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Integration of Varied Spatial Resolution Data

Remote sensing has and continues to change extremely rapidly. Those changes have included varied platforms, new sensors, and improved data processing methods. With the current availability of many imagery types, this column urges renewed educational emphasis on the integration of varied spatial resolution data for improved spatial analysis.

The changes of platforms and sensors is evident in the resolutions of imagery available to scientists and decision makers. Spectral resolution has expanded by the acquisition of hyperspectral imagery with some sensors providing 512 bands. Temporal resolution has always been frequent with meteorological sensors but is now high with fine spatial resolution systems. The small-sat constellation of the commercial company Planet is able to acquire global imagery daily with very fine spatial resolution. Radiometric resolution has increased from the 6 and 7 bits of early Landsats to 12 and 16 bit imagery today.

One of the major changes in resolution has been the availability of fine spatial resolution imagery from satellites. Initially the community thought that this imagery would replace aerial photography but the high initial image costs did not make that viable. However, there is now fine spatial resolution satellite imagery available at little or no cost.

However, as with aerial photography, fine spatial resolution satellite imagery has generally small footprints. The imagery is often 20 km or less per side making it very difficult to acquire and accurately extract information over large areas. Most watersheds and local governmental administrative units would require hundreds of images.

Analysis of medium and coarse spatial resolution satellite imagery (10 m pixels and greater) is an effective way to assess regional, continental or global phenomena because of its synoptic coverage, frequency of image acquisition, large footprint and often inexpensive cost. The disadvantage of medium spatial resolution imagery is the lack of detail. Biases often occur because of the large pixel size of the data. Less common surface features are often underestimated, causing a negative bias, and more common components can be overestimated, causing a positive bias.

The purpose of this column is to establish interest among remote sensing educators in the integration of imagery at different spatial resolutions to provide improved spatial statistics for multiple applications. Many remote sensing scientists believe that the most important information that they can provide are accurate maps. However, the reality often is that many decisions are made based upon statistical analysis such as the extent and rate of wetland loss, deforestation or urban expansion.

Regression Estimation

Regression estimation is a statistical sampling technique to combine the synoptic coverage of a coarse spatial resolution sensor with the improved detail of a finer spatial resolution sensor (Gallego, 2004). This technique requires the analyst to map phenomena first using coarse spatial resolution imagery. Next, fine spatial resolution images are acquired for samples within the study area. Phenomena are likewise mapped with the fine spatial resolution data. A regression analysis or other statistical procedure is then performed to determine a correlation or relationship between the two sets of data. If a good correlation exists, the more accurate, finer spatially detailed imagery can be used to calibrate the coarse spatial imagery using a correction factor (Nelson, 1989). In this manner, regression estimation provides more accurate statistical information than only using coarse imagery.

This column was prompted in part based upon a review of 12 textbooks in remote sensing to determine if they referenced regression estimation or similar approaches for surface inventories. Interestingly, only two had any reference to the method and they were quite dated, thus the concern that the procedure is not commonly included in curriculums.

Applications

There are numerous examples of regression estimation. They generally employ imagery of different spatial resolutions and footprints but the method can also use field data rather than fine spatial resolution imagery. It is also possible to

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have several stages of regression estimation using different spatial resolution sensors (Koeln and Kollasch, 2000). For example, a product at 1 m could be used to adjust 5 m SPOT imagery as a first stage. The corrected SPOT could then be used to adjust 30 m Landsat, and it in turn to correct MODIS 250 m imagery. This is often referred to as nested sampling or Nested Area Frame Sampling and is a module in at least one of the standard image processing systems.

One study using regression estimation was to locate open water in North Dakota suitable for waterfowl. The original Landsat estimates of the area of ponds were only about 70% of the actual open water compared to validation data. The regression estimates using aerial photography samples increased those estimates to within 8% of the actual extent.

Regression estimation was performed over seven land covers with an emphasis on forests in Brazil using aerial photographs and Landsat images. The regression estimation procedure was able to provide accurate results in a time-effcient and cost-effective manner with better results than from Landsat independently. Landsat imagery (30 m) in conjunction with AVHRR (1 km) images accurately estimated Canadian burned forest areas to calculate carbon storage (Fraser, 2004).

A study to ascertain the most accurate method to monitor biomass burning in Central Africa determined the best approach would utilize data from both fine and coarse spatial resolution sensors and a regression estimator strategy. Improved walrus counts were obtained using this strategy for a rookery in the North Pacific Ocean (Barber et al., 1991).

Regression estimation has also been employed for mapping agriculture. One study used field data with Landsat to accurately determine the amount of winter rice area in Bangladesh (Haack and Rafter, 2010). Figure 1 illustrates the relationship between the two data sets. In Tanzania, crop statistics were accurately determined via this approach and similarly aerial photography and Landsat correctly estimated the amount of wheat in a region in Brazil

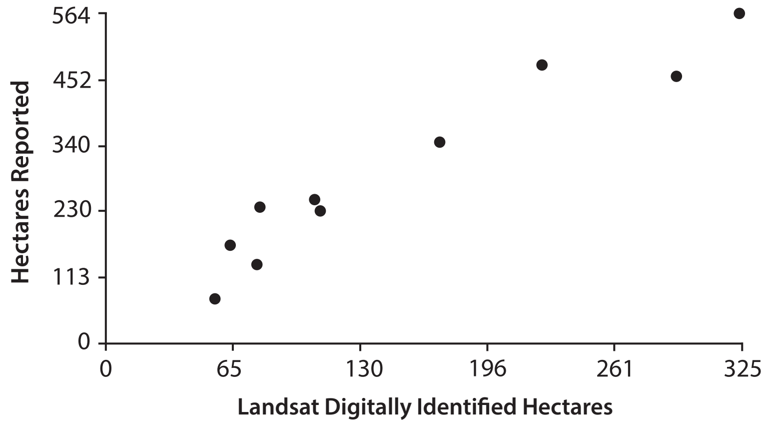

Figure 1. Scatter plot of the relationship between the Landsat identified areas of winter rice and reported estimates by agricultural agents for 10 administrative areas in central Bangladesh. The correlation between the sets of data was 0.98. The average ratio of Landsat to field estimates of boro area was determined to be 0.52 (Haack and Rafter, 2010)

Summary

There is a record of successful applications of the regression estimation strategy to improve the spatial statistics of a variety of surface features. Unfortunately, this method does not seem to be widely used, understood or even included in current remote sensing textbooks. Given the increased availability of fine spatial resolution satellite-based remote sensing data at minimal or no cost, this column encourages wider introduction of this very effective technique in university curriculum.

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