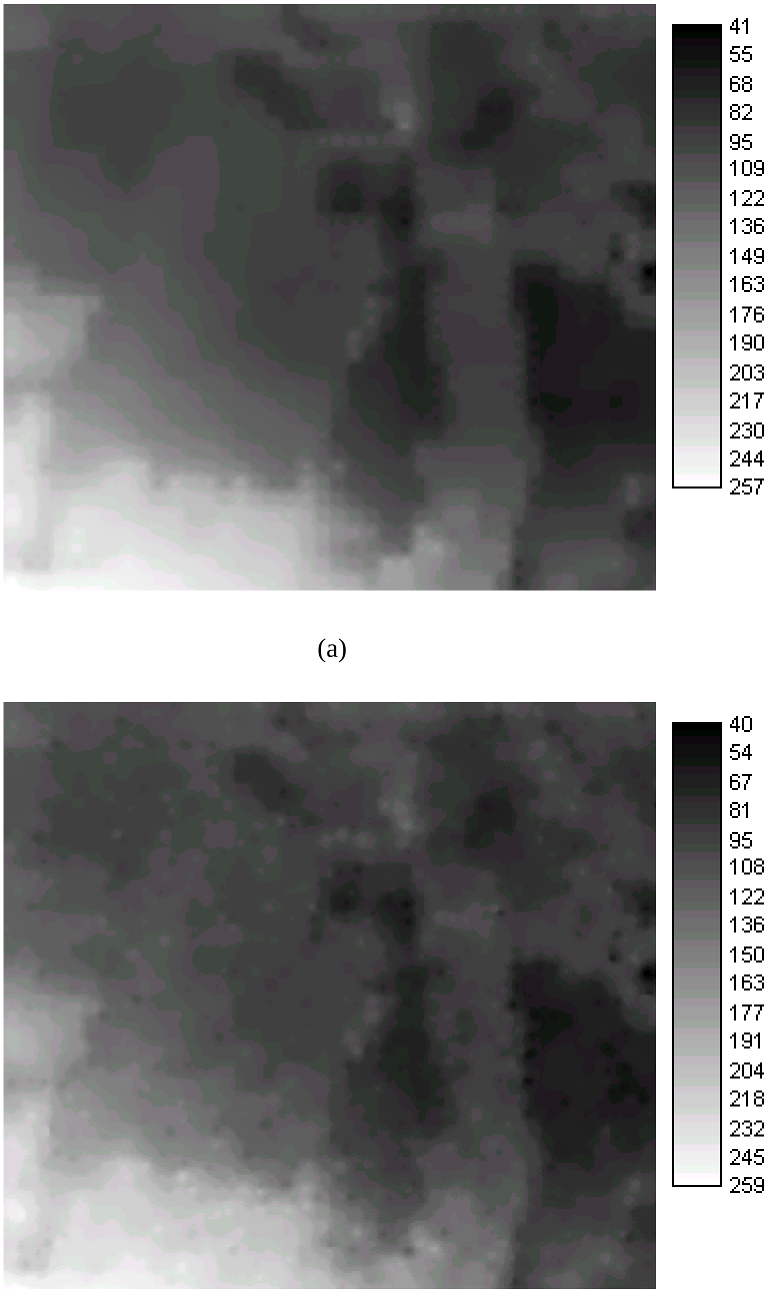
Figure caption

Figure 1. DEM showing terrain height (m) used in the evaluation of topographic map accuracy. (a) the actual, and assumed error-free, surface and (b) the mapped representation derived from (a) which satisfies standard map accuracy criteria.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(a)

(b)

Figure 1