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Influence of reconstruction scale, spatial resolution and pixel spatial relationships on the sub-pixel mapping accuracy of a double-calculated spatial attraction model

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ABSTRACT

Mixed pixels universally exist in remote sensing images, and they are one of the main obstacles for further improving the accuracy of land cover recognition and classification. Since the concept of sub-pixel mapping (SPM) is proposed, SPM technology has rapidly become an important method to solve the problem of mixed pixels. To further improve SPM accuracy, this paper first proposes a double-calculated spatial attraction model (DSAM) combining the advantages of the spatial attraction model (SAM) and the pixel swap model (PSM). Then, based on the full validation of the proposed DSAM, how multiple factors affect the SPM accuracy is analyzed using the multispectral remote sensing (MRS) images. Finally, by analyzing the maximum variations in the ranges of the overall accuracy and the kappa coefficient under different multiple factors, the order of factors influencing SPM accuracy is determined as follows: reconstruction scale > image spatial resolution > pixel spatial relationships. The results can serve as a reference for other scholars in setting model parameters and selecting the appropriate remote sensing data, thereby helping them achieve more accurate SPM results.

1. Introduction

Mixed pixels universally exist in remote sensing images, and they are one of the main obstacles to further improving the accuracy of remote sensing classification and land cover recognition tasks (Tatem et al., 2002; Verhoeye and De Wulf, 2002; Mertens et al., 2004). The effects of mixed pixels make it difficult to meet the accuracy requirements for remote sensing classification when relying solely on the traditional hard classification methods (Yang et al., 2010; Nigussiea et al., 2011). In recent decades, spectral unmixing technology has been used to solve the problems of mixed pixels and to improve the accuracy of remote sensing classification and land cover recognition tasks. As a follow-up means of effective spectral unmixing technology, the sub-pixel mapping (SPM) technique, also called the super-resolution mapping technique, was first proposed by Atkinson et al. (1997) and mainly focused on thematic mapping at a finer resolution relative to the original spatial resolution of the input image (Meyera and Okinb, 2015).

Currently, SPM models mainly include the spatial attraction model (SAM), the pixel swap model (PSM), the neural network model, etc. Among them, many studies have focused primarily on SPM theories (Powella et al., 2007; Zhang et al., 2008; Tong et al., 2013; Zhang et al., 2015), model algorithms (Li et al., 2011; Luciani and Chen, 2011; Shao and Lunetta, 2011; Wang et al., 2014), error analysis (Liu and Wu, 2005; Muslim et al., 2006; Nguye et al., 2006; Ge et al., 2014) and accuracy evaluation (Kasetkasema et al., 2005; Boucher, 2009; Shi and Wang, 2015; Zhong et al., 2015). At present, the results of numerous SPM models and algorithms showed that the existing SPM models each have their own characteristics and advantages—as well as some shortcomings. Thus, it is difficult to obtain more accurate SPM results by relying on any single SPM model. The spatial correlation-based SPM models are an important type of sub-pixel level mapping technique that can be combined with a variety of simulation algorithms to map sub-pixels in a quick, simple and efficient manner. The SAM (Mertens et al., 2006) and PSM (Atkinson, 2005) are the mainstream models for SPM

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research, and they are based on spatial correlation theories that allow the creation of organic combinations of the two models. Many scholars have published some relevant papers regarding innovative combinations of SPM models (Shen et al., 2009; Su et al., 2012a; Su et al., 2012b; Li et al., 2016). Among them, Shen et al. (2009) proposed the modified pixel swapping model (MPSM) by combining SAM with PSM, but the advantages of PSM were not fully exploited.

At the same time, based on the analysis of former studies about the existing SPM models, comprehensive analysis and evaluation of the factors that influence SPM models are lacking. Although some scholars carried out research on SPM models using different remote sensing data and conducted relevant experiments on the factors that influence SPM accuracy (Shao and Lunetta, 2011; Tong et al., 2013), most of those studies only evaluated a single factor (e.g., reconstruction scale, image spatial resolution, pixel spatial relationships, spectral resolution, unmixing accuracy, etc.) that influences SPM accuracy (Atkinson et al., 1997; Mertens et al., 2006; Wang et al., 2014). Therefore, it is necessary to conduct a series of experiments to evaluate how SPM accuracy is influenced by various factors using remote sensing data at different spatial resolutions in a typical experimental area based on integrating different SPM models.

To further improve remote sensing classification accuracy at the sub-pixel level, combining the advantages of the SAM and the PSM, a double-calculated spatial attraction model (DSAM) was proposed in this paper. Compared with the SAM, PSM and MPSM, an SPM experiment was carried out to verify the proposed DSAM. Then, using DSAM, the multispectral remote sensing (MRS) images were used to conduct an SPM experiment to evaluate how SPM accuracy was influenced by various factors. The goal of this research was to provide a reference that could help with setting the parameters of SPM models and selecting appropriate remote sensing data.

2. Material and methods

2.1. Principle and algorithm of the proposed DSAM

2.1.1. Main principle behind DSAM

The proposed DSAM is a spatial correlation-based SPM model that combines SAM and PSM, which were put forward by Atkinson (2005) and Mertens et al. (2006), respectively. In a spatial correlation-based SPM model, it is assumed that interactions exist between sub-pixels/pixels which are named attractions. The attraction between sub-pixels/pixels is the most important basis for spatial correlation; therefore, determining how to best assess the strengths of the attractions between pixels is one of the key research issues. Scholars have performed numerous studies that focused on the issues of assessing the strength of attractions between pixels (Mertens et al., 2006; Shao and Lunetta, 2011; Wang et al., 2012; Ling et al., 2013). Among these, the spatial attraction algorithm was introduced to describe attractions between pixels, and it achieved better mapping effects and larger mapping accuracy at the sub-pixel level (Mertens et al., 2006). Based on the same theory, gravity was also introduced to describe the attractions between pixels in this research.

The law of universal gravitation states that a particle attracts every other particle in the universe using a force that is directly proportional to the product of their masses and is inversely proportional to the square of the distance between them. If each pixel can be regarded as a particle, the mixed pixel's abundance can be treated as the pixel's mass. Meanwhile, when the distance between pixels becomes larger, the attraction between the pixels becomes weaker, and the attraction is to be inversely proportional to the distance. Therefore, the mass product of two particles in the law of universal gravity can be used to describe the pixel weight, which reflects a certain land-cover proportion in a mixed pixel, and the square of the distance between two particles in the law of universal gravitation can better reflect the actual land-cover distribution. Based on the SAM and the law of universal gravitation, Eqs. (1) to (3) show the procedures for calculating the attractions between pixels.

It is assumed that a remote sensing image is classified into ω classes land cover and that p_m is a mixed pixel that can be divided into $s \times s$ sub-pixels, where $z(p)$ denotes the proportion of class z and can be obtained based on mixed pixels according to the spectral unmixing model. Thus, the strength of the attraction between all the sub-pixels in mixed pixel p_m and each adjacent mixed pixel of class z can be expressed as follows:

$$z(\omega_{in}) = z(p_m)\cdot z(p_n)\cdot\left(\frac{1}{k}\sum_{j=1}^{k}\frac{1}{R_{ij}^2}\right) \tag{1}$$

where $z(p_m)$ is the proportion of land cover class z in the mixed pixel p_m; $z(p_n)$ is the proportion of land cover class z in mixed pixel p_n that is adjacent to p_m; i denotes the subscripts of the sub-pixels x in mixed pixel p_m, where $i = 1,2,3, \ldots, s^2$; k is the number of sub-pixels of land cover class z in p_n; j denotes the subscripts of the sub-pixels of land cover class z in p_n, where $j = 1,2,3, \ldots, k$; $z(\omega_{in})$ is the strength of the attraction between all the sub-pixels in the mixed pixel p_m and an adjacent mixed pixel p_n.

According to the algorithm of the original SAM, in the proposed DSAM, the Euclidean distance is still used to calculate the attractions between two sub-pixels. This assumes that the attractions of each two sub-pixels/pixels exist between their centers, and the Euclidean distances are calculated from one sub-pixel/pixel center to another sub-pixel/pixel center. R_{ij} is the Euclidean distance from sub-pixel x_i to sub-pixel y_j, which is a sub-pixel in the mixed pixel.

$$R_{ij} = \sqrt{(m_i - m_j)^2 + (n_i - n_j)^2} \tag{2}$$

where (m_i, n_i) represents the coordinates of x_i, and (m_j, n_j) represents the coordinates of y_j.

Following the hypothesis of Mertens et al. (2006), attractions only exist between the sub-pixel and its 8 surrounding mixed pixels that are in a homogeneous land cover class. To obtain a reasonable attraction of the sub-pixel, the average attraction of the 8 surrounding mixed pixels is regarded as the final attraction strengths of the sub-pixel. The attraction $z(\omega_i)$ between the mixed pixel p_m and all mixed pixels of class z in its 8-pixel neighborhood is calculated as follows:

$$z(\omega_i) = \sum_{n=1}^{8} z(\omega_{in}) \tag{3}$$

2.1.2. Algorithm and mapping process of DSAM

Step 1: Calculate the attraction between pixels

The spatial attraction between the mixed pixel p_m and each adjacent mixed pixel containing each land cover class is calculated by Eq. (1). Because land cover classes are not assigned to sub-pixels in mixed pixels, the mixed pixels p_m and p_n are regarded as an entire pixel in the calculation, and Eq. (1) needs to be simplified to Eq. (4). The schematic diagram of step 1 is shown in Fig. 1a, and R_{mn} is the Euclidean distance from mixed pixel p_m to mixed pixel p_n.

$$z(\omega_{in}) = z(p_m)\cdot z(p_n)\frac{1}{R_{mn}^2} \tag{4}$$

Step 2: Initialize the algorithm

If the random allocations of sub-pixels are applied in the initialization (first assignment of sub-pixel land covers) of the sub-pixel, all the different land cover classes of sub-pixels will need to be swapped, which will lead to excessive iterations and operation time. The symmetric pattern is used to initialize the sub-pixels in the central mixed pixel in this study, and only the different sub-pixels of the symmetrical region need to be swapped, and the efficiency of the operation will be greatly improved.