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Where can pixel counting area estimates meet user-defined accuracy requirements?

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ABSTRACT

Pixel counting is probably the most popular way to estimate class areas from satellite-derived maps. It involves determining the number of pixels allocated to a specific thematic class and multiplying it by the pixel area. In the presence of asymmetric classification errors, the pixel counting estimator is biased. The overarching objective of this article is to define the applicability conditions of pixel counting so that the estimates are below a user-defined accuracy target. By reasoning in terms of landscape fragmentation and spatial resolution, the proposed framework decouples the resolution bias and the classifier bias from the overall classification bias. The consequence is that prior to any classification, part of the tolerated bias is already committed due to the choice of the spatial resolution of the imagery. How much classification bias is affordable depends on the joint interaction of spatial resolution and fragmentation. The method was implemented over South Africa for cropland mapping, demonstrating its operational applicability. Particular attention was paid to modeling a realistic sensor's spatial response by explicitly accounting for the effect of its point spread function. The diagnostic capabilities offered by this framework have multiple potential domains of application such as guiding users in their choice of imagery and providing guidelines for space agencies to elaborate the design specifications of future instruments.

1. Introduction

Land mapping and area estimation are among the most common applications of remote sensing. Even though they are complementary, they answer to different needs – area estimation having a more direct economic impact and more stringent accuracy requirements defined by statistical standards (Gallego, 2004). Agriculture and forestry are at the forefront of these efforts (for instance, see Soares et al., 2008; Chen et al., 2016; Mayaux and Lambin, 1995). Gallego (2004) categorized the use of remote sensing for area estimation in three groups. In the first group, remote sensing plays the essential part in the estimation. The role of ground data is confined to the calibration of the classification algorithm, or to sub-pixel analysis. The second group comprises methods that integrate inaccurate satellite-derived information with accurate samples often collected *in situ*. They include for instance regression (Gonzalez-Alonso et al., 1997), calibration based on the confusion matrix (Hay, 1988; Conese and Maselli, 1992; Wall et al., 1984; Chhikara et al., 1986; Deppe, 1998; González-Alonso and Cuevas, 1993; Lewis and Brown, 2001) and small area estimators. In the third and last group, the satellite imagery supports the design of an area frame sampling, *e.g.*, see Tsiligirides (1998). The focus of this article rests on the first group.

The most common approach to estimate areas – referred to as pixel counting – is to count the number of pixels belonging to a specific class and to multiply the pixel count by the pixel area. This approach seems to have been accepted in the early days of remote sensing (Gallego, 2004). Despite criticism on its lack of statistical justification, it is still widely adopted (see Wardlow and Egbert, 2010; Shao et al., 2010; Vinciková et al., 2010; Potgieter et al., 2013; Yang et al., 2007; Immitzer et al., 2016; Müller et al., 2015; Bartalev et al., 2016). Nonetheless, the accuracy of these estimates is known to be related to that of the maps from which they are derived. Even with very accurate maps, errors in area estimates may occur (Moody and Woodcock, 1994; Pax-Lenney and Woodcock, 1997). In fact, the pixel counting estimator is known to be biased (Hay, 1988; Card, 1992; Czaplewski and Catts, 1992) because there is no guarantee that the omission error and the commission error will counterbalance one another. Empirical assessments have shown frequent asymmetry in the error distribution. In his paper, Czaplewski (1992) presented an informal method to anticipate the magnitude misclassification bias in areal estimates. However, it is extremely challenging to foresee the accuracy of a classification method as, even when using the same input

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data, it depends on many factors such as the choice of the classifier (Löw et al., 2015; Waldner et al., 2016), the location (Waldner et al., 2016), the typology, the proportion of the classes and the number of training pixels (Zhu et al., 2016). Nonetheless, the ever-increasing spectral content and revisit frequency of recent and upcoming satellites (and their combination) is expected to progressively reduce the classifier error in the future. Stehman (2005) formulated a model to compare area estimates derived from wall-to-wall mapping and statistical sampling through their respective mean square error. For both approaches, the mean square error can be partitioned into two components, bias and variance, the former being attributable to classification error. Unlike wall-to-wall mapping, statistical sampling is also affected by a sampling variance because different sampling realizations will produce different area estimates. Such a model is instrumental to identify which approach is most appropriate approach for area estimation.

The influence of spatial resolution on classification accuracy and subsequently, on area estimation is a question that has long interested the remote sensing community. A comprehensive study of the effect of spatial resolution on classification accuracy was undertaken by Markham and Townshend (1981) and concluded that classification accuracy reflects a trade-off between two factors: (i) the within-class variability and (ii) the boundary effect (Toll, 1985; Latty et al., 1985). On the one hand, the increased spectral variance of land cover types associated with finer spatial resolution may decrease the spectral separability of classes and result in lower classification accuracy. Empirical studies (Landgrebe et al., 1977; Latty et al., 1985; Williams et al., 1984; Toll, 1985) have observed that an increased spatial resolution does not necessarily improve the classification accuracy. A finer spatial resolution could lead to larger within-class variances, yielding higher classification errors (Cushnie, 1987; Treitz et al., 1992). This indicates that highly-separable classes (low variance) are less likely to suffer from the deterioration of classification performance due to an increased spatial resolution (Hsieh et al., 2001). On the other hand, the fact that some pixels in an image at a certain resolution are mixed – composed of multiple land cover classes – can also introduce uncertainty into the area estimates. Mixed pixels and the problems they cause have long been reported (Atkinson and Curran, 1995; Turner et al., 1989). Boschetti et al. (2004) introduced the concept of the Pareto boundary to quantify and isolate the effect of the spatial resolution (mixed pixels) on the accuracy of a map. They illustrated how, for a given resolution, mixed pixels introduce a bias acting as a conflicting objective when trying to minimize the omission or the commission error. This approach has been successfully applied in several contexts such as cropland mapping (Vintrou et al., 2012; Waldner et al., 2016), Desert locust habitat monitoring (Waldner et al., 2015), and burned area mapping (Mallinis and Koutsias, 2012). As retrieving area estimates from coarse spatial resolution is inaccurate due to the effect of spatial aggregation on class proportions, Mayaux and Lambin (1995) implemented an inverse calibration model (Czaplewski and Catts, 1992) by integrating a fragmentation metric in the double sampling approach. The approach was further improved by integrating texture information (Mayaux and Lambin, 1997).

When scaling up landscape data, the magnitude of the errors in the estimation of land cover proportion depends on the spatial resolution of the map, the initial proportion of the landscape in the different land cover types, and their spatial arrangement at the initial resolution (Turner et al., 1989; Moody and Woodcock, 1994). At a given resolution, the number of pixels with mixed land cover is linked to the intrinsic characteristic of the features on the ground and it is a function of their shape, size and fragmentation (Eva and Lambin, 1998; Mayaux and Lambin, 1995; Woodcock and Strahler, 1987). By extension, some landscapes exhibit larger errors in area estimates than others when mapped at the same resolution because of their respective fragmentation (Ozdogan and Woodcock, 2006).

The simulation of remotely sensed data at different resolution requires a good understanding of the processes involved in image acquisition. In fact, the spatial resolution of an instrument is a concept that is more complex to apprehend than what it might appear at first blush. The image is never an exact reproduction of a landscape because small details are blurred. This blurring can be characterized by the net sensor point spread function (PSF) which expresses the sensor spatial responsivity of the sensor (Schowengerdt, 2006). The net PSF has three components that are related to the optics, the detectors and the motion of the sensor. The optical PSF refers to the spatial distribution of the signal in the image of a point source because an optical instrument never perfectly forms a point image of a point source. The PSF of the detectors describes the spatial blurring caused by the non-zero area of each detector while the motion PSF relates to the blurring occurring if the image moves across detectors during the time taken to integrated the signal for a pixel. Alternatively, the PSF can be expressed by its Fourier transform, the Modulation Transfer Function (MTF) (Williams and Becklund, 1989). Several studies have investigated the impact of the PSF/MTF on land cover classification (Huang et al., 2002), sub-pixel landscape feature detection (Radoux et al., 2016), sub-pixel class proportion estimation (Huang et al., 2002; Townshend et al., 2000; Wang and Atkinson, 2017).

Pixel counting estimators would be competitive for area estimation if one could ensure that the bias of the estimates would always remain below a certain user-defined target. This target defines the maximum classification bias in area that can be tolerated. With this as backdrop, the present paper addresses the question of the joint effect of pixel size and spatial pattern for area estimation. A framework is proposed to decouple the classification bias into two components: (1) the resolution bias (the bias due to the spatial resolution itself) and (2) the classifier bias (the bias due to classification errors of the classifier). To demonstrate its applicability, the framework is then applied over South Africa for cropland area estimation. It should be noted that the assessment method described in this paper has been developed for binary cases, *e.g.*, a class of interest (the foreground) versus all other land cover classes (the background). However, it can be extended to multi-class problems by successively grouping the classes in the background class.

2. Concepts and methods

The conceptual framework is based on simulating how the resolution bias varies across landscapes and spatial resolutions. It is driven by the following rationale. The proportion of mixed boundary pixels results from the combined effect of the spatial resolution and the spatial patterns of a class in the landscape. Regardless of the spatial patterns of that class, the number of mixed pixels will decrease as the spatial resolution increases. Eventually, and for any spatial pattern, there is a resolution at which the proportion of boundary pixels becomes marginal compared to that of pure pixels. At this point, the area estimate is very close to the true area value. So whether or not the omitted and committed areas offset one another becomes irrelevant as, even if extremely unbalanced, they do not affect the area estimation significantly. Conversely, as the resolution coarsens, sub-pixel proportions are no longer concentrated at the extremes of the class patches and the area estimation error can be large depending on landscape spatial structure. This phenomenon is illustrated for four actual landscapes of increasing landscape fragmentation in Fig. 1.

The rationale as explained above details the case of a theoretical map not affected by misclassifications. Of course, it is very unlikely for maps derived from remote sensing to be unaffected by