ISPRS Journal of Photogrammetry and Remote Sensing 64 (2009) 665–673

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Evaluating effects of spectral training data distribution on continuous field mapping performance

L. Mathys [a,b,*], A. Guisan [b], T.W. Kellenberger [c], N.E. Zimmermann [a]

[a] Land Use Dynamics, Swiss Federal Research Institute WSL, CH-8903 Birmensdorf, Switzerland
[b] Department of Ecology and Evolution, University of Lausanne, CH-1015 Lausanne, Switzerland
[c] Remote Sensing Laboratories, University of Zürich, CH-8057 Zürich, Switzerland

ARTICLE INFO

Article history:
Received 4 May 2008
Received in revised form
1 April 2009
Accepted 21 April 2009
Available online 2 July 2009

Keywords:
Continuous field
Generalised linear model
Spectral space
Mixed pixels

ABSTRACT

Continuous field mapping has to address two conflicting remote sensing requirements when collecting training data. On one hand, continuous field mapping trains fractional land cover and thus favours mixed training pixels. On the other hand, the spectral signature has to be preferably distinct and thus favours pure training pixels. The aim of this study was to evaluate the sensitivity of training data distribution along fractional and spectral gradients on the resulting mapping performance.

We derived four continuous fields (tree, shrubherb, bare, water) from aerial photographs as response variables and processed corresponding spectral signatures from multitemporal Landsat 5 TM data as explanatory variables. Subsequent controlled experiments along fractional cover gradients were then based on generalised linear models.

Resulting fractional and spectral distribution differed between single continuous fields, but could be satisfactorily trained and mapped. Pixels with fractional or without respective cover were much more critical than pure full cover pixels. Error distribution of continuous field models was non-uniform with respect to horizontal and vertical spatial distribution of target fields. We conclude that a sampling for continuous field training data should be based on extent and densities in the fractional and spectral, rather than the real spatial space. Consequently, adequate training plots are most probably not systematically distributed in the real spatial space, but cover the gradient and covariate structure of the fractional and spectral space well.

1. Introduction

Land cover represents the surface composition of the earth and relates to relevant biotic and abiotic landscape pattern and processes (DeFries et al., 1995; Schaepman, 2007). Land cover thus forms the basis for most landscape management and mapping activities. Land cover mapping often addresses landscapes larger than a square kilometre and therefore primarily uses remote sensing as the source of information. Remote sensing based land cover mapping is thus an important tool for effective landscape management, but requires that relevant surface properties are adequately represented in the final product.

Mapping of land cover generally follows two approaches: either using discrete land cover classes or continuous fields. Discrete land cover mapping, also known as hard classification, represents landscapes as a spatial mosaic of classified entities and is a widely applied approach (e.g. Anderson et al., 1976; Belward et al., 1999; DeFries et al., 1998; Friedl et al., 2002; Hansen et al., 2000; Homer et al., 2004; Mücher et al., 2000; Running et al., 1995). Each landscape entity, i.e. a remotely sensed pixel, is exclusively attributed to one land cover class and thus pools multiple land cover gradients. As a consequence, discrete classes cannot be disentangled to reproduce the full range and variability in landscape gradients that are often necessary to adequately quantify and manage landscape patterns and processes (DeFries et al., 1995). Moreover, the variable range included within discrete classes may vary considerably between land cover gradients and classes (Mathys et al., 2006), and therefore make different spatio-temporal representation of land cover incomparable. Effective landscape management thus also requires continuous field approaches (DeFries et al., 1995; Fernandes et al., 2004; Mathys et al., 2006; Schwarz and Zimmermann, 2005).

A single continuous field (SCF), also termed fractional or sub-pixel cover, is a gradient in landscape property (see Fernandes

* Corresponding address: Sigmaplan, Thunstrasse 91, CH-3006 Bern, Switzerland. Tel.: +41 31 356 65 65; fax: +41 31 356 65 60.
E-mail address: lukas.mathys@sigmaplan.ch (L. Mathys).

0924-2716/$ – see front matter © 2009 International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS). Published by Elsevier B.V. All rights reserved.
doi:10.1016/j.isprsjprs.2009.04.005

et al., 2004; Ichoku and Karnieli, 1996, for a review on nomenclature and methodological approaches). Every landscape entity consists of multiple SCFs, each representing a separate property of the landscape. By this, the necessary diversity and range of land cover gradients is conserved and not reduced to one land cover class (Di Gregorio and Jansen, 1998). SCFs have been investigated for example for tree vegetation (DeFries et al., 2000; Fernandes et al., 2004; Hansen et al., 2002a; Schwarz and Zimmermann, 2005), impervious areas (Deguchi and Sugio, 1994; Ji and Jensen, 1999; Lu and Weng, 2006; Yang et al., 2003), and snow cover (Foppa et al., 2004; Rosenthal and Dozier, 1996; Salomonson and Appel, 2004). However, land cover is rarely described by one SCF, but mostly a composition of multiple continuous fields (MCF). Adequate land cover mapping needs to include all relevant SCFs, which sum up to the entire landscape. Ridd (1995) proposed an MCF approach to map urban ecosystems as a ternary model of vegetation, impervious surface and soil (V-I-S), which has been implemented for several optical data sources and study areas (Hung and Ridd, 2002; Phinn et al., 2002; Rashed et al., 2003). Others have investigated MCFs ranging from impervious surface-managed/unmanaged lawn-tree cover (Lee and Lathrop, 2005) to fire–woody–herbaceous–barren–water (Shabanov et al., 2005) and forest property gradients (Mathys et al., 2006). More generally, Di Gregorio and Jansen (1998) provided a generic continuous field approach for the composition of entire landscapes. Hence a great variety of models and approaches exist to model single continuous fields.

A multiple continuous field approach addresses several land cover gradients at the same time. Hence, one spectral combination at one pixel is simultaneously referred to separate SCFs, which corresponds to a one-to-many relationship in the spectral domain. In contrast, discrete mapping approaches relate the spectral combination at one pixel to one class and therefore have to solve only a one-to-one relationship. The mapping performance of a MCF approach thus depends on: (1) the spatial composition of the SCFs within the pixels of a landscape, and (2) the spectral property of the respective SCFs. So far, fractional (Fernandes et al., 2004) and spectral properties (Schaepman, 2007) of SCFs have been studied intensively, but mostly separately.

We hypothesise that spatial composition and spectral properties of SCFs depend on each other in an MCF approach and consequently result in different sampling strategies for training remotely sensed data. The ultimate goal of MCF mapping is to fully represent SCF gradients. This requires that the whole gradient is present in the landscape and sampled accordingly in the training datasets. Often however, a landscape is far from ideal and certain ranges of a SCF are under- or over-represented (e.g. aggregated landscape elements result in many pixels with full or without respective cover). Mapping of SCFs in an MCF approach thus faces two contradicting requirements. On one hand, the MCF approach requires that SCF gradients be well represented in the training data and therefore favours mixed pixels. On the other hand, a robust calibration of remote sensing data requires distinct spectral signatures for characterizing end-members as purely as possible, which is better achieved with spectrally pure pixels.

The aim of this study was therefore to investigate (1) the fractional and (2) the spectral dependency of SCFs in an MCF approach. Specifically, we were interested in testing the effects that different sampling approaches along compositional gradients have upon fractional land cover mapping performance, i.e., (1) no, fractional, and full SCF cover, and (2) spectrally mixed to pure pixels. Hence, we selected four SCFs that were (1) spatially aggregated (many pixels with no or full SCF cover) versus scattered (many pixels with fractional cover), and represented (2) spectrally similar versus differing types: tree vegetation, shrubherb vegetation, bare areas and open water. SCF training and evaluation data were derived from aerial photographs in a regularly spaced 500 m sampling design. For each sample plot we processed the corresponding spectral signature from multitemporal Landsat 5 TM images. Hence, SCFs were our response variables and the corresponding spectral signatures our explanatory variables. We then performed selected fractional and spectral experiments using generalised linear models to infer the fractional-spectral relationship of SCF mapping in an MCF approach. Using this design, we aimed at testing our hypotheses that the mapping performance of SCFs depends on the compositional structure (MCF) and the resulting spectral discrimination within a pixel. The results ultimately aim at finding an optimal sampling strategy for SCF training and evaluation data.

2. Material and methods

2.1. Study area

In order to evaluate the fractional and spectral dependency of SCFs in an MCF approach, we selected a study area, where the fractional and spectral variability were high but the temporal variability was low. We therefore chose a rectangular study area in Western Switzerland (74.6 km $\times$ 45.1 km with the lower left corner at $47°0'39.57''$ N/$7°4'24.15''$ E and the upper right corner at $47°24'54.44''$ N/$8°3'30.36''$ E) that included large gradients in landscape fractions, and where all training and evaluation data were available for the same time period. The north–western and south–eastern sections of the study area were more rural landscapes characterised by a rich structured forest-pasture and village mosaic. The central part also included cities and intensive agricultural areas. Hence, the study area included forest, pasture and urban transformation gradients.

2.2. Response single continuous fields

Response variables used to train and evaluate SCFs were derived from a National Landscape Inventory, NLI (Mathys et al., 2006), which is part of the Swiss National Forest Inventory (NFI© 2009 WSL). The NLI samples the landscape at regularly 500 m spaced sample plots of 50 m $\times$ 50 m dimension. At each sample plot, manual interpreters assessed SCFs based on 25 (5 by 5) regularly distributed and 10 m spaced lattice points. The corresponding SCFs were interpreted from digital true colour aerial photographs using a 3D stereo softcopy station (Socet Set 5.0, BAE Systems). The photographs were taken in 1998 at a scale of 1:30 000 and scanned at a resolution of 14 μm, resulting in an average ground resolution of 0.42 m and a RMSE after triangulation of <1 m. Each of the 25 lattice points within each NLI sample plot was attributed to one of the following land cover elements and a corresponding height in metres above ground: tree vegetation (woody vegetation ≥ 3 m), shrubs (woody vegetation <3 m), grasses and herbaceous vegetation, gravel/sand/soil, rock, impervious areas, constructed objects, open water and snow/glacier. The value for a SCF per sample plot was derived as the fraction of respective land cover lattice points per sample plot. To perform our experiments we aggregated the elements to four SCFs based on our hypotheses: tree (tree vegetation), shrubherb (shrubs, grasses and herbaceous vegetation), bare (gravel, sand, soil, rock, impervious areas and constructed objects), and water (open water). Snow and glaciers were not present in this study area.

2.3. Explanatory spectral signatures

Explanatory variables were derived from multitemporal spectral signatures of three cloud-free Landsat 5 TM images (Satellite Image© ESA/Eurimage/swisstopo, NPOC), path 195/row 27 (study