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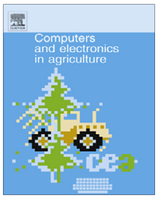

Original papers

Estimation of croplands using indicator kriging and fuzzy classification

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ABSTRACT

The knowledge of the land use is important for the agricultural economy and for defining the deployment of new crops. Thus, a tool for the mapping and quantification of crops is necessary. The development of a tool is possible with the use of remote-sensing images and efficient algorithm classifiers. The objective of this study was to verify the accuracies of indicator kriging and fuzzy classification as supervised classifiers in identifying sugarcane and citrus crops, which are more cultivated in São Paulo, Brazil. The investigated area was located on the border of the municipalities of São Manuel and Botucatu, São Paulo State, Brazil. We used digital images from satellite IRS-P6 (ResourceSat-1; path/row 329/94, January 29, 2011) with a spatial resolution of 23.5 m. In the pre-processing phase, images were prepared for classification using several techniques, such as enhancement, geometric rectification and registration and reduction of dimensionality. In the process of image classification for citrus and sugarcane areas, two methods of classification were utilized, namely indicator kriging (IK) and fuzzy classification, and compared to the visual classification, which was assumed to reflect the reality on the ground (citrus, sugarcane, native vegetation, forest regeneration, soil and water). The classifications were made based on bands 2, 3, 4 and 5 and were evaluated using the kappa index. From the results of the classification of the pictures used for the discrimination and quantification of areas cultivated with citrus and sugarcane, the following conclusions can be drawn: the multispectral bands showed spatial dependence for both citrus and sugarcane, whereas a comparison of the maps revealed that the IK classifier confused citrus with areas of vegetation, and the fuzzy classifier confused citrus with forest regeneration; the IK classifier overestimated the areas of sugarcane crops, whereas the fuzzy classifier underestimated these areas. Based on the kappa index, band 2 (0.52–0.59 μm) better represented the citrus and sugarcane areas, whereas band 5 (1.55–1.70 μm) had the worst classification for both the IK and fuzzy algorithms. Citrus crop were best identified using the fuzzy classifier, and the sugarcane crop was best identified using the IK classifier.

1. Introduction

Agricultural commodities have played an important role in the economic development of Brazil since its discovery by the Portuguese in 1500 (Fausto, 1999). According to the World Bank, Brazil is the largest net exporter of food worldwide. Thirty percent of all exported goods from Brazil are raw food and agricultural materials (World Bank, 2009), and only 6% of imports are raw food or agricultural materials.

Brazil's food production has increased nearly 5-fold since the 1860s, whereas the population has grown only 2.6 times larger. Because of these results, Brazil has become a net exporter of food and agricultural goods. Most of the increase in food production has been a result of more efficient land use; however, a notable amount of the increase is the result of incorporating new areas into agricultural production. Accordingly, one important factor that affects the future growth of food production is the availability of new land resources (Gauder et al., 2011).

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According to a crop estimations released by the Brazilian Institute of Geography and Statistics (IBGE) the national citrus crop production in 2011 was estimated at 19.6 million tons. In 2012, a decline was predicted to occur due to the biennial bearing (after a heavy crop, the tree often responds by carrying a light crop), and the crop production was expected to reach 18.03 million tons (Kist et al., 2012).

The State of São Paulo is responsible for approximately 75% of the entire national citrus crop production. The latest orange survey conducted by the National Supply Company (Conab), covering the 2011/12 season, indicated that 375.7 million 40.8 kg boxes were produced in São Paulo. According to Conab, the citrus planted area in the 2011/2012 crop year in São Paulo will reached 569.461 hectares. In the previous year, the plantations totaled 608,600 ha, with a comparative variation below 6.4%. In addition to the fact that smaller plantations gave way to sugarcane fields, another reason for the reduction was the eradication of unproductive orchards (Kist et al., 2012).

Citrus crops comprise a large group of plants of the genus *Citrus* and other related genera (*Poncirus* and *Fortunella*) or hybrids of the family Rutaceae. Citrus trees are medium-sized, reaching an average of four feet tall, with a dense canopy that is usually rounded in shape. The spacing used in the cultivation of citrus in Brazil is approximately 6–7 m between rows and 3–5 m along the line (Mattos Junior et al., 2005).

Brazil is the world's largest sugarcane producer and is responsible for approximately 25% of the global crop production. In 2011, there was an expansion of the planted area of sugarcane by 4.7% compared with the previous year. If the estimates are confirmed, the Brazilian 2011/12 sugarcane crop will reach 588.9 million tons from a planted area of 8.4 million ha, with yields estimated at 69.8 tons/ha. The State of São Paulo is still the largest national producer of sugarcane, responsible for 52.6% of the total production (Carvalho et al., 2011).

Sugarcane is a semi-perennial grass that belongs to the Graminae family and propagates vegetatively. Stem cuttings are used as planting material. The plant crop is harvested between approximately 18 and 24 months of age. One of the main needs expressed by the sugarcane industry worldwide is the ability to obtain information on the progress of a harvest throughout the harvest season, which generally lasts between 4 and 8 months. The availability of information over large areas can help improve the organization of the harvest campaign, thereby increasing work efficiency in both the field and the factory. The use of satellite image time series is a promising approach to meeting this need (Hajj et al., 2009).

Remote-sensing images offer information that can be used for the planning and exploitation of natural resources, monitoring of environmentally sensitive areas, and detection of sudden changes in an area. Over the years, there has been a surge in the production of remote-sensing images, amounting to an extremely large volume of images. Human interpreters are often superior to computers in identifying remote-sensing images, but high-quality indexing is usually very time-consuming (Su et al., 2011). A shortage of manpower can easily cause poor indexing on a large volume of images, resulting in the improper use of a substantial portion of the images (Su et al., 2011).

The knowledge of the land use is important for the agricultural economy and for defining the deployment of new crops. Thus, a tool for the mapping and quantification of crops is necessary. The development of a tool is possible with the use of remote-sensing images and efficient algorithm classifiers. The objective of this study was to verify the accuracies of indicator kriging and fuzzy classification as supervised classifiers in identifying sugarcane and citrus crops, which are more cultivated in São Paulo, Brazil.

2. Background

The classification of different land cover regions is essential to efficiently interpret remote-sensing images (Richards and Jia, 2006; Lu and Weng, 2007; Tso and Mather, 2009).

The incorporation of geostatistics procedures in environmental studies based on kriging techniques has been used in several areas of science. Many remote-sensing researchers (Van der Meer, 1994a; Duveiller and Defourny, 2010; Pardo-Iguzquiza et al., 2010; Mulder et al., 2011; Pardo-Iguzquiza et al., 2011) have applied these procedures, especially with regard to land use mapping and the classification of digital images. The incorporation of these procedures into Geographic Information Systems (GIS) has triggered a new phase in the development of conceptual methods of cartographic representation. The association of GIS and geostatistics enhances the traditional procedures of such systems, including image classification, due to the high quality of the estimator.

A comparison between non-parametric indicator kriging and conventional hard and soft classification techniques using data from the Indian Remote Sensing Satellite-1D (IRS-1D) shows that the geostatistical approach is statistically more accurate than the conventional techniques when compared with ground spectroradiometer data (Das and Singh, 2009). Indicator kriging was also used to predict patterns of soil sodicity and salinity from the combined use of remote-sensing data and field measurements of electrical, exchangeable sodium percentage and aggregate stability (Odeh and Onus, 2008). Indicator kriging has also been used to aid in mapping land-cover changes. The expected values from indicator kriging were used to compute class transition probabilities in space and time, which allowed us to improve time-series accuracy of the change detection maps (Boucher and Kyriakidis, 2006).

Within the realm of variogram and kriging techniques, indicator kriging provides a method to capture extreme values (Journel, 1983). Van der Meer (1994b) introduced the indicator kriging algorithm to analyze image data sets. Indicator kriging is a nonparametric geostatistical technique in which variables are transformed to lie within the interval [0, 1]. The continuity of the indicators for each threshold is modeled by an indicator variogram as the structural function. The indicators are then estimated using ordinary kriging to obtain the probability estimate of exceeding or not exceeding the thresholds of interest (Badel et al., 2011).

In the most basic form, indicator variograms treat data as binary indicators with respect to a threshold value (i.e., 1 if the threshold is exceeded; 0 if the threshold is not exceeded). For a more complete discussion of indicator variograms and indicator kriging, along with many possible derivatives in algorithms and methodology, see Goovaerts (1997), Deutsch and Journel (1992) and Chiles and Delfiner (1999).

The adjustments to the variogram, based on assumptions of the stationarity intrinsic hypothesis were estimated as described by Rossi et al. (1994), using the classical Matheron variogram adjusted to the digital number (ND) of an image:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [ND(x_i) - ND(x_i + h)]^2 \qquad (1)$$

where $\gamma(h)$ is half the sum of the square of the difference between the values of the pixel pairs separated by the distance vector h. The variance $\gamma(h)$ is a function that depends on the angle and the distance between the vector h and the number of pairs of pixel values x_i and $x_i + h$.

This threshold was estimated at each location $Z(x_0)$ using nearby control (indicator) points and an ordinary kriging estimator of the type