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# Geostatistical modelling of spatial dependence in area-class occurrences for improved object-based classifications of remote-sensing images

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ABSTRACT

Geographical object-based image analysis (GEOBIA) is widely used for the processing of fine spatial resolution images, with increased research on contextual modelling and classification related to GEOBIA. Specifically, a previously developed object-based image classification method, known as geostatistically weighted *k*-NN (*gk*-NN) method, has shown advantages in increasing classification accuracy. The *gk*-NN method incorporates spatial weighting into the *k*-NN classifier through modelling spatial covariance of underlying area classes. However, change-of-support problem (COSP) due to different geometries of image objects is not considered therein. In this paper, we propose a method based on geostatistical de-regularization and regularization for quantifying spatial dependence in area-class occurrences and accounting for scale discrepancy in image objects and pixels. In this new modelling approach, an area-weighted (AW) distance measure is applied for modelling spatial covariance pertaining to sample image objects. The covariance model fitted with image objects sample data is de-regularized to a point-support one, so the spatial covariance over unsampled image objects can then be computed through regularization of a point-support model (RP). Unlike the previous modelling approach in the object-based *gk*-NN classification, whereby spatial dependence modelling is based on centroids of image objects, this method accounts for change of support and incorporates the geometry of image objects in modelling. The new modelling method was tested on three remote-sensing image subsets with different environments, using regular and irregular segmentation methods at hierarchical scales. It was confirmed that the RP method leads to largely significant increases in classification accuracies (with an average increase of 38.09% in classification accuracy with eighteen cases), compared with that by geostatistical modelling with image object centroids. The proposed method can be used for the modelling of spatial dependence in block-support data which are common in many geospatial applications.

## 1. Introduction

Geographical object-based image analysis (GEOBIA) has been commonly adopted to classify remotely sensed images of fine spatial resolution (Blaschke and Strobl, 2001; Castilla and Hay, 2008). In GEOBIA, segmentation is first applied to an image, decomposing it into relatively homogeneous objects (also known as segments) based on the arrangement of pixel values across the image, which should reflect real-world entities of interest (Newman et al., 2011). Then, classification is undertaken based on certain chosen discriminant features of image objects rather than individual pixels (Tang et al., 2016a). Proper descriptions of image objects features are important for their robust classifications (Huang and Zhang, 2013; Georganos et al., 2018), with spectral and geometric features conventionally used.

The importance of incorporating spatial contextual information (from neighbouring image objects) in image object classifications is increasingly recognized, as it is a general consensus that combined use of spectral and spatial contextual information will improve object-based classifications. Textural measures, indicators of spatial correlation, and landscape metrics have been used. In Chen et al. (2011), each image object and its neighbours were treated as a natural window/kernel for calculating a new set of object-based image texture measures, with extension work done by Chen et al. (2017). Local indicators of spatial association (LISA) measures (e.g., Moran's *I*) were used to calculate spatial autocorrelation in image objects (Kim et al, 2009; Johnson, 2015). Landscape metrics (Han et al., 2012; Zheng et al., 2017) were

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applied to extract semantic meaning for GEOBIA.

Spatial context for an image object is used in this paper as a general term to refer to its neighbourhood and the associated spatial dependence among image objects (their features and underlying class memberships) in the neighbourhood. Geostatistics provides a sound framework to quantify spatial dependence in spatial distributions (conceptualized as random fields, such as land cover classes and image intensities) based on covariance functions or variograms. It has been applied to increase accuracy in pixel-based classifications through proper modeling and incorporating spatial dependence in image classifications (Atkinson and Lewis 2000; Atkinson, 2004; van der Meer, 2012; Adjorlolo and Mutanga, 2013). Tang et al. (2016a, 2016b) extended pixel-based geostatistically weighted classifiers to object-based image classifications, and confirmed that incorporating contextual information leads to greater classification accuracies.

In the aforementioned studies, however, geostatistical modelling of spatial dependence in image objects is a simple extension of pixel-based approaches. In particular, by naïve treatment of image objects, distance measures are based on image objects centroids regardless of their differing geometry (e.g., Tang et al., 2016a, 2016b). This implies that models built from a set of sample image objects may not be adaptive or applicable to image objects of different geometries and configurations due to irregularities in image objects and the underlying landscapes.

As a matter of fact, the limitations of conventional modelling approaches lie in their ignoring the so-called change-of-support problem (COSP) (Cressie, 1996), which arises due to gaps between data supports (i.e., individual pixels, segments of pixels, and their complex configurations). The scale discrepancy due to different data supports needs to be considered when transforming information from data across different scales. Past work on geostatistical regularization and de-regularization (more challenging than regularization) techniques for cross-scale spatial dependence modelling is reviewed next, as they could be usefully synthesized for spatial structural modelling and predictive mapping with irregular spatial objects. Using a de-regularization technique for estimating point-support variograms, Kyriakidis (2004) proposed area-to-point (ATP) kriging, which allows predictions of punctual values from areal data, following the earlier works of Cressie (1996) and Gotway and Young (2002, 2004). Many researchers have applied or extended ATP kriging methods. Liu et al. (2008) used ATP residual kriging to disaggregate population-density data from irregular census units, while Dobarco et al. (2016) applied ATP kriging along with descriptive statistics for predicting soil texture. The ATP kriging method has also been extended to applications involving image data. For example, Pardo-Igúzquiza et al. (2006) proposed a downscaling cokriging (DSCK) method used for image sharpening, in which different supports are accounted for by estimating point-support variograms and cross-variograms (Pardo-Igúzquiza and Atkinson, 2007). Wang et al. (2015, 2016) applied ATP regression kriging for image sharpening and downscaling. For inversion of point-support variograms, Goovaerts (2008) described a deconvolution (i.e., de-regularization) method for geostatistical interpolation using health data measured over geographical units with different sizes and shapes. Truong et al. (2014) used Bayesian ATP conditional simulation to estimate point-support variogram parameters from expert knowledge and block-support data.

The aforementioned methods for handling COSP are either based on pixels (mostly for applications in remote sensing) or areal units (for applications in health, ecology, etc.). They are not specifically designed for image objects. In other words, there is a lack of methods suited for modelling spatial dependence in image objects of different geometries and configurations. This provides the motivation for this paper to explore methods to characterize spatial dependence accommodating irregularities in image objects. Therefore, in this paper, a geostatistical framework based on de-regularization and regularization techniques is proposed and customized to quantify spatial dependence in area-class occurrences of irregular image objects.

The methods section describes an improved $gk$-NN method for object-based image classification. This follows an illustrated discussion of what the conventional geostatistically weighted $k$-NN method lacks and detailed descriptions of procedures of de-regularization (for point-support model inversion) and regularization (for block-support model extension). The experiment section reports a study conducted as a supplement of a previously tested object-based geostatistically weighted $k$-NN ($gk$-NN) classification method. The focus of this study is not to pursue merely increased classification accuracies through classifier optimization, as in most applications regarding image classifications, nor to compare with other state-of-the-art classifiers, as done in previous research (Tang et al., 2016a, 2016b). Instead, the goal is to propose a geostatistical strategy to enhance classifications of image objects through spatial dependence modelling with flexible and effective handling irregular image objects.

## 2. Methods

### 2.1. The conventional geostatistically weighted k-NN method

The $gk$-NN method and its extension from point data to image objects is briefly reviewed, so we can have a clear view of what existing methods lack. In the remainder of the text, image objects are also referred to as objects. In the traditional $k$-NN method, the classifier allocates pixels to the neighbours to which it is closest in feature space (Steele and Redmond, 2001). In a geostatistically weighted $k$-NN classifier ($gk$-NN), the probability that a pixel $u$ belongs to class $m$ can be evaluated as follows (Atkinson and Naser 2010):

$$p_{gk-\mathrm{NN}}[c(u)=m] = \frac{\sum_{k=1}^{K}[S_g \times p_{m,m}(\mathbf{h}_{uk}) \times \omega_{uk} + (1-S_g)\times \omega_{uk}]}{\sum_{m'=1}^{M}\sum_{k=1}^{K}[S_g \times p_{m,m'}(\mathbf{h}_{uk}) \times \omega_{uk} + (1-S_g)\times \omega_{uk}]} \tag{1}$$

where the subscript $uk$ of $\mathbf{h}$ indicates lag between pixel $u$ and its neighbour $k$. $\omega_{uk}$ is a nearest neighbour weighting function. Inverse distance weighting (IDW) is applied here, based on the distance between $u$ and $k$ in feature space. Term $m'$ is a class index for $m' = 1, \ldots, M$ classes, and $m$ is the class of interest. $S_g$ is a geographical weight factor between 0 and 1. $p_{m,m}(\mathbf{h}_{uk})$ and $p_{m,m'}(\mathbf{h}_{uk})$ refers to class-conditional probabilities, which can be inferred from models of spatial covariance fitted with sample data. The class-conditional probability of a pixel $u$ belonging to class $m$, given a neighbour $k$ in class $m'$ at a given lag $\mathbf{h}$, is estimated by:

$$p_{m,m'}(\mathbf{h}_{uk}) = \frac{\sum_{i=1}^{N} I[c(\mathbf{h}) = m' | c(u) = m]}{\sum_{i=1}^{N} I[c(u) = m]} \tag{2}$$

where $N$ is the number of sample pixels in the image, and $c(\mathbf{h})$ represents the class value at lag $\mathbf{h}$ (i.e., the class at the neighbouring pixel location $k$). The $gk$-NN method can account for the spatial dependence between an unknown location and its $k$-NN (in the feature space) pixels. Therefore, both spectral and spatial information affect classification results.

For object-based image classifications, Tang et al. (2016a, 2016b) substituted pixels $u$ with image objects $v$ in Eqs. (1) and (2) based on an image segmentation result, where the lag $\mathbf{h}$ between objects $v$ and $k$ was calculated from the centroids of two objects. However, two problems arise with this. First, the lag (spatial distance) is not appropriately calculated when ignoring image objects geometry. Second, models of spatial covariance estimated from sample objects may not be applicable to the entire image being used due to irregularities of image objects.

Fig. 1 shows examples of a pair points, a pair of regular image objects, and a pair of irregular image objects, respectively. The distances between points in Fig. 1(a) and centroids of image objects in Fig. 1(b)

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