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Temporal optimisation of image acquisition for land cover classification with Random Forest and MODIS time-series

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ABSTRACT

The analysis and classification of land cover is one of the principal applications in terrestrial remote sensing. Due to the seasonal variability of different vegetation types and land surface characteristics, the ability to discriminate land cover types changes over time. Multi-temporal classification can help to improve the classification accuracies, but different constraints, such as financial restrictions or atmospheric conditions, may impede their application. The optimisation of image acquisition timing and frequencies can help to increase the effectiveness of the classification process. For this purpose, the Feature Importance (FI) measure of the state-of-the art machine learning method Random Forest was used to determine the optimal image acquisition periods for a general (Grassland, Forest, Water, Settlement, Peatland) and Grassland specific (Improved Grassland, Semi-Improved Grassland) land cover classification in central Ireland based on a 9-year time-series of MODIS Terra 16 day composite data (MOD13Q1). Feature Importances for each acquisition period of the Enhanced Vegetation Index (EVI) and Normalised Difference Vegetation Index (NDVI) were calculated for both classification scenarios. In the general land cover classification, the months December and January showed the highest, and July and August the lowest separability for both VIs over the entire nine-year period. This temporal separability was reflected in the classification accuracies, where the optimal choice of image dates outperformed the worst image date by 13% using NDVI and 5% using EVI on a mono-temporal analysis. With the addition of the next best image periods to the data input the classification accuracies converged quickly to their limit at around 8–10 images. The binary classification schemes, using two classes only, showed a stronger seasonal dependency with a higher intra-annual, but lower inter-annual variation. Nonetheless anomalous weather conditions, such as the cold winter of 2009/2010 can alter the temporal separability pattern significantly. Due to the extensive use of the NDVI for land cover discrimination, the findings of this study should be transferrable to data from other optical sensors with a higher spatial resolution. However, the high impact of outliers from the general climatic pattern highlights the limitation of spatial transferability to locations with different climatic and land cover conditions. The use of high-temporal, moderate resolution data such as MODIS in conjunction with machine-learning techniques proved to be a good base for the prediction of image acquisition timing for optimal land cover classification results.

Introduction

Analysis of land cover is one of the principal applications in terrestrial remote sensing, however, the timing and frequency of image acquisition, among other factors, can limit the accuracy with which different land cover types and changes can be distinguished (Carrão et al., 2008; Lunetta et al., 2004). If the optimal number and dates of images for land cover classification can be identified in advance, the efficiency with which the image processing is undertaken can be enhanced. In practice, the optimal acquisition date(s) are often determined following assessment of the variability in spectral signature of classes of interest for site specific applications. With the systematic examination of remote sensing time-series and feature selection techniques this process can be automated.

While feature selection processes are important for improved image classification, or for an increased understanding of the classification rules (Liu et al., 2005), their most frequent field of application is in bioinformatics; where predictive variables are extracted from gene sequences (Díaz-Uriarte and Alvarez de Andrés, 2006). To date, only a limited number of studies

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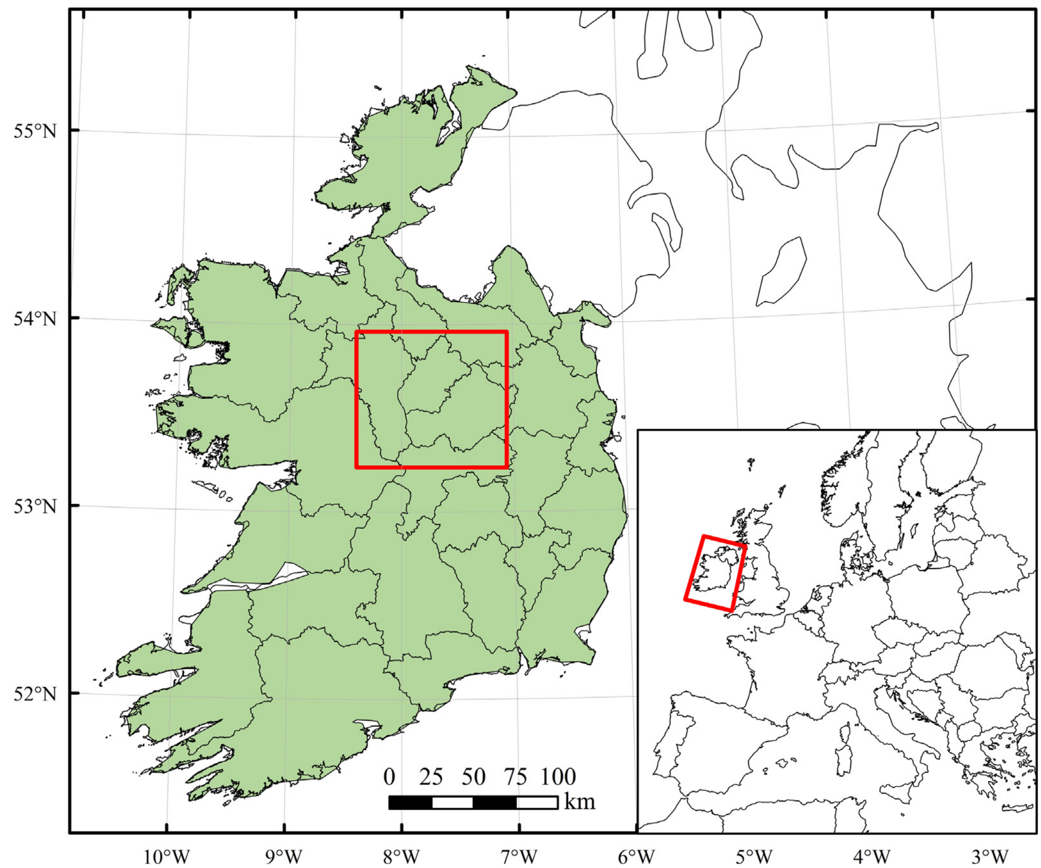

Fig. 1. Geographical location and extent of the study area.

have been published, which explore methods of advanced feature selection within multispectral or multitemporal imagery. Van Niel et al. (2005) used the Jeffries–Matusita (JM) distance for crop classification in Australia, Carrão et al. (2008) utilised a median Mahalanobis distance for general land cover classification in Portugal and Lhermitte et al. (2011) compared time-series of different Vegetation Indices with several mathematical distance metrics. In contrast, hyperspectral remote sensing approaches to feature selection have been widely used for the reduction of dimensionality (e.g. Serpico and Bruzzone, 2001; Pal, 2006; Guo et al., 2008; Pal and Foody, 2010). Analogous to bioinformatics, different embedded approaches like Recursive Feature Elimination (RFE) for Support-Vector-Machines (SVM) (Pal and Foody, 2010) and the Feature Importance measure within Random Forest (Stumpf and Kerle, 2011), as well as distance based measures, such as Bhattacharyya or JM (Guo et al., 2008) have been widely used.

Hyperspectral and hypertemporal datasets have a very similar structure; containing a high number of correlated spectral bands. The difference lies in their variable dimension, namely the spectral domain for hyperspectral data and the temporal domain for hypertemporal data. Therefore, methodologies for the reduction, or selection, of the data used in the former should be transferrable for the optimisation of data acquired over a period of time. Hypertemporal data are generated from a platform which offers a high temporal resolution and a sufficiently long time-series such as AVHRR (Hill et al., 1999; Hermance et al., 2007), MERIS (Zurita-Milla et al., 2009; Carrão et al., 2010; O'Connor et al., 2012) or MODIS (Lunetta et al., 2006; Carrão et al., 2008; Wardlow and Egbert, 2008; Pringle et al., 2012). Typically, Normalised Difference Vegetation Index (NDVI) or other sensor-specific Vegetation Indices (VI) serve as the base for land-cover and crop type classification or phenological analysis from regional to global scales. Although universally applied, NDVI has its drawbacks. It is susceptible to soil and atmospheric influences and saturates in dense vegetation canopies (Huete et al., 2011). Sensor specific VIs such as the MODIS Enhanced Vegetation Index (EVI) captures vegetation phenology more accurately and can demonstrate sharper growing season peaks and greater sensitivity to canopy structure differences (Xiao et al., 2003; Huete et al., 2011).

Due to cloud contamination, atmospheric variability and bidirectional effects, the signal of the time-series of hyper-temporal datasets can be severely affected by noise, demonstrating highly volatile behaviour in their raw state. In countries like Ireland, where cloud cover and atmospheric attenuation are persistent, time compositing procedures such as extraction of maximum values over a given period are widely applied (O'Connor et al., 2012), but noise can still prevail (Chen et al., 2004). To overcome the random spikes in the composited time-series, different smoothing techniques have been used, ranging from Fourier based filters (Sellers et al., 1994; Chen et al., 2004) to different types of curve fitting functions (Jonsson and Eklundh, 2002; Chen et al., 2004; Beck et al., 2006; Atzberger and Eilers, 2011).

In this paper we present an analysis of the separability of different land-cover classes at different times of year using a MODIS Terra 16-day composite time-series and the internal Feature Importance measure of the machine-learning Random Forest algorithm (Breiman, 2001). The performance of NDVI and EVI vegetation index time-series are compared, and single year fluctuations as well as long-term trends are analysed over a 9-year period.