Available online at www.sciencedirect.com
SCIENCE DIRECT
ELSEVIER
ISPRS Journal of Photogrammetry & Remote Sensing 59 (2005) 369–376
PHOTOGRAMMETRY & REMOTE SENSING
www.elsevier.com/locate/isprsjprs

Stratified sampling of satellite images with a systematic grid of points

F. Javier Gallego

JRC, tp. 268, 21020 Ispra (Va), Italy

Received 11 January 2004; received in revised form 11 January 2005; accepted 2 October 2005
Available online 14 November 2005

Abstract

Sampling satellite images presents some specific characteristics: images overlap and many of them fall partially outside the studied region. A careless sampling may introduce an important bias. This paper illustrates the risk of bias and the efficiency improvements of systematic, pps (probability proportional to size) and stratified sampling.

A sampling method is proposed with the following criteria: (a) unbiased estimators are easy to compute; (b) it can be combined with stratification; (c) within each stratum, sampling probability is proportional to the area of the sampling unit; and (d) the geographic distribution of the sample is reasonably homogeneous. Thiessen polygons computed on image centres are sampled through a systematic grid of points. The sampling rates in different strata are tuned by dividing the systematic grid into subgrids or replicates and taking for each stratum a certain number of replicates.

The approach is illustrated with an application to the estimation of the geometric accuracy of Image2000, a Landsat ETM+ mosaic of the European Union.

Keywords: Sampling; Statistics; Surveying; Random; Error; Mosaic

1. Introduction

Satellite images are especially useful to study large areas. In some cases, the area can be very large (e.g., a continent) and it may be necessary to consider only a sample of images. This can happen, for example, when fine- or medium-resolution images are used to estimate the changes of forest area in the tropical belt or worldwide. Some authors have expressed doubts on the possibility of obtaining valid global estimates of forest area change from a sample of Landsat TM images (Tucker and Townshend, 2000); Czaplewski (2003) explains that the accuracy of estimates depends more on the number of sampling units than on the sampling rate: it makes sense to sample 10% of 1000 images, but sampling 10% of 40 images leads to poor estimates.

The easiest approach is a simple random sample of a set of images covering the region. Random sampling can often be improved introducing systematic sampling and stratification. However, sampling satellite images is not a straightforward application for two reasons: (a) images generally overlap, and therefore, they are not a partition of the area under study, and (b) boundary images are only partially inside the studied area.

This paper gives a method to sample images from sensors with approximately fixed image frames, such as

E-mail address: javier.gallego@jrc.it.

0924-2716/$ - see front matter © 2005 International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS). Published by Elsevier B.V. All rights reserved.
doi:10.1016/j.isprsjprs.2005.10.001

Landsat TM. The problem is slightly different for satellites with off-nadir pointing capacity, such as SPOT or very high-resolution satellites. The method is illustrated with an application to the assessment of geometric correction of a mosaic of ETM+ images of the European Union (EU).

2. Some examples of satellite image sampling

The TREES-2 project estimated rainforest changes between 1993 and 1997 (Achard et al., 2002). A sample of 100 Landsat TM images (full or quarter scenes) was selected and photo-interpreted for both dates. The sampling method was statistically sound but too complicated (Richards et al., 2000). This paper is partly a result of the post-project reflection on how sampling should have been carried out in an easier and more efficient way.

The FAO Forest Resources assessment 1990 (FRA-90) used a stratified sample of 117 Landsat TM frames. Frames containing less than 10,000 km^2 of land were disregarded. The variable overlap of images is not considered important in tropical areas and disregarded (FAO, 1996). Tomppo et al. (2002) discuss the precision that can be achieved on global forest area estimations with a sample of TM images, but do not analyse how to take into account the variable area coverage of TM images due to image overlap and images that straddle the boundaries of the region. The same authors consider square tessellations of 10 km × 10 km and 150 km × 150 km to assess the potential use of samples of Landsat ETM or Ikonos images for the estimation of forest change between the current date and 2010 (Czaplewski and Tomppo, 2003).

The MARS project of the EU used images of a sample of square sites 40 km × 40 km for rapid estimates of crop area change (Meyer-Roux, 2000), but the sampling method is not well documented. For the extension to Central Europe, a two-phase sample was used with unequal subsampling probability in the second phase (Gallego, 1999). Jeanjean et al. (1998) make a simulation to compare different sampling plans for pan-European forest assessment (including European Russia) based on a tessellation of 40 km^2. Squares with more than 50% outside the studied region were excluded. Both systematic and stratified sampling are shown to be more efficient than simple random sampling, but combining systematic and stratified sampling is not considered.

3. Sampling methods for satellite images

A sampling frame is a representation of the population to be sampled. In the case of satellite images, we can consider a double sampling frame: a region Ω, represented in a cartographic projection with total area A, and a set D of N images that cover the region. Some of the images fall partially outside Ω: we should consider only the part of the image inside Ω. Therefore, the area A_i of each image is not homogeneous. The images in D generally overlap: they are not a partition of Ω. We assume we want to estimate TX, the total of variable X in Ω from a simple random sample of n images.

To illustrate the effect of each sampling method and each estimator, we have made simulations using a land cover map as pseudo-truth. Using a fully known pseudo-truth makes the comparison of different estimators easier. The map we have used is CORINE Land Cover (CLC), produced by photo-interpretation of satellite images (mainly Landsat TM) with common rules in most countries in Central and Western Europe (CEC-EEA, 1993). The nomenclature of CLC has 44 classes that we have regrouped into 9 to simplify the example. The minimum mapping unit of CLC is 25 ha; smaller units are included in the dominant land cover type around or grouped in an area coded as heterogeneous. We have used a raster version of CLC with a pixel size of 1 ha. The data set used includes Romania, Bulgaria and the EU, excluding Sweden, Cyprus, Malta and several islands and overseas territories. 421 Landsat TM frames are fully or partially in this area (Fig. 1a). The class "heterogeneous" is important due to the relatively coarse scale of CLC.

We call X_i the area of a CLC class in the TM scene i, A_i the total area of the image and $x_i = X_i/A_i$. We can consider an estimator $T\hat{X}_1$ for the total of X based on the areas or $T\hat{X}_2$ based on the proportions. $T\hat{X}_3$ uses the average proportion, attributing a weight A_i to image i.

$$T\hat{X}_1 = \frac{N}{n}\sum_{i=1}^{n} X_i \tag{1}$$

$$T\hat{X}_2 = A\bar{x} = \frac{A}{n}\sum_{i=1}^{n} x_i \tag{2}$$

$$T\hat{X}_3 = A\bar{x}_w = A\frac{\sum_{i=1}^{n} A_i x_i}{\sum_{i=1}^{n} A_i} = \frac{A}{\sum_{i=1}^{n} A_i}\sum_{i=1}^{n} X_i \tag{3}$$

For readers that are not used to statistical terminology, we remind that the bias is the difference between the real value to be estimated and the expected value of the estimator. The bias corresponds to the idea of systematic deviation from the real value, not of random deviation.

Table 1 shows the bias of these three estimators with simple random sampling considering the full Landsat TM frames as sampling units. In this case, we know the