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Smallholder crop area mapped with wall-to-wall WorldView sub-meter panchromatic image texture: A test case for Tigray, Ethiopia

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A B S T R A C T

Global food production in the developing world occurs within sub-hectare fields that are difficult to identify with moderate resolution satellite imagery. Knowledge about the distribution of these fields is critical in food security programs. We developed a semi-automated image segmentation approach using wall-to-wall sub-meter imagery with high-performance computing to map crop area (CA) throughout Tigray, Ethiopia that encompasses over 41,000 km^2. Multiple processing streams were tested to minimize mapping error while applying five unique smoothing kernels to capture differences in land surface texture associated to CA. Typically, very-small fields (mean < 2 ha) have a smooth image roughness compared to natural scrub/shrub woody vegetation at the ~1 m scale and these features can be segmented in panchromatic imagery with multi-level histogram thresholding. Multi-temporal very-high resolution (VHR) panchromatic imagery with multi-spectral VHR are sufficient in extracting critical CA information needed in food security programs. A 2011 to 2015 CA map was produced, using over 3000 WorldView-1 panchromatic images wall-to-wall in 1/2° mosaics for Tigray, Ethiopia. CA was evaluated with nearly 3000 WorldView-2 2 m multispectral 250 × 250 m image subsets by seven expert interpretations, and with in-situ global positioning system photography. CA estimates ranged from 32 to 41% in sub regions of Tigray with median maximum per bin commission and omission errors of 11% and 1% respectively, with most of the error occurring in bins < 15%. This empirical, simple, and low direct cost approach via U.S. government license agreement to access commercial VHR data, could be a viable big-data high-performance computing methodology to extract wall-to-wall CA for other regions of the world that have very-small agriculture fields with similar image texture.

1. Introduction

1.1. Background of crop area mapping in Africa

The anthropogenic imprint on global vegetation productivity is increasing through land allocation to food and fiber production for the Earth's growing human population (Foley et al., 2011; Haberl et al., 2007; Imhoff et al., 2004; Running, 2012). Ethiopia's population alone, over the past ~70 years, has increased from ~20 million in 1955 to over 100 million today (CIA, 2017; WorldBank, 2017; worldometers 2017). Approximately 80% of Ethiopians are rural rain-fed subsistence farmers or livestock producers dispersed throughout the country (FarmAfrica, 2017). This rapid, 2 to 3% per year population growth rate, has increased demand for food/fiber production and expanded crop area (CA) placing pressure on ecosystems by reducing the extent of natural wildland cover through conversion to pasture and subsistence agriculture (Ellis and Ramankutty, 2008). The impact of this pressure has already been documented in East Africa (Brink et al., 2014). Growth of CA is expected to continue throughout this century, and the most rapid global trends over the next 30 years are estimated to occur in sub-Saharan Africa (SSA) where population densities are anticipated to increase (Haney and Cohen, 2015).

Monitoring CA change and enhancing geospatial knowledge of regions that are more susceptible to drought impacts are fundamental

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goals of famine early warning systems (See et al., 2015). Weather index insurance programs have been established in which an insurance policy is linked to an index, such as rainfall, temperature, humidity or vegetation greenness rather than actual crop loss. This approach solves typical problems of implementing a traditional crop insurance in rural parts of developing countries (Hazell et al., 2010; Hellmuth et al., 2009) by linking payouts to critical variable thresholds during sensitive periods of the agricultural season. Since payouts are decoupled from crop yield, whose assessment is very costly for small farm sizes, index insurance pays out faster and is usually more affordable. Weather index insurance programs have been implemented to increase the food security of smallholder farmers to protect them against financial ruin from drought events that could induce widespread famine (Greatrex et al., 2015; Tadesse et al., 2015) and to promote prudent risk taking with regard to agricultural inputs. For successful implementation, weather index insurance requires robust meteorological data coupled with other remote sensing products (Brown et al., 2011; Enenkel et al., 2016).

The assumption used with index insurance is typically villages only have one weather station representing an area of 20–25 km in radius and farms within this domain are expected to have similar agro climatic conditions, e.g. homogenous topography and farming systems. This becomes problematic when topography, soil conditions and more diverse agro-ecologies exist (Gommes and Gobel, 2013), which is common in many SSA countries, such as Ethiopia. Remote sensing data coupled with in situ validation could reduce this deficiency. Five important applications of remote sensing for weather index insurance include: 1) CA mapping, 2) vegetation vigor and drought stress monitoring, 3) assessment of crop phenology development, 4) biomass and yield estimation, and 5) mapping of disturbances and land use/land cover changes (Atzberger, 2013). In this study, a focus on CA mapping was applied because a field-scale map could provide critical spatial information about the distribution of stakeholders that could be susceptible to crop failure, similar to the data needed for crop insurance policies available to growers in the U.S (Shields, 2015) via the U.S. Department of Agriculture (USDA) Risk Management Agency (RMA).

Current estimates of CA in SSA differ greatly due to the very small size of fields under cultivation and the overall lack of consistent government estimates (Ramankutty et al., 2008; Samberg et al., 2016; See et al., 2015). In Ethiopia, these fields are rain-fed and sub-hectare in size, typically $< 50 \times 50$ m, which makes resolving their distribution difficult with moderate resolution (30–500 m) satellite imagery (Leroux et al., 2014). A potential solution to this problem could be using satellite remote sensing data products at resolutions < 5 m wall-to-wall for large areas (Waldner et al., 2015). In most cases, this would be considered impractical, due to limited data availability and the high costs of acquiring ($>$ \$10 U.S. per km^2 for archived commercial imagery (LANDinfo, 2017)) and processing these data. However, these limitations are waning due to three primary factors that reduce costs and improve processing efficiency including:

1) no-direct cost access to very-high resolution (VHR) DigitalGlobe (DG) imagery that supports U.S. government interests (Neigh et al., 2013);
2) increased access to high-performance computing (HPC), at lower costs, to process these data (Lee et al., 2011); and
3) open-source software (GDAL, 2017; Shean et al., 2016) that can be distributed in a HPC environment to process sub-meter imagery in a timely manner without the high cost of proprietary software.

Many opportunities exist to develop CA mapping algorithms and process sub-meter data in an automated and/or semi-automated manner. This information is critical because smallholder farms are the most prevalent form of agriculture in the world, producing over half of several major crops and supporting the majority of the Earth's vulnerable populations (Samberg et al., 2016).

Prior satellite remote sensing land cover maps for Africa have used moderate to coarse resolution ($>$ 30 m spatial resolution) data (Bartholome and Belward, 2005; Eidenshink and Faundeen, 1994; Ellis and Ramankutty, 2008; Friedl et al., 2010; Fritz et al., 2015; Mayaux et al., 2004; Pittman et al., 2010; Ramankutty et al., 2008). Large discrepancies exist between CA maps in SSA due to differences in classification schemes and the ability of these data to resolve small agriculture fields (Fritz et al., 2011; Leroux et al., 2014; Waldner et al., 2015). Prior investigations of CA maps in SSA have used model-based approaches to fill spatial gaps of knowledge from lack of sub-national statistical reporting and available air and spaceborne remote sensing data to map field distributions. At the coarse scale ($>$ 1 km), You et al. (2009) used a cross-entropy approach to model plausible pixel-scale assessments by fusing production statistics, land use data, satellite imagery, biophysical crop suitability assessments, population density/distribution, and prior distribution knowledge to map agriculture cover at 10 km resolution for 20 major crops in SSA. A number of different approaches have been performed at the moderate (30–~250 m) scale. Pittman et al. (2010) used a set of 39 multi-year MODerate Resolution Imaging Spectroradiometer (MODIS) metrics incorporating four MODIS land bands and sub-pixel training data in a classification tree model to estimate a global 250 m cropland probability map. Yu et al. (2013) combined Pittman et al.'s (2010) map with a global 30 m land cover map in a regression tree model to estimate crop cover at 30 m and found Africa to have one of the highest discrepancies of estimated CA as compared to other regions of the world. Husak et al. (2008) used logistic regression model combining a stratified sampling of Landsat interpretations, IKONOS, land-cover and Shuttle Radar Topography Mission (SRTM) data in Central Ethiopia to estimate CA. Vancutsem et al. (2013) combined 10 existing land cover/land use datasets over Africa and validated the result with Google Earth imagery. Fritz et al. (2015) used prior EarthStat cropland map (Ramankutty et al., 2008) with crowdsourced interpretation of Google Earth imagery to produce a global CA map and estimate of field sizes. This work built upon prior work from See et al. (2013) who used crowdsourcing of Google Earth imagery via tools in a Geo-Wiki to estimate CA at 1 km spatial resolution in Ethiopia. Delrue et al. (2013) used a combination of moderate and VHR imagery (4 m resolution) in West Shewa, Ethiopia to map CA, although wall-to-wall coverage of VHR data was not available at the time. These studies have defined CA in SSA with a number of different techniques by combining multi-resolution remote sensing data. However, none to our knowledge, have attempted to map CA wall-to-wall with a classification at 1 m resolution for Tigray, Ethiopia beyond our recent effort which described the ‘big data’ processing approach implemented herein (McCarty et al., 2017).

1.2. Object based approaches for crop area mapping

Object based image analysis (Blaschke, 2010) methods provide a systematic approach to extract information from VHR data. Typically these methods involve expensive software packages such as E-Cognition (Baatz, 2004) or open source computationally expensive algorithms such as H-seg (Le Moigne and Tilton, 1995) that require rule sets to be applied to individual images or subsets of individual images due to workstation input and output (I/O) limitations, and random access memory (RAM) limitations. These software and rule sets are often scene dependent and computationally expensive. Considering prior efforts, this study was motivated to investigate the viability of enhancing prior approaches to reduce CA mapping error of very small agriculture fields in the complex landscape of Tigray, Ethiopia. The Otsu (1979) approach of image segmentation has been shown to be effective at rapidly extracting information from a number of different types of images (Huang and Wang, 2009; Wang et al., 2010; Xu et al., 2011). But, to our knowledge, no studies have attempted to apply this simple approach to thousands of DG VHR satellite images to understand the distribution of very-small agriculture fields.