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Assessment of a Markov logic model of crop rotations for early crop mapping

Julien Osman, Jordi Inglada *, Jean-François Dejoux

CESBIO – UMR 5126, 18 avenue Edouard Belin, 31401 Toulouse Cedex 9, France

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ABSTRACT

Detailed and timely information on crop area, production and yield is important for the assessment of environmental impacts of agriculture, for the monitoring of the land use and management practices, and for food security early warning systems. A machine learning approach is proposed to model crop rotations which can predict with good accuracy, at the beginning of the agricultural season, the crops most likely to be present in a given field using the crop sequence of the previous 3–5 years. The approach is able to learn from data and to integrate expert knowledge represented as first-order logic rules. Its accuracy is assessed using the French Land Parcel Information System implemented in the frame of the EU's Common Agricultural Policy. This assessment is done using different settings in terms of temporal depth and spatial generalization coverage. The obtained results show that the proposed approach is able to predict the crop type of each field, before the beginning of the crop season, with an accuracy as high as 60%, which is better than the results obtained with current approaches based on remote sensing imagery.

1. Introduction

Detailed and timely information on crop area, production and yield is important for the assessment of environmental impacts of agriculture (Tilman, 1999), for the monitoring of the land use and management practices, and for food security early warning systems (Gebbers and Adamchuk, 2010). Yield production can be forecasted using models which need information about the surface covered by each type of crop (Resop et al., 2012).

There are different ways of gathering this information, such as statistical surveys or automatic mapping using Earth observation remote sensing imagery. Statistical surveys are expensive to implement, since they need field work, which is time consuming when large areas need to be covered. The use of remote sensing imagery has been found to produce good quality maps when using high resolution satellite image time series (Inglada and Garrigues, 2010). These approaches use supervised classification techniques which efficiently exploit satellite image time series acquired during the agricultural season. Describing the approach used for the supervised classification of satellite images is beyond the scope of this paper and the details can be found in (Inglada and Garrigues, 2010; Petitjean et al., 2012) or (Petitjean et al., 2014).

As an example of these approaches, Fig. 1 presents a 5-class crop map obtained using a time series of 13 images acquired by the Formosat-2 satellite during 2009 over a study site near Toulouse in Southern France. The data set is described in Osman et al. (2012). The supervised classification is performed using a Support Vector Machine as described in Inglada and Garrigues (2010). The resulting classification has an accuracy close to 90%. However, this accuracy can only be achieved at the end of the agricultural season when all images are available. This delay in crop map production has led the remote sensing community to develop near-real-time approaches, where the maps are updated during the season every time a new image is available. Fig. 2 shows the evolution of the accuracy of each map produced during the season. A point in the curve represents the accuracy obtained using all the images available up to a given date. In this particular example, one can observe that a quality close to the maximum can be obtained before 200 days into the year. However, no information is available before the first image is acquired at the end of January. For many crop systems, the beginning of the season coincides with the end of Autumn or the beginning of Winter. In this period, satellite images are very likely to be cloudy and therefore of little use for crop mapping. Furthermore, the accuracy of the

* Corresponding author.
E-mail address: jordi.inglada@cesbio.eu (J. Inglada).

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0168-1699/

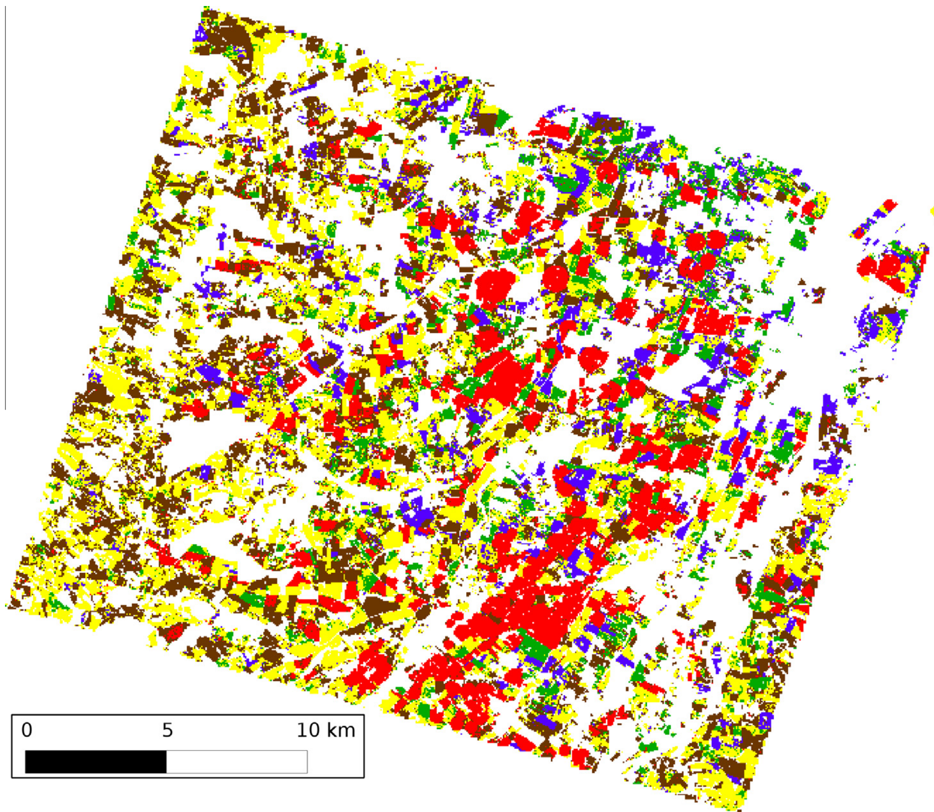

Fig. 1. Example of crop map obtained by supervised classification of satellite image time series. Only croplands are classified. Corn (red), wheat (yellow), rapeseed (purple), barley (green), sunflower (brown). White areas represent non croplands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

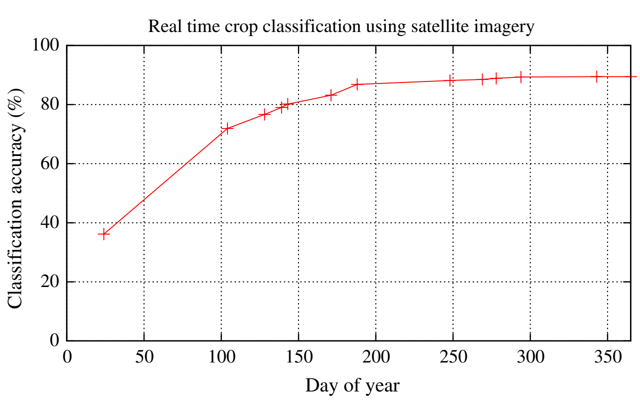

Fig. 2. Classification accuracy obtained with satellite image time series. Each cross represents a new image acquisition. The accuracy increases when more images are available.

land cover classification obtained with only one image is below 40%, which is not enough for most applications.

The goal of this paper is to introduce an approach which is able to produce land cover maps for agricultural areas at the beginning of the crop season without relying on remote sensing imagery. We propose to use the knowledge about the crop type which was present in every field the previous seasons to predict the crop grown the current year. The proposed approach uses a statistical model for crop rotations.

Crop rotations – specific sequences of crops in successive years – improve or maintain crop yield while reducing input demands for fertilizers and pesticides, and therefore they are widely used by farmers. This regularity on the agricultural practices allows predicting with some accuracy the type of crop present in a given field at one point in time if the previous crop sequence is known.

Many crop rotation models exist, ranging from purely agronomic (crop-soil simulation models (Wechsung et al., 2000)), to approaches integrating expert knowledge and field data (Dogliotti et al., 2003). The complexity of these models makes them difficult to adapt to variable situations and evolving conditions. Crop rotations may evolve in time, either slowly due to for instance climate change impact in rain-fed crops, or very quickly due to environmental regulations dealing with the use of pesticides or water management. Economic factors, as for instance seed prices, can also introduce drastic changes. Hence, crop rotation models which can be easily updated and which can exploit the history of the different territories are needed.

Yearly cropland mapping can be obtained either using farmers administrative declarations or maps produced using remote sensing data at the end of the season (like the one of Fig. 1). Therefore, the history of the fields can be known.

We propose a machine learning approach to model crop rotations which can predict, at the beginning of a season, with good accuracy, the crops the most likely to be present in a given field, using the crop sequence of the previous 3–5 years.

We assess its accuracy using the French Land Parcel Information System RPG in different settings in terms of temporal depth and spatial generalization coverage.

The paper is organized as follows. In Section 2, we review several approaches for crop rotation modeling in the literature. Section 3 presents the proposed approach. In Section 4, we present the type of data on which our approach relies and we define the experimental setup used for this work; then, we present the details