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Remote sensing of small and linear features: Quantifying the effects of patch size and length, grid position and detectability on land cover mapping

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ABSTRACT

The accurate mapping of small, often fragmented and linear vegetation patches is of key importance for natural resource management because of their ecological significance. However, due to their small size and the quantised nature of remote sensing imagery they may be under-represented in the landscape when mapped using earth observation. This paper investigates the effect of patch area and patch elongation on the accurate mapping of these vegetation patches. Using synthetic images to simulate sub-pixel patch location, we investigated classification accuracy and extraction probability resulting from differences in the geometric properties of the raster grid and the feature alone. We simulated the effect of grid position, detectability, feature size and shape on classification. This represents the highest achievable accuracy using the remote sensing raster grid, where other factors influencing classification such as classification algorithm, radiometric calibration and sensor characteristics are excluded. We found that mapping error was highest when the scale of the feature and the raster grid coincided. We showed that the spatial resolution of the grid should be many times finer in order to extract these features accurately. For square patches with a mean classification accuracy of 75%, the grid pixel area was 11 times smaller than patch size. When patches were small and/or elongated, the probability of extraction was reduced, mapping accuracies decreased and variability in accuracy due to the effects of grid position increased. For example, a square shaped patch needed an area of at least 11 pixels to achieve a mean accuracy of 75%, whilst a linear patch with a width to length ratio of 4 needed an area of 12.3 pixels. This paper quantifies the limitations of remote sensing for the accurate detection of small and linear features and provides guidelines on the appropriate spatial resolution required to map these features. Using our results, map users can estimate the probability of a map classifying small and linear features independently of the error matrix. Furthermore, we provide a more precise estimate of the size of the smallest discernable feature taking into account the random position of the remote sensing grid with respect to the feature as well as its shape. An understanding of this phenomenon is critical for making good land management decisions based on a thorough understanding of the limitations of remote sensing data.

1. Introduction

The use of remote sensing imagery for the creation of land use and land cover maps is common place within landscape ecology and natural resource planning (Antrop, 2007; Hilty et al., 2006). Thematic maps derived from remote sensing imagery can be used to characterize landscape structure and composition and relate these to landscape processes (Metzger, 2008) such as species migration (e.g. LaRue & Nielsen, 2008) or landscape change (e.g. Nagendra et al., 2006). Features such as small remnant and linear vegetation patches have ecological value that is proportionally greater than their areal extent. The presence or absence of these features change landscape pattern related properties such as connectivity and degree of fragmentation. Of key importance is an understanding of the process of mapping these patches. This paper simulates the process of classifying small and linear features, which allows for a basic understanding of the appropriate spatial resolution required to extract these patches when mapping using remote sensing imagery.

Small and linear vegetation patches are ecologically significant and can be found as roadside vegetation, hedge rows, scattered trees, riparian areas and greenways or are purposely built to facilitate connectivity (Bennett, 1990; Gergel et al., 2007; Hilty et al., 2006; Manning et al., 2006). In rural landscapes trees and hedgerows are important biological and ecological components and function as windbreaks, field boundaries, erosion control, as well as for ecological

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and biodiversity value (Thornton et al., 2006). Small and linear vegetation is also important for wildlife habitat and can function as wildlife corridors which have been shown to have a positive effect on biodiversity and species persistence (Suter et al., 2007). The accurate mapping of wildlife corridors is essential as physical attributes of corridors such as width and length can affect the use of corridors by wildlife (Hilty et al., 2006; Lindenmayer & Fischer, 2007). However, it is due to the relatively narrow width of corridors that they may be under-represented in the landscape when mapped using remote sensing (e.g. Vogt et al., 2007) or traditional field based mapping. The accurate mapping of linear vegetation is key to the development of ecological models as such habitat suitability models. Landcover and vegetation maps which do not accurately represent the size and/or number of patches are a source of uncertainty within spatially explicit models (Minor et al., 2008).

Of great importance to map users interested in these small and linear vegetation patches is estimating what is the smallest discernable feature at any given spatial resolution and the accuracy at which these features are mapped. To the best of our knowledge, formal rules do not exist for describing the appropriate spatial resolution required. This is likely caused by the complexity of the problem, as the classification technique, landscape features, desired land cover classes and sensor resolution and characteristics will all affect the outcome of a classification (Lu & Weng, 2007). Appropriate areas or dimensions required in order to extract features have been suggested, described in terms of pixels for measurement purposes, as in this study. The pixel traditionally represents the smallest discernable feature (Tatem et al., 2002) and limits the size of the feature that can be extracted (Aplin, 2006). Estimates of the smallest discernable feature vary. According to Hengl (2006), at least four pixels are required to detect the smallest objects and at least two pixels to represent the narrowest objects. Cracknell (1998), however, suggested that we can detect an object which is of comparable size to the instantaneous field of view (IFOV) of the sensor. Regarding the detection of small and linear vegetation features a reasonable consensus exists; less than 4 to 5 m spatial resolution is required. Jensen and Cowen (1999) concluded that high spatial resolution imagery between 0.25 to 10 m is required for environmentally sensitive habitat in urban areas where vegetation is found in patches as small as median strips and backyards. Lausch and Herzog (2002) suggested that spatial resolution should be below 5 m to capture linear features such as wildlife corridors. Finally, Congalton et al. (2002) suggested that sensors with finer spatial resolutions such as IKONOS with 4 m multispectral sensor will be more appropriate for features with smaller areas such as riparian vegetation.

Previous research on the appropriate spatial resolution for mapping small and linear objects is mainly based on qualitative examinations. So far, a proper quantification with probabilistic tools, however, is missing. Extraction probability and classification accuracy is a function of the size, shape and the random position of a feature with respect to the sensor array's grid (Fig. 1). Additionally, they are a function of both its spectral characteristics and those of the surrounding objects. This study extends previous qualitative investigations by simulating imagery in order to model the sub-pixel location of features with respect to the grid; testing the effect of grid position, contrast and feature size and shape in isolation. However, classification will be affected by other factors such as image registration, view angle, radiometric calibration, image acquisition time and sensor characteristics such spatial and radiometric resolution and bandwidth (Cracknell, 1998; Townshend et al., 1991). Thus classification accuracy and extraction probability as calculated in this study is the result of the geometric properties of the grid alone, representing the best case scenario for remote sensing where the above factors are ignored.

The aim of this paper is to: 1) determine the effect of the position of the raster grid in relationship to small and linear landscape features on classification, 2) provide a basic understanding of the appropriate spatial resolution required to extract features of various degrees of elongation and area and 3) examine the effect of differing spectral contributions of the object and its surrounds on classification.

1.1. Background to the problem

Rough single figure estimates do not recognize the effect of the random location of the sensor array's grid with respect to the feature. The lack of recognition of this random effect is common, as when using the traditional hard classifiers (which have one class per pixel) the unstated assumption is that landcover fits well into a grid consisting of square shaped spatial units (Fisher, 1997). As features will not generally be placed to match the position of the grid, this can result in small features being lost when they only make up a portion of a cell or are found at the intersection of several cells (Cunningham, 2006; Wehde, 1982). The grid position effect can be a significant source of mapping error for individual map features (Wehde, 1982). Cunningham (2006) noted that winding river channels of ecological importance can easily be lost in this way using 30 m Landsat imagery. Problems of this type are particularly common in highly fragmented environments such as urban and peri-urban areas. For example, Australian road side vegetation can be around 2 to 4 m wide, whilst high spatial resolution satellites such as Quickbird and SPOT XS have a multispectral spatial resolution of 2.4 m and 10 m respectively.

Other factors that contribute to the misclassification of small and linear features are its local contrast with the surrounding objects and the objects contribution to the pixel's spectral signal (Hengl, 2006). When pixel to pixel contrast decreases, the target will ultimately be below the detection limit resulting from measurement uncertainty (Adams & Gillespie, 2006). Detectability is scene and sensor specific (Adams & Gillespie, 2006) and decreases with increasing spectral similarity between target and surrounding objects (Forshaw et al., 1983) and sensors' sensitivity. Another spectral factor contributing to misclassification is the difference in physical area of the target object with respect to its information class. A hard classification often assumes that the class occupies the majority of the area of the pixel (Fisher, 1997). However a tree with a sparse canopy, for example, may

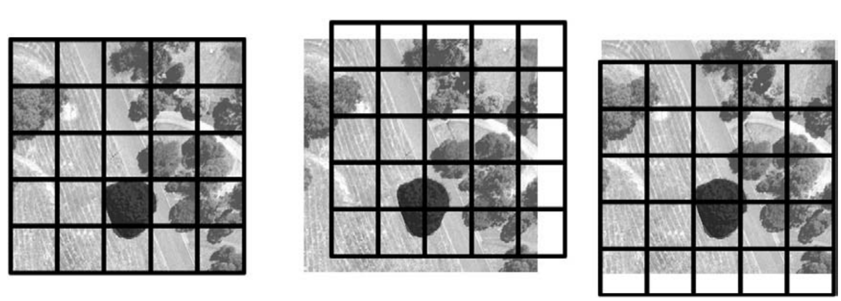

Fig. 1. The position of a satellite sensor array's grid is random with respect to features in the landscape. An example of 3 different possible positions of the grid out of an infinite number of possibilities. Notice the location of the darker tree (centre bottom). Classification of the tree will be more accurate when it is located in the centre of a pixel as opposed to the intersection of many pixels.