Hydrol. Earth Syst. Sci. Discuss., 3, 3439–3472, 2006
www.hydrol-earth-syst-sci-discuss.net/3/3439/2006/

Hydrology and Earth System Sciences Discussions

Papers published in *Hydrology and Earth System Sciences Discussions* are under open-access review for the journal *Hydrology and Earth System Sciences*

Uncertainties in land use data

G. Castilla[1] **and G. J. Hay**[2]

[1]Institute for Regional Development, University of Castilla La Mancha, Albacete, Spain
[2]Department of Geography, University of Calgary, Calgary, Canada

Received: 20 April 2006 – Accepted: 3 November 2006 – Published: 10 November 2006

Correspondence to: G. Castilla (Guillermo.Castilla@uclm.es)

Abstract

This paper deals with the description and assessment of uncertainties in gridded land use data derived from Remote Sensing observations, in the context of hydrological studies. Land use is a categorical regionalised variable returning the main socio-economic role each location has, where the role is inferred from the pattern of occupation of land. There are two main uncertainties surrounding land use data, positional and categorical. This paper focuses on the second one, as the first one has in general less serious implications and is easier to tackle. The conventional method used to asess categorical uncertainty, the confusion matrix, is criticised in depth, the main critique being its inability to inform on a basic requirement to propagate uncertainty through distributed hydrological models, namely the spatial distribution of errors. Some existing alternative methods are reported, and finally the need for metadata is stressed as a more reliable means to assess the quality, and hence the uncertainty, of these data.

1 Introduction

Land use is an important variable influencing both hydrological and hydrogeological processes. Regarding the former, land use affects the volumes of surface runoff and the velocity of flow that in turn influence infiltration and soil erosion. As for the latter, land use greatly impacts evapotranspiration and as a result, considering also the aforementioned effects on infiltration, diffuse recharge. Therefore, uncertainties in land use data may propagate through models and diminish the reliability of their predictions. A sound assessment of these uncertainties, if incorporated in the decision-making, would increase the legitimacy of policy decisions based on those predictions, and then foster greater stakeholder acceptance of whatever outcome results from these decisions.

The goal of this paper is to raise awareness among practitioners who deal with land use data in hydrological studies on i) the uncertainties they bear; ii) the limitations of the conventional methods used to assess these uncertainties; and iii) alternative methods to describe them. After clarifying some concepts on the land use v. land cover and raster v. vector distinctions, the uncertainties in land use data are characterised and separated into positional and categorical. The conventional methods to assess them are briefly described and criticised, and some alternatives are outlined. After this, the factors that may influence them are examined, and finally, some conclusions are made.

1.1 Land use and land cover

In this paper, land use is considered a categorical regionalised (spatially distributed) variable that may adopt as many different values as classes have been defined, the actual value being dependent on location. Land use classes describe the main socio-economic role of a given location, such as residential, industrial, agricultural, forestry, recreational, and conservancy. These roles shape and at the same time are shaped by the pattern of occupation of land, i.e. by land cover. The latter refer to what is physically on the Earth surface such as vegetation, water or sand. Strictly speaking, land cover should be confined to vegetated and built-up areas. Consequently, classes like bare soil or sand (desert) describe land itself rather than land cover. However, in practise the scientific community is used to describe those situations under the term land cover (FAO, 1997).

The intimate relationship between land use and land cover fuels some confusion between both terms. As a matter of fact, they are used interchangeably in many maps where natural and semi-natural areas are described with land cover concepts and agricultural and urban areas with land use ones. However, land use is the function of land cover for human activities, therefore they are not not synonyms. Furthermore, both domains lack a one-to-one correspondence. For instance, recreational is a land use class that may be applicable to different land cover classes like e.g. water (an all sports lake), urban (a funfair), or forest (a periurban park). Confusing both terms leads to increased ambiguities and incongruities in class definition, therefore they should be kept apart (Meinel and Hennersdorf, 2002).

Notwithstanding, this paper deals with the common maps currently used by hydrologists, which include both land use and land cover concepts in their legend. Hence it is assumed that land use concepts appearing in the legend can be inferred from the pattern of occupation of land. This assumption is necessary because the focus of this paper is on those land use data that are assimilated into models at the catchment or river basin scale. These are usually derived from Remote Sensing (RS) data, and in the latter, human activity (people manufacturing, harvesting, shopping or playing) cannot be directly observed, at least with current civil satellites. An overview of land use/land cover mapping can be found in Lins (1996).

1.2 Land use data formats and models

Land use data usually come in the form of maps that depict the distribution over a territory of the set of land use classes included in the map legend. The latter must consist of a fixed number of mutually exclusive and collectively exhaustive classes (each one represented by a particular label), so that any given terrain unit can be assigned a label. Land use maps are derived from RS ortho-rectified (i.e. geometrically corrected to some cartographic projection) imagery, either aerial ortho-photos or satellite multispectral ortho-images. In the first case, land use units are usually delineated manually by photointerpretation. This process consists in the identification of semantically homogeneous regions in the ortho-photo, and it is based in the visual differences that different land use classes create. The usual digital representation of maps derived from orthophotos is a polygon vector layer, i.e. a mosaic of non-overlapping contiguous units or polygons representing patches of land whose label, unlike the next case, is necessarily different than the ones of adjacent units. These polygons, being unitary and different from their surroundings, can be regarded as representing geographic objects, thus the conceptual framework underlying this representation can be regarded as object-based.

In the second case (satellite imagery), it is common to apply a semi-automated classification to the multispectral image. This process uses pattern recognition methods to group individual data samples, or signatures, into classes. A signature is an *n*-component vector where each component usually is the value taken by a given individ-

HESSD

3, 3439–3472, 2006

Uncertainties in land use data

G. Castilla

ual pixel in each of n channels or bands. This vector acts as the coordinates of a data point in an n–dimensional space. The non-uniform arrangement of signatures (which usually tend to cluster into more or less discontinuous regions) within this space forms a structure that is seized in the analysis to demarcate the regions of that space occupied by each class of interest. The common digital representation of maps derived from satellite images is a raster or grid made of square cells, where the value at each cell or pixel is the label returned by the automated classifier at that pixel. Hence the basic (areal) units used in this kind of maps are individual pixels rather than polygons. The conceptual framework underlying this representation is field-based, since it considers land use a regionalised variable distributed over the territory, that is, a geographic field. An example of a fictitious land use map, which will be used to illustrate some points, is shown in Fig. 1. The map corresponds to a $19\times12\,\text{km}^2$ region centred at Canon city, Colorado, USA, and it has been derived from a Landsat TM image that can be found in the Tutorial Data CD #2 of the ENVI® (a popular RS image processing package) distribution.

This paper focuses on uncertainties in raster land use data derived from digital classification of RS data, which are more commonly used in water-related studies, since gridded data can be readily assimilated into distributed hydrological models. Notwithstanding, uncertainty in polygon land use data is also addressed briefly, since they are sometimes used in this context by converting them to grid before assimilation. In this respect, users should be aware that vector to raster conversion, albeit a straightforward process, has some implications on the reliability of the result. The conversion not only involves a change of data format, but also of conceptual framework. The object-based model has a higher abstraction level than the field-based model (e.g. it uses relational features between objects that are not applicable in the field-model); hence what could be regarded as an error in the latter is simply a necessary generalisation in the former, as explained next.

An important generalisation mechanism of polygon maps is the minimum mapping unit (MMU), i.e. the minimum size (or sometimes width, when referred to elongated units) that a land parcel must exceed in order to be represented in the map. Isolated land use units having a size below this threshold are aggregated to the surrounding unit. Afterwards, there is no trace in the map of such gaps. An exception is the case of mosaic polygons, which have a compound label representing a mosaic of patches, all smaller than the MMU, from different classes. In this kind of polygons, the percentage cover from each class may be reported, but information regarding their actual distribution within the polygon is missing as a parsimonious exchange for clarity. In general, each MMU will yield a different model of the territory, and the larger the MMU, the greater the fraction of the territory catalogued as mosaic (Castilla, 2003). The conclusion is that when a polygon map is gridded in order to assimilate it into a model, and the grid cell size is several times smaller than the MMU, we cannot be certain that all the cells within a given polygon actually belong to the declared land use class, even if the reported accuracy of the polygon map was 100%. The only clues to assess this uncertainty are the MMU and cell size, and the complexity of the mapped territory.

Finally, there is one more point to include polygon land use data in this paper. The present widespread availability of very high resolution (<5 m pixel size) RS imagery is fostering the use of object-based imaged analysis (OBIA) methods to derive land use maps (e.g. Burnett and Blaschke, 2003). The reason is that, in these images, pixels are too small to be representative of classes whose biophysical description refers to a setting that necessarily encompasses more than a few square metres. OBIA methods, unlike the conventional pixel-based ones, use image-objects as the basic units of the analysis. The latter are delimited (typically by an image segmentation algorithm) regions of the image that are internally coherent and relatively different from their surroundings. By using this kind of units, additional features that cannot be obtained from individual pixels (such as those derived from the shape of the regions and their mutual relations) may be included in the analysis. With such enhanced capabilities, OBIA has the potential to supersede not only conventional pixel-based methods, but also photointerpretation (Castilla et al., 2006). Therefore it is likely that in future most land use data will be derived this way and presented in vector polygon format.

2 Characterising uncertainty in land use data

In this paper, uncertainty is an indication of the amount of distrust with which the data should be regarded or used. That is to say that the higher the uncertainty surrounding a given datum, the more likely is that the actual land use of the piece of terrain to which this datum refers to is not the one registered. Uncertainty so defined influences the extent to which the predictions made by a model using this data are to be believed, and ultimately the strength with which those predictions may support of justify a given environmental decision. The relevance for hydrological modelling of uncertainty in land use data relies in the sensitivity of model output to varying input land use data. Therefore a sensitivity analysis, typically based on Monte Carlo simulation (e.g. Helton and Davis, 2003), may be used to assess the impact of land use data uncertainty on the hydrological model.

Land use data uncertainty may be characterised using the integrated framework provided by Brown et al. (2005) (Table 1). Land use may be conceived as categorical regionalised variable, describing the main type of activity each land unit (i.e. the footprint of each pixel) is devoted to. Regarding its method of determination, the activity is inferred from the particular combination of recurrent elements (such as trees or buildings) that are typically present in the places where this activity is carried out. That setting yields a particular joint reflectance profile when observed from faraway. Such profile can in turn be measured (after accounting for atmospheric interactions) by imaging spectrometers mounted on satellites. Hence land use is determined from pixel signatures through a process called image classification, which consists in demarcating the regions of the multidimensional data space associated with each class of interest c_i (i=1,..., m). The classification is carried out with the aid of a set of discriminant functions g_i (one for each of m classes), such that given a signature X, g_i(X) is greater than the other g_j when X belong to c_i. In other words, X is classified as a member of class c_i if and only if g_i (X)$\geq g_j$ (X) for all j=1,2,... m (Landgrebe, 1999). For example, the map shown in Fig. 1 is the result of applying a maximum likelihood classifier (where the discriminant functions return the probability that the signature belongs to each class assuming that the statistics for each class in each band are normally distributed) to the six optical bands of the Landsat TM image.

Land use belongs to Brown et al. (2005) D3 data category (categorical, varies in time and space), and its empiric uncertainty is assessed quantitatively through the statistics derived from a contingency table of errors (M1 empirical uncertainty category). The instrument quality, if by instrument we refer to the remote sensors that record the data from which land use is inferred, is difficult to assess, because these data are only contingently related to the intensional definition (the set of properties distinguishing a class from all others) of land use classes. Instead, a set of typical signatures or training pixels, usually collected from representative well known locations, is used to construct a surrogate intensional definition of each class. For example, the training pixels used for the map of Fig. 1 are the ones included in the file classes.roi of the can_tm folder of the ENVI® Tutorial Data CD #2. Then the region(s) of the multidimensional data space occupied by each class are demarcated according to this definition. Signatures inside that region(s) constitute the extensional definition (the set of instances belonging to it) of the class. The expected result of this indirect method is that the projection of this extension onto the territory, i.e. the set of terrain plots that belong to each class, coincides to a great deal with the one that would have been obtained should the proper intension (related to human activities) be applied to exhaustive field observations. The degree of success is later verified from a set of reserved (not used for training) samples from known locations. Irrespectively of the particular classifier employed (an overview of the different methods can be found in Richards and Jia 1999), image classification is considered a reliable and common method for deriving land use data from RS data, so it can be assigned to Brown et al. (2005) O3 category.

Finally, regarding the temporal dimension of land use data uncertainty, it can be considered as belonging to category L1 (uncertainty information is known to change over time). Land use maps are snapshots of the territory taken when primary data (e.g. aerial photographs) were collected. Age decreases the reliability of the information portrayed in the map, since the territory is subject to changes that affect land use, such as wildfires, the construction of new infrastructures, and shifts from rural to urban or from agriculture to forestry. The more frequently these changes occur, the more urgent the need for updating. Since the likelihood of changes is not uniform throughout the territory (e.g. it is higher in the urban-rural buffer), age affects unevenly the reliability of these data. Similarly, it is unusual that all data are coetaneous for a given mapping project, especially field surveys, so again the temporal reliability is likely to vary from one sheet to another. An important consequence of temporal uncertainty is that, as the database is updated, past deductions have to be revised as they may be no longer valid. This is known as the "belief maintenance problem" (Frank, 2003). For example, a conservancy area may have been assessed in an earlier study as having a low erosion risk, but after a wildfire that assessment may not be true anymore.

3 Positional uncertainty

There are two main uncertainties contended with when dealing with land use data, positional and categorical (usually termed thematic in the field of RS and GIS) uncertainty. This distinction is debatable, since a label disagreement at given location could be interpreted as being due to either positional (e.g. a systematic coordinate error) or thematic error. However, this separation will be followed here, for two reasons. First, it is common in the literature. Second, it is useful, for it distinguishes two types of uncertainty that are associated to two domains very different in nature, namely the cartographic domain and the classification domain.

In raster maps, positional uncertainty relates inversely to the degree of confidence we may have in that the actual location of the plot of terrain represented by a given cell corresponds acceptably to the coordinates of that cell. Hence positional uncertainty depends mostly on the quality of the geometric correction (ortho-rectification) performed on the satellite image from which the map was derived. Positional accuracy is usually estimated by the Root Mean Square Error (RMSE) of selected points (such as crossroads) clearly identifiable in the image and whose precise coordinates are known from a higher accuracy source (e.g. a high quality topographic map or differential GPS measurements). RMSE is computed as the square root of the mean of the squared errors, and is calculated combining both x- and y-directions. Such estimation assumes that positional errors are random and evenly distributed throughout the imaged scene, which may well not be the case, especially in hilly terrain due to relief distortions.

In general, positional uncertainty is far less serious than the categorical one. For example, in a vegetation mapping study, Green and Hartley (2000) calculated positional error introduced by georeferencing, digitising and subjective interpretation, and found that the latter process accounted for 90% of the total error. So to end up the discussion with a practical hint, it can be said that RMSE is considered acceptable when it is less than the pixel size, a fact that is referred to as subpixel accuracy. In practice , the true location of the centre of a pixel of an image geocorrected at subpixel accuracy can be safely assumed to lie somewhere within a 3×3 block of pixels surrounding that point (Goodchild, 1994). For a review on geometric correction of RS images, see Toutin (2004).

In polygon maps, positional uncertainty relates inversely to the degree of confidence we can have in that the boundary between two given polygons lies in the right place. As previously stated, this uncertainty is inseparable from the categorical one. The reason is that the boundaries being sought and delineated are only those that differentiate the land use classes in the chosen classification scheme (Bie and Beckett, 1973). Therefore the uncertainty attached to boundary placement is proportional to 1) how different the classes separated by the boundary appear in that area; and 2) how fast the transition from one class to the other is, i.e. how sharp the boundary is. Since in any given RS image some boundaries are softer than others, this variance of uncertainty should be estimated independently for each arc in the map.

The estimation could be done through the definition of a probabilistic epsilon band (Honeycutt, 1987) within which the "true" boundary between two polygons has a probability of 99% of being located. The rationale behind epsilon bands is the following.

Assuming a correct classification of polygons, one could argue that a point precisely on the boundary could equally well belong to either class (Blakemore, 1984). Moving away from the boundary towards the centre of the polygon increases the probability of a correct classification, while at the same time the probability that this is where the boundary should lay decreases. The manner in which this probability drops off mainly depends on the two factors mentioned above.

Unfortunately, the epsilon band, being boundary-dependent and arc-specific, is rarely, if ever, computed. Following the example in Green and Hartley (2000), a general procedure for the estimation of the error due to subjective interpretation could be obtained by overlaying several photointerpretations of the same area carried out by different equally-skilled interpreters. After intersecting the vector layers produced by each interpreter, some boundaries will be very consistent, whilst others will vary markedly, resulting in dozens of sliver (i.e. spurious) polygons. The width of the epsilon band corresponding to a given soft boundary would be the mean distance between the inner and outer wrapping lines encompassing the set of sliver polygons existing along that boundary.

Unfortunately again, not only the above procedure is hardly feasible within the context of a mapping project, but it is grounded on an unrealistic assumption. Vg. it assumes that given a territory and both a categorical and a spatial level of detail, it can be achieved an egg-yolk representation (Cohn and Gotts, 1996) of that territory. In the latter, each polygon is like a fried egg that has a yolk (i.e. a core area free of sliver polygons) and a white (the set of sliver polygons surrounding that core), the white being the epsilon band. Such representation assumes that any two high quality photointerpretations of that territory would create the same set of geographic objects but with slightly different boundaries. However it will not be unusual to find that there are some polygons drawn by interpreter A that are crossed in the middle by an arc delineated by interpreter B, and vice versa.

A more feasible alternative for assessing the positional uncertainty of arcs is to express it as a combined measure of boundary distinctness both from the radiometric and semantic points of view. For a given arc, radiometric distinctness could be estimated as the mean gradient magnitude of pixels crossed by the arc. Semantic distinctness could be equated to the value of some biophysical similarity index between the classes being separated by the arc. In addition, positional accuracy could be assessed polygon-wise, preferably for the same sample of polygons that is used to evaluate categorical accuracy, which for the reasons stated in the previous paragraph should consist of non-adjacent polygons. The question to be answered for each polygon in the sample would be: are the boundaries of this polygon delineated in such a way that it can be conceived as representing a coherent land use unit under the view supplied by the classification scheme? The answer could be given qualitatively using a nominal scale, or even quantitatively by computing an epsilon band derived from several interpreters who are given separately the task of improving the delineation of that polygon.

It is worth noting that the former procedure has not been tested operationally. In practice, positional accuracy is estimated through the RMSE of sample points along vector arcs that correspond to sharp boundaries in the image from which the map was derived. This estimation is biased towards man-influenced features, such as the edge between a woodlot and a paddock, since "natural" boundaries are less clear-cut. Therefore, the RMSE method is not suitable to assess how well polygon boundaries represent landscape structure, rather it is an indication of the steadiness of the interpreter's hand (and of the visualisation scale she used).

4 Categorical uncertainty

Categorical uncertainty is inversely related to the degree of confidence we can have that if we visit the plot of terrain corresponding to a given map unit, it would be devoted to the land use class indicated in the map. This uncertainty is commonly assessed using a contingency table of agreement between predicted and observed values, which is usually called the confusion matrix (Table 2). Note that accuracy, which is term usually employed in RS literature, may be considered the antonym of uncertainty in this context, i.e. the more accurate the map is, the less uncertainty it has. For a review on accuracy assessment of land cover maps, see Foody (2002). For a nice example of an accuracy assessment of a national landcover map, see Stehman et al. (2003). The latter is based on the methodological framework put forward by Stehman and Czaplewski (1998), which divides the accuracy assessment in three components: sample design, response design and analysis.

The first component is the protocol used to determine the number, location, spatial support and nature (e.g. aerial photos or field plots) of the sample units that will populate the confusion matrix. The second is the protocol for assigning a label to each sample unit, including the procedures to collect the information used in the assignment. And the last component is the protocol for deriving accuracy statistics from the confusion matrix. Unfortunately, this framework is not worked out explicitly neither reported in most maps. Without such explicitation, users can hardly appreciate how close the accuracy estimates can be expected to be to the "true" map accuracy, and how robust or repeatable they are. A nice example on how to develop a sound accuracy assessment framework, including some useful hints in key decisions that have to be made, can be found in Wulder et al. (2006a).

In practice, the confusion matrix is computed from a subset of pixels from known areas that were not used as training pixels, and it compares for each land use class the predicted class with the actual one on the ground. There are a number of methods to measure accuracy from this table, the simplest being the percent correctly classified, usually called itself "accuracy" (95.72% in the example). The recommended accuracy threshold, below which the resulting map should be discarded for operational purposes, is 85% (Anderson et al., 1976). Another common measure is the kappa index, similar to the former but it ranges from 0 to 1 and is not biased by chance agreement (i.e. it takes into account the expected rate of agreement between predicted and actual datasets based on chance alone). Kappa values over 0.75 indicate very good correspondence between the two datasets, while values below 0.50 indicate poor correspondence. Individual class accuracy may be reported either from the map user's or producer's perspective, or both (Story and Congalton, 1986). The first one relates to errors of commission (to confuse some class with the one reported), whereas the second one is a measure of the omission error (to confuse the class with some other) associated with the class.

The main drawback of this matrix is that it only captures the average error over the entire mapped area, whereas the likelihood of misclassification may vary markedly from one place to another (Goodchild, 1994). For example, in a recent study on spatially constrained confusion matrices derived from the same image, Foody (2005) reported that while the global accuracy for the whole image was estimated to be 84%, local estimates varied from 53% to 100%. In addition to the often biased spatial distribution of errors, there are usually significant differences in error rates among the classes (Davis and Simonett, 1991), albeit this aspect is well displayed in the confusion matrix. The selection of the sample pixels used in the construction of the matrix may also bias optimistically the accuracy estimates (as it actually occurs in the example used throughout this paper), since they are usually picked up in blocks rather than individually (Fig. 2). Blocks usually correspond to homogeneous areas far from boundaries between different land use units. In this way, mixed pixels, which are prone to be misclassified, are systematically excluded from the sample (Plourde and Congalton, 2003). The block sampling procedure also violates the independency assumption of statistical sampling, because near pixels are usually correlated and therefore tend to show similar values.

Another aspect that the usual confusion matrix neglects is the seriousness of the misclassification. In many maps, the errors observed in a classification are between relatively similar classes and sometimes these may be unimportant while other errors may be highly significant (Foody, 2002). For example, it is more serious to confuse a lake with a forest than the latter with sparse woodland. A possible method to account for this is to use a nominal scale to evaluate map v. field comparisons, from "absolutely right" to "absolutely wrong", going through "understable but wrong" and "reasonable assignment" (Gopal and Woodcock, 1994). This scale would easily allow weighing the degree of disagreement between the map and field observations.

It is also worth noting another flaw regarding the source of “ground truth”, that is, the reference data upon which the classification results are validated. Many times, because of financial and logistic constraints, these are not ground data derived from field surveys but aerial photos of higher resolution and/or previously compiled maps, available at some limited parts of the extent covered by the larger map, which are deemed to possess the highest accuracy. In the latter case, caution should be used when interpreting the results of the comparison, due to the likely different conceptual and averaging filters that each map applies to the territory, especially if the areal units of the reference map are polygons (Wulder et al., 2006b). For example, Finke et al. (1999) compared the CORINE landcover map with the Landcover database of the Netherlands and concluded that the former contains considerable errors, reporting that 69% of the area covered by (semi)natural vegetation was misclassified in a combined soil/vegetation map. Such disagreement probably comes from different map legends, spatial support and minimum mapping unit, rather than to shear “error” in the less detailed map. Indeed, mapping errors are “forcible deviations between a representation and actual circumstances” (Chrisman, 1991). But the actual circumstances of a territory must be described at a given scale of observation using a given set of concepts – the map legend. Therefore, in order to estimate error in a map by means of a more detailed map, the latter should use the same concepts than the former, and prior to comparison, it should be upscaled to the same resolution than the former. Otherwise the map uncertainty may be overestimated as in the example.

This problem of the sensitivity of analytical results to the type of the areal units from which data are collected has been conceptualized by Openshaw (1984) as the Modifiable Areal Unit Problem, or MAUP, which is akin to the Change Of Support Problem (COSP) identified in Geostatistics (Cressie, 1996). It arises from the fact that these units are arbitrarily defined and eventually modified to form larger units. Therefore, if the areal units are arbitrary and modifiable, then the soundness of any model based upon them may be rightly questioned. MAUP was identified in the context of socio-economical geography, but is has been also found in Landscape Ecology and Remote

Sensing. Marceau (1999) gives a comprehensive review on the issue.

In conclusion, despite the confusion matrix is widely used as the standard accuracy assessment for RS-derived maps, it is clearly insufficient for propagating land use uncertainties through a distributed model, as it does not take into account the spatial distribution of errors. To illustrate this point, Fig. 3a visually presents the uncertainty landscape (where the altitude of each point is proportional to the accuracy of the class it has been assigned to) that could be inferred from the confusion matrix of Table 2. This landscape conspicuously differs from the more realistic one derived from the output of the Maximum Likelihood (ML) classifier (Fig. 3b), in which the altitude of each point is proportional to the estimated probability that the point actually belong to the class it was assigned to. There are two already proposed alternatives that may tackle this deficiency of the confusion matrix.

One is the general error model proposed by Goodchild et al. (1992). In their model, each pixel is associated with an m-component vector of probabilities giving the probability that the pixel belongs to each class 1 through m. The classes allocated to the pixels in the map represent one realization of a stochastic process defined by these vectors. That is to say that over a large number of realizations, the proportion of times a pixel is assigned to each class will converge on each class's probability at that pixel. In addition, within any given realization, the outcomes in neighbouring pixels are correlated, so that the model also includes parameters describing the level of spatial dependence. Sample realizations can be obtained as the outcome of a classification performed using a randomly selected subset of training pixels. The parameters of the model can be calibrated by adjusting them so that the range of outcomes matches reasonably the range observed in reality. An example of its application can be found in Horttanainen and Virrantaus (2004). Despite being an interesting alternative, and as these authors note, the crux of this method is how to define the parameter that controls the level of spatial dependency. This is not easy since there is no analytical method for defining it, as no single variogram can adequately capture how spatial autocorrelation varies across the image.

Another alternative would be the computation of spatially constrained confusion matrices to characterize the spatial variation of accuracy throughout the scene (Foody, 2005). Given a set of *n* predefined locations of interest situated well apart from each other, *n* confusion matrices could be computed from the *k* nearest samples to each location. The approach assumes that enough samples are available around the locations of interest, which may not be always the case. Also, different choices in the selection of these locations and the number of samples per location will in all likelihood produce different accuracy estimates. However, it is a simple an inexpensive means of extending the conventional approach with information on how classification accuracy varies across the mapped territory. Further details can be found in Foody (2005).

Turning now to the case of polygon maps, the comparison between predicted and actual land use class should consider the polygon as a whole. This becomes troublesome if the validation method consists of field surveys, because it is difficult to infer the polygon label from plot or transect data due to the inevitable heterogeneity of polygon interiors. This difficulty may be tackled using field plots larger than the MMU, but this may hinder the cost-effectiveness of the sampling design, or simply be unfeasible when the MMU is larger than say 1ha. Also, if there is considerable variability in polygon size, care should be taken when selecting the sampling design (Stehman and Czaplewski, 1998), since error estimates should be referred to total area rather than to the number of polygons.

5 Factors that influence land use data uncertainty

The main factors influencing the reliability of (raster) land use data can be identified as 1) the quality of the image(s) used as input for classification; 2) the quality of the training pixels used to define quantitatively the classes; 3) the degree of correspondence between the proper definition of classes and their radiometric definition.

Satellite images are measurements, distributed at a fixed ground sampling interval (equal to the pixel size), of regionalised variables. These variables are usually related to some electromagnetic property of the Earth surface and the atmosphere, such as the radiance recorded by optic sensors at several bands of the spectrum. The latter depends not only on the reflectance of the surface, but also on atmospheric conditions and on incidence and viewing angles. So the clearer the atmosphere and the flatter the terrain, the more can be expected that reflectance estimates derived from the recorded values are equally good for all the pixels in the image. Assuming that the image either fulfils these requirements or has been adequately corrected for atmospheric and relief effects, each pixel can then be considered as a sample introduced in a desktop spectrometer. The resulting signature is then compared to the ones of selected samples (training pixels) of each material that can be found in the imaged territory – scene. After comparison (i.e. classification), the material having the most similar signature(s) to the one under analysis is selected as the class to which that pixel belongs.

This discourse can be extended to cases where signatures are not spectral, like e.g. crop classification using multitemporal radar images. The key point is that the set of images used in the analysis allows for a good discrimination between classes, i.e. that no two signatures from different class are similar. In order words, in order for the classification to be successful, signatures should clump into clusters in the n-dimensional data space, where each cluster is composed of signatures of a prevailing class, and where clusters from different classes are separated by quasi-empty space. Conversely, the greater the overlap between two given classes, the higher the probability that they will be confused (Schowengerdt, 1997). Therefore a high quality multiband image in this context is one where signatures are segregated in the data space according to their class, enabling an accurate classification. As explained earlier, the latter consists in locating the regions of the data space where each class prevails. The demarcation is performed with the aid of a set of known signatures, the training pixels.

An issue related to image quality is what is the best combination, in type and number, of images that can be used to analyse land use, from a given data set. This is a classic problem of pattern recognition, called feature selection (where feature stands for band), consisting of two inter-related parts: feature extraction (the transformation and/or combination of the original images/bands into new ones) and feature reduction (the reduction of the dimensionality of the data set by selecting the smallest subset of bands providing an acceptable discriminative power). Feature selection is generally considered a process of mapping the original measurements into more effective features. Unfortunately, in many applications, the important features are nonlinear functions of original measurements. Since there is no general theory to generate mapping functions and to find the optimum one, feature selection becomes very much problem oriented (Fukunaga, 1972). In any case, the two main approaches used are class separability analysis and eigenanalysis (Mausel et al., 1990).

Regarding training pixels, the accuracy of image classifications depends heavily on their quality, even more than on the actual classifier used (Buttner et al., 1989). Moreover, the same classifier is likely to produce different results on the same image when trained with a different set of training pixels (Smits et al., 1999). As a consequence, the result is prone to reflect inconsistencies in the selection of training samples. Thus "good" training pixels must be fully representative of their respective class, so that a good number of instances of the set of typical signatures of that class are included. This implies e.g. that they should be well distributed across the scene, as there may be "local varieties" of the material, where each variety may conform a separate cluster in the data space.

Another requirement is that the piece of terrain over which the measurement is made is large enough as to include a representative number of the elements constituting the biophysical definition of the class (Woodcock and Strahler, 1987). For example, if the class forest is defined as "an area densely covered by trees", a forest pixel must include at least several trees so as to represent a typical forest signature. Since each class has a specific minimum spatial support (from the few decimetres of grassland to the hundred of meters of urban), the conclusion is that the classification should be performed at several resolutions. One way to achieve this while keeping fixed the pixel size is to segment the image into differently sized homogeneous regions, and then extract average signatures from those regions. Another way is to incorporate some texture measure as an adjunct to the spectral ones, in the hope that classes requiring a support larger than the pixel size will show a particular textural pattern that may help to discriminate them.

Regarding the last factor, classes are defined quantitatively through the signatures of training pixels. In doing so, it is assumed that there is a bijection between location in data space and location in the categorical space defined by the classification scheme of the map. In other words, if a signature is located in a region of the data space that belongs to the class forest, it is expected that the plot of terrain from which that signature was extracted is "densely covered by trees". In addition, the signature of any given place densely covered by trees is expected to lie within some cluster of the data space that has been allocated to the forest class. Such correspondence does not depend alone on the quality of both the image and training pixels, but also on the very definition and number of classes. The more adapted the set of classes to the structure of the data space, the better the correspondence and therefore the accuracy. Conversely, if we include in the map legend two classes that share the same tracts of the data space, the classification results will be poor. In general, the higher the number of classes, the higher the number of both attributes (bands) and training samples (pixels) required for a good classification.

In any case, the correspondence cannot be perfect, as the classes must fulfil some conflicting requirements. On the one hand, classes must be meaningful for users and meet their needs, covering exhaustively all the possible land uses that can be found in the mapped territory. On the other hand, classes must be separable to an adequate degree in the data space. For example, there will always be some patterns of occupation that lie in between the definition of two classes. Vg. a given area may have such a tree density that it cannot be considered a forest, but neither a sparse woodland. If such areas are common in the mapped territory, it would be advisable to create a new class, say open forest. But it is likely that the signatures of the new class will overlap with the ones of the former classes, so that the accuracy of the map is decreased.

In a similar way, there always are pixels that are crossed by an edge separating different land patches, the so called mixed pixels. Their signature consists of a mixture of two (or more) classes and may be located in tracts of the data space occupied by other classes. For example, a Landsat pixel situated between a corn field and a bare field has a mixed signature that may be confused with the signature of a class having a low green cover fraction, such us sparse woodland. The abundance of mixed pixels depends on the resolution of the image and the complexity of the landscape (Markham and Townshend, 1981), so that the odds of a correct classification decreases with decreasing patch size and increasing heterogeneity (Smith et al., 2003). Since, in addition to other factors, the problem of mixed pixels is inversely related to the problem of the spectral heterogeneity of classes, it is impossible to achieve a 100% accuracy. For instance, the proportion of mixed pixels may be reduced by decreasing the pixel size, but at the expense of increasing intraclass variability. In short, classes should be defined in such a way that can be distinguished with the satellite data used to map them. Attempting to include classes that consists of instances with radiometric signatures very different among them (e.g. the class urban in Landsat imagery) and similar to the ones of other classes (e.g. wheat and barley) will result in a poor and inconsistent map.

Finally, in the case of polygon land use maps derived from photointerpretation, the last two factors mentioned in the beginning of this section may be replaced with the quality of the interpretation. This depends in turn on the skills and experience of the interpreters, and on the time allocated for interpretation (and even on the interpreter's mood during that time). Since this quality may change from sheet to sheet due to different interpreters doing the job, it is of outmost importance to standardise observational techniques (e.g. digitising scale) and criteria (through e.g. a photointerpretation key consisting of several examples for each class) among interpreters (Lillesand et al., 2003).

6 Conclusions

The confusion matrix is the standard means for assessment of categorical uncertainty in RS-derived land use raster maps. An example of an accuracy assessment protocol based on it can be found in Stehman et al. (2003). Unfortunately, this matrix does not take into account the fact that land use is a regionalised variable, i.e. is does not provide the spatial distribution of errors. There are two already proposed alternatives to tackle this deficiency. One is the error model of Goodchild et al. (1992), an applied example of which can be found in Horttanainen and Virrantaus (2004). The other is the local characterisation of classification accuracy though spatially constrained confusion matrices (Foody, 2005). In any case, despite the apparent objectivity of the quantitative estimates derived from any given method, it is important that they are interpreted with care, since there are many factors that may result in a misleading interpretation drawn from an apparently objective uncertainty statement (Foody, 2002).

For this reason, quantitative analytical results must be complemented with qualitative insights on how reliable the map is. The whole picture could be gained by a thorough inspection of (well documented) metadata. The latter would provide users with a sense of the amount of distrust with which the data should be used. In order to make such intuitive assessment, metadata should not only describe comprehensively the material –images and ancillary information- used in the compilation of the map, but the methods, including the location of training and/or verification samples (Stehman and Czaplewski, 1998). This is relevant as current maps metadata tend to be poor, and user awareness of this need would increase producer care about metadata. Within this scope, the International Metadata Standard for Geographic Information ISO 19115 defines more than 300 metadata elements structured into 14 packages, most of which can be applied optionally. Metadata are usually stored in XML format, which can be accessed with standard text editors. If for a given map the package related to Data_Quality_Information is not empty, then the user may have information on the accuracy of the map. An example of how that package may look like can be found in Table 3. In this example, overall accuracy is 59%, meaning that this map is not reliable for most operational applications.

Notwithstanding, the overall accuracy estimate derived from a confusion matrix of a land use map could in general be used when propagating uncertainty in e.g. a hydrogeological model that uses that map as one of the input layers to estimate evapotranspiration (ET). But in order for this propagation to make sense, the model must just give an overall ET estimate for the whole study area, i.e. it should be a non-distributed model, unless we are ready to assume that accuracy is uniformly distributed throughout the map. A better alternative for propagating uncertainty due to land use data in a distributed model would be a distributed error model associated to the land use data, which unfortunately is not provided by mapmakers in current compilations. Nevertheless, if in this latter scenario we had the confusion matrix of the map, we could, having class-specific ET estimates, propagate uncertainty in the distributed model. However, in doing this we would be relying again on a unrealistic assumption, that is, that errors are randomly distributed in space.

Finally, in the sadly common case of a land use map for which accuracy information is lacking, a possible solution would be, using the threshold proposed by Anderson et al. (1976), to grant the map a 85% overall accuracy, on the assumption that the agency that entrusted the map uses high standards that in turn were followed by the contractor, and apply it to all the cells within the model. If that solution can be regarded as reasonable by both managers and stakeholders, then the outcome of the uncertainty propagation exercise may well be wrong, but at least it will be legitimate (the research by Hofmann and Mitchell (1998) supports this kind of approach). In short, the key question when assessing uncertainty in land use maps is to what degree the map allows managers/models to make decisions/computations that do not differ significantly from those that they would have made if they had a direct knowledge/perfect map of that territory. Current practice does not provide a full answer to this question. The gaps may be filled by common-sense assumptions, preferably based on metadata, which should seem reasonable for stakeholders/experts. A final recommendation for users is to compel map producers to compile well documented standard metadata files, on the grounds that no map is acceptable as input to a numerical model without them.

Acknowledgements. The present work was carried out within the Project “Harmonised Techniques and Representative River Basin Data for Assessment and Use of Uncertainty Information in Integrated Water Management (HarmoniRiB)”, which is partly funded by the EC Energy, Environment and Sustainable Development programme (Contract EVK1-CT2002-00109). This manuscript has also been generously supported by a University of Calgary Start-up Grant, an Alberta Ingenuity New Faculty Grant, and an NSERC Discovery grant to G. J. Hay. The opinions expressed here are those of the authors, and do not necessarily reflect the views of their funding agencies. Finally, the authors also wish to thank two anonymous reviewers for helpful comments.

References

Anderson, J., Hardy, E., Roach. J., and Witmer, R.: A Land Use and Land Cover classification system for use with remote sensor data, U.S. Geological Survey, Professional Paper 964, Washington D.C., 1976.

Bie, S. W. and Beckett, D. H. T.: Comparison of four independent soil surveys by air-photo interpretation, Paphos area (Cyprus), Photogrammetria, 29, 189–202, 1973.

Blakemore, M.: Generalization and error in spatial databases, Cartographica, 21, 131–139, 1984.

Brown, J. D., Heuvelink, G. B. M., and Refsgaard, J. C.: An integrated framework for assessing uncertainties in environmental data, Water Sci. Technol., 52(6), 153–160, 2005.

Burnett, C. and Blaschke, T.: A multi-scale segmentation/object relationship modelling methodology for landscape analysis, Ecol. Modell., 168(3), 233–249, 2003.

Buttner, G., Hajos, T., and Korandi, T.: Improvements to the effectiveness of supervised training procedures, Int. J. Remote Sens., 10(6), 1005–1013, 1989.

Castilla, G.: Object-oriented analysis of remote sensing images for land cover mapping: conceptual foundations and a segmentation method to derive a baseline partition for classification, Ph.D. Thesis, Polytechnic University of Madrid, http://www.montes.upm.es/Servicios/biblioteca/tesis/GCastillaTD_Montes.pdf, 2003.

Castilla, G., Hay, G. J., and Ruiz-Gallardo, J. R.: Size-constrained region merging (SCRM): an automated delineation tool for assisted photointerpretation, Photogramm. Eng. Rem. S., in press, 2006.

Cohn, A. G. and Gotts, N. M.: The "Egg-Yolk" Representation of Regions with Indeterminate Boundaries, in: Geographic Objects with Indeterminate Boundaries, edited by: Burrough, P. A. and Frank, A. U., 171–188, Taylor and Francis, 1996.

Chrisman, N. R.: The error component in spatial data, in: Geographical Information Systems: Principles and Applications, edited by: Maguire, D. J., Goodchild, M. F., and Rhind, D. W., Longman Scientific and Technical, 1991.

Cressie, N. A. C.: Change of support and the modifiable areal unit problem, Geogr. Systems, 3, 159–180, 1996.

Davis, F. W. and Simonett, D. S.: GIS and remote sensing, in: Geographic Information Systems: Principles and Applications, edited by: Maguire, D. J., Goodchild, M. F. and Rhind, D., Longman, Essex, England, 191–210, 1991.

Finke, P. A., Wladis, D., Kros, J., Pebesma, E. J., and Reinds, G. J.: Quantification and simulation of errors in categorical data for uncertainty analysis of soil acidification modelling, Geoderma 93, 177–194, 1999.

FAO: Africover land cover classification. Environment and Natural Resources Service, FAO, Rome, 1997.

Frank, A. U.: Ontology for Spatio-temporal Databases, Lecture Notes in Computer Science, 2520, 9–77, 2003.

Fukunaga, K.: Introduction to Statistical Pattern Recognition. Academic Press, New York, 1972.

Foody, G. M.: Local characterization of thematic classification accuracy through spatially constrained confusion matrices, Int. J. Remote Sens., 26(6), 1217–1228, 2005.

Foody, G. M.: Status of land cover classification accuracy assessment, Remote Sens. Environ., 80, 185–201, 2002.

Gopal, S. and Woodcock, C.: Theory and methods for accuracy assessment of thematic maps using fuzzy sets. Photogramm. Eng. Rem. S., 60(2), 181–188, 1994.

Goodchild, M. F., Sun, G., and Yang, S.: Development and test of an error model for categorical data, Int. J. Geogr. Inf. Syst., 6(2), 87–104, 1992.

Goodchild, M. F.: Integrating GIS and remote sensing for vegetation analysis and modelling: methodological issues, J. Veg. Sci., 5, 615–626, 1994.

Green, D. R. and Hartley, S.: Integrating photointerpretation and GIS for vegetation mapping:

some issues of error, in: Vegetation Mapping: From Patch to Planet, edited by: Millington, A. and Alexander, R., Wiley, 103–134, 2000.
Helton, J. C. and Davis, F. J.: Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems, Reliability Engineering and System Safety, 81, 23–69, 2003.
Hofmann, N. and Mitchell, B.: The RESPECT model: evolving decision-making approaches in water management, Water Policy, 1, 341–355, 1998.
Honeycutt, D. M.: Epsilon bands based on probability, Proceedings of Autocarto-8, 1987.
Horttanainen, P. and Virrantaus, K.: Uncertainty evaluation of military terrain analysis results by simulation and visualization, Proc. 12th Int. Conf. on Geoinformatics, 474–480, Gävle, Sweden, 2004.
Landgrebe, D.: Information extraction principles and methods for multispectral and hyperspectral image data, in: Information Processing for Remote Sensing, edited by: Chen, C. H., The World Scientific Publishing Co., New Jersey, 1999.
Lillesand, T. M., Kiefer, R. W., and Chipman, J. W.: Remote Sensing and Image Interpretation, 5th Edition, John Wiley and Sons, New York, 2003.
Lins, K.: Land use and land cover mapping in the United States: An overview and history of the concept, in: Gap Analysis: A landscape approach to biodiversity planning, edited by: Scott, M., Tear, T., and Davis, F., ASPRS, Bethesda, Maryland, 57–66, 1996.
Marceau, D. J.: The scale issue in social and natural sciences, Can. J. Remote. Sens., 25, 347–356, 1999.
Markham, B. L. and Townshend, J. R. G.: Land cover classification accuracy as a function of sensor spatial resolution, Proc.15th Int. Symp. Remote Sens. Environ., Ann Arbor, 1075–1090, 1981.
Mausel, P. W., Kramber, W. J., and Lee, J. K.: Optimum Band Selection for Supervised Classification of Multispectral Data, Photogramm. Eng. Rem. S., 56(1), 55–60, 1990.
Meinel, G. and Hennersdorf, J.: Classifications systems of land cover and land use and their challenges for picture processing of Remote Sensing data – Status of international discussion and programs, Proc. 3rd Int. Symp. Remote Sens.of urban areas, Istambul, 472–479, 2002.
Openshaw, S.: The Modifiable Areal Unit Problem, Concepts and Techniques in Modern Geography (CATMOG), 38, 41, 1984.
Plourde, L. and Congalton, R.: Sampling method and sample placement: How do they affect the accuracy of remotely sensed maps? Photogramm. Eng. Rem. S., 69(3), 289–297, 2003.

Richards, J. A. and Jia, X.: Remote Sensing Digital Image Analysis: An Introduction, Springer, Berlin, 1999.
Schowengerdt, R. A.: Remote Sensing, models and methods for image processing, Second edition, Academic Press, London, 1997.
Smith, J. H., Stehman, S. V., Wickham, J. D., and Yang, L.: Effects of landscape characteristics on land-cover class accuracy, Remote Sens. Environ., 84, 342–349, 2003.
Smits, P. C., Dellepiane, S. G., and Schowengerdt, R. A.: Quality assessment of image classification algorithms for landcover mapping: a review and a proposal for a cost-based approach, Int. J. Remote Sens., 20(8), 1461–1486, 1999.
Stehman, S. V. and Czaplewski, R. L.: Design and analysis for thematic map accuracy assessment: Fundamental principles, Remote Sens. Environ., 64(3), 331–344, 1998.
Stehman, S. V., Wickham, J. D., Smith, J. H., and Yang, L.: Thematic accuracy of the 1992 National Land-Cover Data (NLCD) for the eastern United States: statistical methodology and regional results, Remote Sens. Environ., 86, 500–516, 2003.
Story, M. and Congalton, R. G.: Accuracy assessment: a user's perspective, Photogramm. Eng. Rem. S., 52, 397–399,1986.
Toutin, T.: Geometric processing of remote sensing images: models, algorithms and methods, Int. J. Remote Sens., 25(10), 1893–1924, 2004.
Woodcock, C. E. and Strahler, A. H.: The factor of scale in remote sensing, Remote Sens. Environ., 21, 311–332, 1987.
Wulder, M. A., Franklin, S. E., White, J. C., Linke, J., and Magnussen, S.: An accuracy assessment framework for large area land cover classification products derived from medium resolution satelite data, Int. J. Remote Sens., 27(4), 663–683, 2006a.
Wulder, M. A., White, J. C., Luther, J. E., Strickland, G., Remmel, T. K., and Mitchell, S. W.: Use of vector polygons for the accuracy assessment of pixel-based land cover maps, Can. J. Remote Sens., 32(3), 268–279, 2006b.

Table 1. Characterisation, following the method by Brown et al. (2005), of land use data quality and uncertainty.

Variable name	Land use
Method of determination	Semi-automated classification
Data category	D3 (categorical variable that varies in space and time)
Type of empiric uncertainty	M1 (mean classification error derived from a contingency matrix)
Instrument quality	I2 to I3 (instruments well fitted to not well matched, depending on spectral and spatial resolution)
Sampling strategy	S2 (limited number of both training and verification samples)
Overall method	O3 (Reliable method common within discipline)
Longevity of uncertainty info.	L1 (change over time)

HESSD
3, 3439–3472, 2006

Table 2. Sample confusion matrix for the fictitious map of Fig. 1.

Class	agriculture	forest	barren	Total	User Acc. %
agriculture	275	8	1	284	96.83
forest	27	459	2	488	94.06
barren	1	6	273	280	97.50
Total	303	473	276	1052	
Prod. Acc.%	90.76	97.04	98.91		95.72

Table 3. Sample package (Data_Quality_Information) from the metadata file of a landcover mapping project. (http://sdrsnet.srnr.arizona.edu/data/azgap99/metadata/azgapveg.html).

Attribute_Accuracy:
Attribute_Accuracy_Report: A comprehensive accuracy assessment was performed. Overall map accuracy is 58.8%. See the special technical report, The Arizona Gap Project Final Report for more information on per class accuracy.
Logical_Consistency_Report: Polygon topology was built on 2003-04-22.
Completeness_Report: The map covers the entire state of Arizona.
Positional_Accuracy:
Horizontal_Positional_Accuracy_Report: minimum mapping unit of 40 ha
Lineage:
Source_Information:
Publication_Date: 1991 with some 1990 and 1992 scenes
Title: Landsat Thematic Mapper imagery
Source_Scale_Denominator: 30 m resolution
Source_Contribution: used in unsupervised classification
Source_Information:
Publication_Date: fall 1991, summer 1992
Title: Airborn video of Arizona
Other_Citation_Details: Airborn video imagery (1/3 to 1/2 mile horizontal swath width in wide angle, with interval zooms to 12X occurring approximately every 9 s, or 1500 m) was flown in the fall 1991 and summer 1992. Most video transects were spaced approximately 30 km apart in an E-W trajectory.
Source_Contribution: used in supervised classification
Process_Step:
Process_Description: Landsat Thematic Mapper imagery was digitally classified using a hybrid unsupervised and supervised classification methodology. First, 3 input bands (NDVI, a 5/4 band ratio indicating moisture content of vegetation, and a local texture band built from the NDVI) were used in an unsupervised maximum likelihood classification procedure. The result of the unsupervised classification was then used with DMA elevation data as input for a supervised classification procedure in which buffered GPS-referenced airborne video sample points indicating vegetation association were used as training sets. The resulting image was then edited manually to correct classification errors, then converted to ARC/Info vector format. A series of Arc eliminate and dissolve operations were used to get the map to GAP program-mandated minimum mapping unit of 100 ha for upland vegetation types, and 40 ha for riparian vegetation types. Vegetation descriptions are based on a modified Brown, Lowe, and Pase classification system, and will be cross-walked to a UNESCO coding scheme for National GAP Program purposes.
Process_Date: 1995
Process_Step:
Process_Description: Converted from grid to vector. Added JBK classification. Reprojected from NAD27 to NAD83.
Process_Date: 1998
Process_Step:
Process_Description: Dropped extraneous fields (L. Graham classification). Dissolved on JBK classification. Eliminated state boundary polygons (relict from conversion of grid to vector).
Process_Date: 2003-04-22

HESSD
3, 3439–3472, 2006

Uncertainties in land use data

G. Castilla

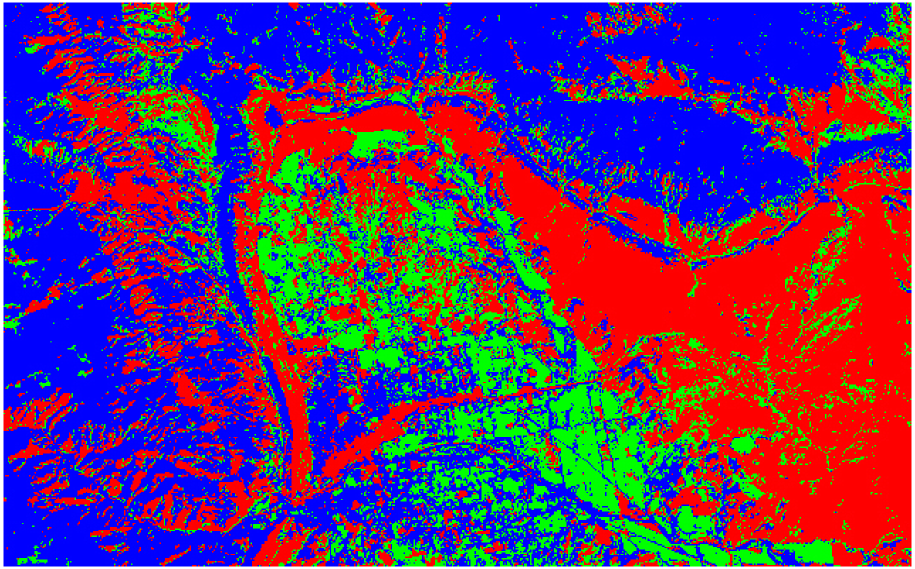

Fig. 1. Fictitious land use map with three classes, agriculture (green), barren (red), and forest (blue).

HESSD

3, 3439–3472, 2006

Uncertainties in land use data

G. Castilla

EGU

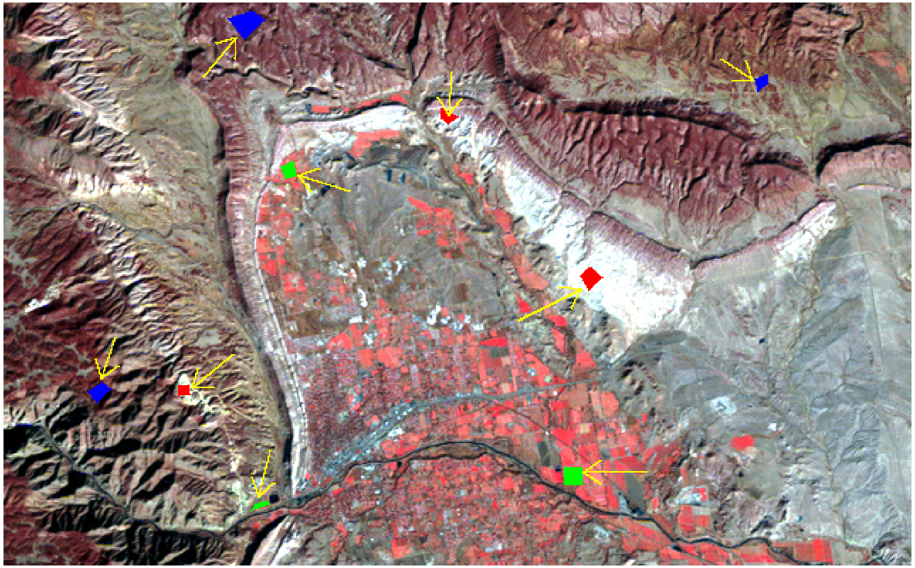

Fig. 2. Location of ground truth pixels used to construct the confusion matrix of Table 2.

HESSD

3, 3439–3472, 2006

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

EGU

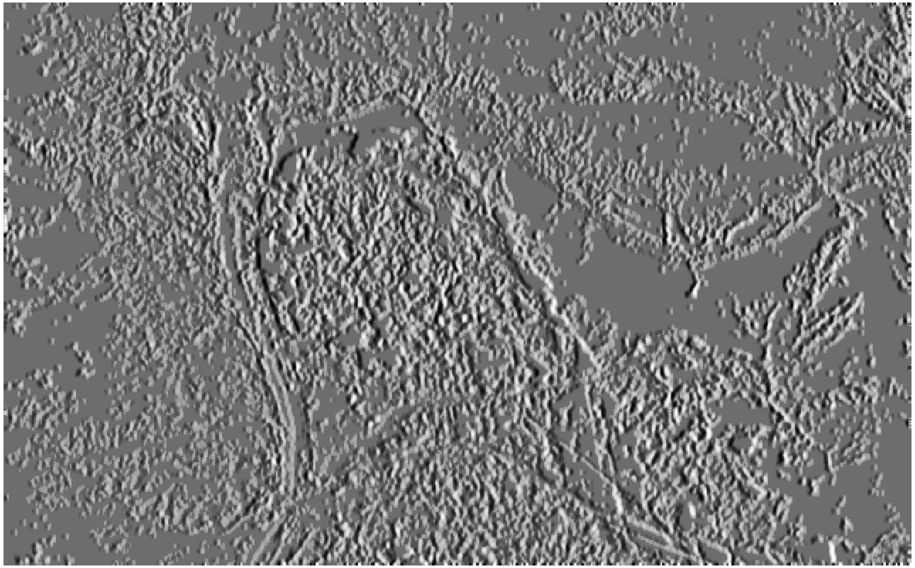

Fig. 3a. Uncertainty landscape derived from the confusion matrix of Table 2.

HESSD

3, 3439–3472, 2006

Uncertainties in land use data

G. Castilla

Fig. 3b. Uncertaintty landscape derived from ML classifier.