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Local adjustments of image spatial resolution to optimize large-area mapping in the era of big data

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ABSTRACT

Sentinel-2 has opened a new era for the remote sensing community where 10-m imagery is freely available with a 5-day revisit frequency and a systematic global coverage. Having both frequent and detailed observations across large geographic areas are ideal characteristics that can potentially revolutionize applications such as crop mapping and monitoring. However, such large volumes of high-resolution data pose challenges to users in terms of problem complexity, computational resources and processing time, beckoning the increasingly relevant question: at which resolution should this imagery be processed? Here, we develop a methodology to characterize resolution-dependent errors in cropland mapping and explore their behavior when we move across spatial scales and landscapes, taking special care to include the effects of the instrument's Point Spread Function (PSF). Results show how local upscaling of 10-m imagery, *e.g.*, from Sentinel-2, to 30 m mitigates most the adverse effects generated by the PSF when comparing it to native 30-m imagery, *e.g.*, from Landsat-8. Extending this logic, we demonstrate for two nationwide cases how maps can be calculated showing the optimal spatial resolution that keeps resolution-dependent errors below a user-defined threshold. Based on these maps, we estimate that 31% of Belgium and 59% of South Africa could be processed at 20 m instead of 10 m, while keeping the increase of resolution-dependent errors below 3%. These local resolution adjustments lead to a reduction in data volume and processing time by 23% and 44%, respectively.

1. Introduction

The Sentinel-2 constellation has opened a new era for satellite Earth Observation. Systematic acquisition at decametric spatial resolution, *i.e.*, 10 m, with 5-day revisit frequency are now available at no cost for the entire globe. This unique observational configuration guaranteed by the operational commitment of the Copernicus Program of the European Union has the potential to revolutionize many applications as the traditional bottleneck of data availability is being lifted. This may bring a paradigm shift towards more data-intensive scientific research and discovery (Hey et al., 2009), as well as enabling the development of many new services for society as a whole.

This great opportunity to increase knowledge of the Earth System also comes with great challenges for both scientists and information technology experts (Nativi et al., 2015). In operational applications, a new bottleneck of a different nature has emerged: timeliness. Data availability can take the form of a data tsunami, posing serious challenges to store, process and deliver remote sensing products to users in due time. This can be a problem for stakeholders as diverse as cloud services providers, who need to optimize on-the-fly data processing and delivery across the Internet, and users with limited computational and communication infrastructures.

Yet, for many applications, the spatial resolution requirements may vary spatially depending on the structure and fragmentation of the landscape (Ozdogan and Woodcock, 2006; Duveiller and Defourny, 2010; Löw and Duveiller, 2014; Waldner and Defourny, 2017). In this new data-rich environment, could we not reduce the burden of overload by finding an optimized resolution that can be spatially adjusted, and to which imagery can be aggregated to, thereby reducing the cost and time of storage, processing, and distribution while minimizing the loss of precision?

Finding the optimal pixel size is a general subject of interest in cartography and geosciences (Hengl, 2006). In the satellite remote community, it has been a particularly recurring and intense topic of investigation. Various authors have explored the question by aggregating fine spatial resolution imagery to increasingly coarser resolutions whilst analyzing the behavior of specific metrics calculated at every step (Woodcock and Strahler, 1987; Marceau et al., 1994; McCloy

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and Bocher, 2007; Duveiller and Defourny, 2010; Löw and Duveiller, 2014). Others have utilized geostatistics and variograms to identify an optimal spatial resolution based on the landscape's spatial heterogeneity (Atkinson and Curran, 1995, 1997; Curran and Atkinson, 1998; Garrigues et al., 2006). However, the question has typically been framed in a context of identifying the coarsest tolerable spatial resolution for a given application, so as to guide the choice of an instrument/platform amongst those available that satisfy other criteria (such as sufficient revisit frequency). That question can now be asked from the point of view of data volume reduction. We have moved from a situation dominated by what Strahler et al. (1986) described as an L-resolution model to that of an H-resolution model. In the H-resolution, image pixels are smaller than the actual objects in the image (*i.e.*, the crop specific fields for agricultural applications) whereas, in the L-resolution, the pixel size exceeds the object size. This has a strong impact on image classification. When the image objects are smaller than the pixels (L-resolution), one faces the typical challenge of classifying mixed pixels. But classification can also be difficult when image objects are larger than the pixels (H-resolution), as the within-class variance is likely to be high and could thus decrease class separability and accuracy (Marceau et al., 1994). This has progressively led to the emergence of the geographic object-based image analysis (GEOBIA) paradigm (Blaschke et al., 2014). However, a major problem in GEOBIA is the additional computational cost and parametrization that are required for image segmentation. Furthermore, typical region-growing segmentation is generally not easily scalable and transposable. Therefore, a strong incentive remains in exploring how optimizing pixel size could reduce data size while retaining the squared structure of the pixels, such as with quad-tree compression algorithms (Spann and Wilson, 1985), but maintaining the properties of the imagery necessary for a given application, such as land cover classification.

The objective of this study is to evaluate the feasibility of local adjustments of image spatial resolution to reduce the data volume and thus optimize data processing and delivery in the context of large-area mapping. By local adjustments, we mean to coarsen the native resolution of images to resolutions according to the landscape complexity. To achieve this, we develop a methodology to characterize resolution-dependent errors and explore their behavior across spatial scales and landscape fragmentations, taking special care to model the effects of the Point Spread Function (PSF) of the sensor. We choose to focus on cropland mapping at country scale, an application that has strong requirements in terms of accuracy, timeliness, and frequency of product delivery. The final outcomes are maps of the coarsest acceptable spatial resolution that would maintain resolution-dependent errors under a given threshold, along with the associated gains in computing time and storage size.

2. Background

Before addressing this question directly, it is worth recalling some key concepts about spatial resolution and scale in remote sensing. The scale can be defined as the number and the size of the spatial sampling units used to partition a geographic area (Lam and Quattrochi, 1992). However, a distinction must be made between the physical sampling of the observations by the instrument and the spacing of the grid in which the data is provided. Here, we refer to the on-ground distance between the centers of two observations as the Ground-projected Sampling Interval (GSI; see Fig. 1 and Table 1 for definitions of the main scale-related terms).

The spacing between the ground projection of two pixels is referred to as pixel size (and denoted ν). These can differ even on a single scan line on whiskbroom instruments such as the MODerate resolution Imaging Spectroradiometer (MODIS), where increasing viewing angle combined with Earth's curvature lead to larger GSI at the edge of the swath than at nadir, while the pixel size of the delivered image remains the same. Another common misconception is that the shape of the observation footprint corresponds to the rectangular ground projection of the pixel (Cracknell, 1998). Instead, a substantial portion of the measured radiance originates from surrounding areas (Townshend, 1981; Forster and Best, 1994). At every ground sampling interval, a detector measures the incoming radiance within its instantaneous field of view (IFOV) during a specific time interval. The IFOV is an angular measure and its ground projection is known as the GIFOV. The width of the GIFOV does not exactly match the GSI because of several factors such as the optics of the instrument, the electronics of the detector, and the image motion (Markham and Barker, 1986; Schowengerdt, 2007). Thus the image of the scene viewed by the sensor is not a completely faithful reproduction of the real ground features. Small details are blurred relative to larger features and this blurring effect can be characterized by the net sensor point spread function. The PSF is sometimes described by the Modulation Transfer Function (MTF) which is its equivalent in the frequency domain. Several studies investigated the impact of the PSF/MTF on land cover classification (Huang et al., 2002), sub-pixel landscape feature detection (Radoux et al., 2016), and sub-pixel class proportion estimation (Huang et al., 2002).

3. Data and study sites

To best illustrate our approach, we require national-scale study sites that offer varying field sizes and landscapes, and for which accurate field boundary data are available. We identify Belgium and South Africa as two contrasting countries that fit these selection criteria. Belgium is located in the northwest of Europe, between 51°30′ and 49°30′N, and 2°33′ and 6°24′E. In spite of its small size (30,528 km^2), agricultural landscapes are quite diverse. They occupy almost 60% of the land, with a decreasing the proportion of cropland to pasture along the North-South gradient. South Africa is located on the southern tip of the African continent and lies between latitudes 22° and 35°S, and longitudes 16° and 33°E spreading over 1,221,037 km^2. Only 12% of South Africa's land is used for crop production, and only 22% of this is high-potential arable land. The main growing regions lie along the fertile soils of the Western Cape and KwaZulu-Natal provinces. Both smallholder and large-scale industrial farming systems are present.

Nationwide field boundary datasets are available for both countries in the form of vector files of field boundary polygons. Field boundary polygons describe the smallest management unit for crop production. Each digitized field typically corresponds to a single crop, except in mixed-cropping systems. These vector datasets are first rasterized to 3 m pixels, which corresponds approximately to the spatial resolution at which the fields were originally digitized. To avoid having to process the entire national extent, a regular sampling scheme is adopted to select representative blocks of 3 m pixels that will serve to characterize the spatial resolution requirements at those specific sample areas. The rationale to define the extent of the sample blocks is that these should be larger than the size of the spatial features of interest (*i.e.*, the fields) by a couple of orders of magnitude, but remain smaller than the agro-ecological region that characterizes the spatial patterns of the landscape. In practice, this amounts to sample blocks of $5{,}000 \times 5{,}000$ pixels, or 15×15 km, over which a binary mask is extracted which takes the value of 1 where it covers the target fields and 0 otherwise. Sample blocks with less than 100 cropland pixels are discarded. The grid spacing isadjusted for each country to better represent their respective landscape variability, resulting in grids with sample blocks of the same size but with different densities. In total, 380 sample blocks were available for South Africa, and 120 for Belgium. These will henceforth be referred to as very high resolution (VHR) binary maps.

4. Methods

This section is organized into four parts. In Section 4.1, we recall the concept of the Pareto boundary and introduce how it can be extended across scales. In Section 4.2, we detail the three different modeling