



Estimating agricultural production in marginal and food insecure areas in Kenya using very high resolution remotely sensed imagery



Kathryn Grace ^{a,*}, Greg Husak ^b, Seth Bogle ^a

^a Department of Geography, University of Utah, USA

^b Climate Hazards Group, University of California, Santa Barbara, USA

ARTICLE INFO

Article history:
Available online

Keywords:
Kenya
Food insecurity
Land use
High resolution imagery

ABSTRACT

Regularly monitoring the amount of food produced in food insecure, isolated, subsistence farming areas can be used to help identify households or communities who may be in need of additional food resources. Measuring seasonal food production in developing countries, particularly at a sub-national level, is complicated by lack of data. In this study we use high resolution remotely sensed data to calculate cultivated area in two different growing areas, during two different seasons in Kenya. The results of the research support the usefulness of this approach for agricultural monitoring in the developing world and suggest that monitoring cultivated area requires attention to the specific growing characteristics of an area.

© 2014 Elsevier Ltd. All rights reserved.

Introduction

Agricultural production in developing countries, while generally relatively consistent year to year at the country-level, can mask large variation in sub-national production. In fact, it is a common occurrence to observe notable food production failures in one area of a country while another area experiences average or even above-average yields. Because developing countries are characterized by limited food storage and transportation infrastructure, moving food from one high producing part of the country to a less productive part of the country with food needs can be difficult. Regularly monitoring the amount of food produced in food insecure, isolated, subsistence farming areas can be used to help identify households or communities who may be in need of additional food resources.¹ Measuring seasonal food production in developing countries, particularly at a sub-national level, is complicated by lack of data. It is difficult and costly to access all of the farming households engaged in subsistence farming. However, recent research has focused on the use of remotely sensed data to aid in the estimation

of area under cultivation. Because food production is the measure of yield (production per hectare) multiplied by area (number of hectares), we can use the area measure to reduce uncertainty in small-scale food production estimates.

One strategy for estimating cultivated area relies on manual interpretation of very high resolution data. With sufficient very high resolution data it is possible to construct estimates of cultivated area, even in communities where fields are small, as is commonly the case in poor, subsistence communities. While this strategy has been used effectively to estimate cultivated area (Grace, Husak, Harrison, Pedreros, & Michaelsen, 2012; Husak et al., 2008; Marshall et al., 2011), questions remain about the spatial and temporal generalizability of this approach. Specifically the ability of this approach to approximate cultivated area in both marginal and highly productive growing areas is unknown.

The purpose of this paper is to examine the ability of the technique to estimate cultivated area in two very different agricultural areas of Kenya, a highly food insecure country in East Africa, during two different agricultural seasons. The results of this research are twofold. First, this research will provide insight into the ability of this estimation strategy to estimate cultivated area for different years, in one high producing and one marginally productive area, based on a suite of readily accessible input variables. Second, the results will provide a remotely-sensed based estimate of cultivated area for two sub-regions of Kenya for two different time periods. As no comparable sub-national data on cultivated area for Kenya exists, this information will be helpful in establishing a baseline of

* Corresponding author.

E-mail addresses: grace@geog.utah.edu, katgrace@gmail.com (K. Grace), husak@geog.ucsb.edu (G. Husak), bogle@geog.utah.edu (S. Bogle).

¹ According to the established definition of food insecurity adopted by the FAO, an individual is food secure when food is available, accessible, able to be utilized and is stable (World Food Summit, 1996). This research, focused on small-scale agricultural yield and production relates to the availability component of food insecurity.

food production for two different growing regions in a food insecure country.

Using remotely sensed data to estimate agricultural production

Observed rainfall and remotely sensed based estimates of vegetation are often used as measures or serve as proxies for the amount of cultivation or vegetation in a particular area (Cracknell, 2001; Tucker, 1979). The satellite-based estimate of vegetation, Normalized Difference Vegetation Index (NDVI) is frequently used to estimate small-scale food production (De Beurs & Henebry, 2004; Funk & Budde, 2007; Grace, Brown, & McNally, 2014; Townshend & Justice, 1986; Tucker, 1979). Rainfall can be used as a proxy measure of yield and food production on its own (Grace et al., 2012) but can be used in combination with NDVI to help identify growing areas where, for example, some type of irrigation is employed (Omuto, 2011).

Research has found, however, that estimates of the amount of land area under cultivation may be improved through the use of other types of supporting data beyond simply rainfall or vegetation measures. The presence of cultivation is likely dependent on many factors including topographical and landscape features in addition to rainfall and vegetation estimates. In conjunction with NDVI, researchers have used various land cover classifications developed from high resolution imagery and pixel counting methods to estimate the amount of cultivated area (Bauer, Hixson, & Davis, 1978; Fang, 1998; Sridhar et al., 1994). Issues of mixed pixels² (Genovese, Vignolles, Nègre, & Passera, 2001; Omuto, 2011; Rojas, 2007), coregistration errors and spatially coarse (rainfall or other remotely sensed) data can make any estimate based on a single data source problematic. These issues may be particularly acute in developing countries where subsistence farms, small in size by their very nature, abut areas of natural vegetation (Ozdogan & Woodcock, 2006). Using multiple types of data available at different scales may improve the understanding of what is actually happening on the ground and mask out areas where agricultural production is not relevant (Husak et al., 2008; Rojas, 2007).

Here we use existing remotely sensed data and build on the area frame sampling approach.³ This approach involves selecting sampling units at various scales and estimating statistical relationships of the outcome of interest, in this case cultivated area, and the supporting independent data (in this case this is topographic information). We use very high resolution imagery gathered during the local growing season (this data is only available for a subset of the area of interest and serves as the finest sampling unit) and combine the imagery with landscape and geophysical information to construct a model of cropped area at a sub-national to national scale. As Husak et al. (2008), Marshall et al. (2011) and Grace et al. (2012) have shown, this approach is well suited to monitor land cover in areas of complex topography, and where farm sizes are small. No existing applications of this methodology, however, have explored the usefulness of this technique for predicting future or past cultivation. Additionally the usefulness of these models has not been compared in the context of different types of growing areas, specifically areas where the agricultural intensity varies dramatically. In this study, we compare the models used to predict cropped area for two distinct growing areas as well as compare the models' usefulness in prediction. This research will expand scientific understanding of the usefulness of high resolution imagery for

agricultural monitoring in a country characterized by diverse topography.

Kenya context

Kenya is heavily dependent on agriculture for food and income. Nearly 75% of the labor force is involved in agriculture (Kenya National Bureau of Statistics, 2006). In most cases irrigation is inefficient (Mati, Mutie, Gadain, Home, & Mtaló, 2008) and fertilizer use is relatively low (Duflo, Kremer, & Robinson, 2008) leaving the majority of farmers heavily dependent on rainfall for crop production. While cropping strategies and growing seasons vary across the country, maize represents one of the largest crops grown and it is grown for both personal consumption and for sale. Periods of inconsistent rainfall, drought and the resultant reductions in agricultural production followed by significant food insecurity are not uncommon in Kenya (Funk et al., 2008). Kenya's agricultural production varies dramatically across the country. This variation is related to differences in social/development factors (Jayne & Muyanga, 2012), rainfall onset, duration and consistency where drought and dry-spells during the rainy season impact the eastern areas of the country more than any other area (Funk et al., 2008; Ngetich et al., 2014). Alternatively, near the middle of the country around Lake Victoria and just west of Nairobi, these highlands represent some of the most productive zones in Kenya where droughts and dry-spells are much less common (Ngetich et al., 2014). The dependence on rainfed agriculture and this area's consistent rainfall patterns result in extensive planting to generate income in some way.

Moving east of the capital towards the south there exists some of the most marginal and inconsistent production areas in the country. More marginal areas have historically reported less area under cultivation because of inconsistent rainfall (Ngetich et al., 2014). What is particularly noteworthy is that even though this area of the country receives more rainfall than the eastern arid area because rainfall is less reliable the people who live here may be at greater risk of food insecurity than the people who live in, and are habituated to, the drier northern regions where drought/dry-spells occur more often and with greater severity. What may be occurring is that farming households depend on the marginal areas for agricultural production and if and when the rains are delayed, sporadic or limited, the resulting reduction in agricultural production leaves these households in a precarious food situation (Osman-Elasha, 2007). Because there are significant spatial variations in agricultural productivity (Funk et al., 2008; Ngetich et al., 2014), regularly examining agricultural production at the sub-national-level is pivotal to identifying communities at risk for food production challenges (Jayne & Muyanga, 2012; Osman-Elasha, 2007).

Because of the dependence on rainfed agriculture and the low level of development, Kenya is one of 18 countries that the Famine Early Warning System Network (FEWS NET - a division of research climatologists and earth scientists supported by US Agency for International Development) regularly monitors for indications of climate/weather issues that might impact food security. A component of the FEWS NET monitoring strategy is the development of livelihood maps. These maps reflect the dominant livelihood (wage and food producing) strategies of an area and are constructed using climate, topographic, economic and local farmer/expert knowledge (<http://www.fews.net/east-africa/kenya/livelihood-description/thu-2011-09-29>). In this study, we focus on the rich, highly fertile area in the highlands of Kenya near Lake Victoria – this is known as the “Western High Potential Zone” (we will refer to this as HPZ in the remainder of the text) in the FEWS NET livelihood descriptions. We also focus on the marginal area to the south of Nairobi, where

² One pixel may represent more than one land cover type.

³ A report produced by the Food and Agricultural Organization (FAO) in 1998 explores different applications of the area frame sampling approach.

Download English Version:

<https://daneshyari.com/en/article/6538687>

Download Persian Version:

<https://daneshyari.com/article/6538687>

[Daneshyari.com](https://daneshyari.com)