Remote sensing: a key tool for monitoring food resources in a changing world

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Abstract

Remote sensing (RS) has been adapted as standard technology for monitoring the earth's surface. Especially in data-poor countries or in areas under conflict, remote sensing imagery is often the only independent data source available. Both the USA and Europe offer a range of low-resolution satellite products (spatial resolution of 1 km by 1 km) available to the general public that can be used as indirect or direct proxy for food production. Based on these images, food-monitoring tools mostly focusing on crop production are readily distributed. In addition to the models available for crop food production, there is a need for monitoring livestock production as in many African countries livestock is an important resource that contributes to food security, improves the quality of life of farmer communities and strengthens the development of the economy. Crop and animal health both impact directly on the obtained production. Additionally, zoonoses, i.e. diseases that can be transmitted from animals to human, may also have an important impact on public health, especially when seen from a One-Health perspective.

This paper discusses the advantages and disadvantages of currently available spatial decision-making tools using RS as input both for crop and livestock production in Africa. The potential increase of existing diseases and the risk of emerging diseases under global change are illustrated with a case study in Zambia.

Introduction

Over the last thirty years, remote sensing data have become a prime data source to be used as a tool for monitoring food resources. Remote sensing data are independent, allow measurements in areas difficult to reach due to remoteness or societal upheaval, provide continuous measurement of the earth surface in multiple spectral channels and have a long-term sustainability.

In general, RS sensors can be grouped into two categories: passive and active sensors. Passive sensors are the most well known group of sensors. The platform will sense the reflectance of the sunlight on the earth's surface in multiple channels and these reflectance values can be post-processed to create indices for vegetation status and hence crop status (Lillesand et al, 2004) using vegetation indices (see Jiang et al 2008 for review). Other indices include for example temperature indices (Price, 1984; Wan, 2008).

Each sensor is carried onboard a satellite platform which is either geostationary or polar-orbiting. The geostationary satellites, as the name states, take images constantly over the same area. All geostationary satellites combined sense the entire globe (with exception of the very high latitudes). MSG satellites (EUMETSAT) have their focus on Africa (www.eumetsat.int). Polar-orbiting satellites are moving around the globe and have a revisit time of the same area ranging between one day (Aqua http://aqua.nasa.gov; Terra http://terra.nasa.gov; SPOT VEGETATION http://www.vgt.vito.be) to two-three weeks (SPOT www.astrium-geo.com/en/143-spot-satellite-imagery, Landsat http://landsat.gsfc.nasa.gov) or even ad hoc (Quickbird http://www.satimagingcorp.com/satellite-sensors/quickbird.html, Ikonos http://www.satimagingcorp.com/satellite-sensors/ikonos.html, Worldview 2 https://www.digitalglobe.com/about-us/content-collection). Clouds limit the use of passive RS data as the satellite platform cannot measure areas covered by clouds. Especially in the tropics this can hamper routine sensing a study site. Compositing techniques can overcome this through the identification of pixels contaminated by clouds (Holben, 1986; Jönsson and Eklundh, 2002, 2004; Ma and Verourstraete, 2006; Julien and Sobrino, 2010). The data are usually composited between 7 and 16 days.

Active sensors send out actively a signal that is consequently recaptured by the same sensor. This type of radar sensing is commonly used for hydrological purposes, mainly to assess soil moisture. Sometimes active sensors are used in areas under heavy cloud contamination e.g. in tropical areas during the wet season, as the active signal can penetrate the clouds and thus can 'see' through the clouds (e.g. Bwangoy et al, 2010).

Remotely sensed imagery is characterized by four types of resolution: spatial, temporal, spectral and radiometric resolution. The spatial or ground resolution is probably the most well known type of resolution and refers to the size of the smallest object that can be resolved on the ground. It is determined by the

Instantaneous Field of View (IFOV) of the remote sensing system, which is the cone angle within which incident energy is focused on a sensor's detector, and the distance between the satellite platform and the target being imaged. The smaller the IFOV is, the higher the spatial resolution and the finer the spatial detail that can be distinguished. The spatial resolution is usually expressed in meter, ranging from coarse (> 100 m), over medium (30–100 m) and high (4–30 m) to very high (<4 m). The temporal resolution or revisit time specifies the amount of time needed to revisit and acquire data for a specific location. This depends on the orbital characteristics of the platform and characteristics such as swath-width. The geostationary satellites sense the same area continuously and provide a measurement every 15 min. Polar orbiting satellites have a revisit time from 1 day up to 2–3 weeks. By using multiple satellites with the same sensors, the revisit time is sometimes reduced to half a day (e.g. Terra and Aqua satellites carrying the MODIS sensor). The spectral resolution is determined by the amount of bands or channels used to measure the reflectance from the earth's surface, going from a simple RGB sensor (3 channels) over multispectral (5–30 channels) to hyperspectral cameras (>100 very narrow channels). Finally, the number of bits used to store the reflectance values onboard the satellite determines the radiometric resolution, i.e. the sensor's ability to discriminate very slight differences in reflected or emitted energy.

Remote sensing as tool for food monitoring

Remote sensing data products have found numerous applications in the agricultural sector (crops, livestock and fisheries) and have become an increasingly important component in improving food and nutrition security and developing famine early warning systems (Brown, 2008; Atzberger, 2013; Mulla, 2013). The choice of which spectral bands to use and the temporal and spatial resolution required to meet the study objectives will provide the basis for selecting the appropriate satellite sensor. Vegetation indices, such as the Enhanced Vegetation Index (EVI) or Normalized Difference Vegetation Index (NDVI), derived from multi-temporal satellite data with a medium to coarse spatial resolution have been successfully used for crop monitoring over extensive areas (e.g. regional and national scales). These vegetation indices combine the absorptive and reflective characteristics of vegetation in the visible red and near-infrared portions of the electromagnetic spectrum to obtain a measure of canopy greenness, which is used to quantify vegetation amounts and vigor (Bannari et al, 1995). Several studies have demonstrated the utility of 1 km NDVI time-series derived from the Advanced Very High Resolution Radiometer (AVHRR) instruments on board the National Oceanic and Atmospheric Administration (NOAA) satellites for agricultural monitoring at large spatial scales, e.g. for studying rangeland condition (Hielkema et al, 1986; Minor et al, 1999; Weiss et al, 2001; Geerken and Ilaiwi, 2004), crop phenology (Wenbin et al, 2009; Seghal et al, 2011; You et al, 2013), and crop area estimation and yield forecasting (Huang et al, 2013). Major aid organizations such as the Food and Agricultural Organization (FAO) have set up operational early warning systems based on the integrative use of medium to coarse spatial resolution sensors and crop growth modeling to mitigate food insecurity (e.g. Hielkema and Snijders, 1994). If the study objective is to monitor crop status at farm level, imagery with a high spatial resolution and moderate temporal resolution will be needed. For instance, the improved resolution characteristics of the Moderate Resolution Imaging Spectroradiometer (MODIS, 36 spectral bands and daily global imagery at spatial resolutions of 250–500 m) provide a substantially improved basis for retrieval of crop biophysical parameters at both field and regional scales that could be integrated in crop yield simulation models (Doraiswarmy et al, 2005; Arvor et al, 2011). Other examples include the use of Landsat TM or SPOT images (Rudorff and Batista, 1991; Conrad et al, 2010; Yang et al, 2011). Careful balancing is required as the combination of high spatial and high temporal resolution is still limited. SPOT will be able to offer now 10 m images every day with the new program, but for current operational monitoring this is yet to become integrated.

While research has primarily focused on the use of RS data for crop monitoring, livestock monitoring has been left out, even though the World Bank assessed the potential contribution of the livestock sector to agricultural/economic growth and poverty alleviation very high. Meat and dairy are considered high value livestock products, and a significant unidirectional relationship between

livestock development and GDP has been established in 33 developing countries including the Democratic Republic of Congo (Pica et al, 2008). Robinson et al (2007) provided maps of livestock distribution and livestock production globally. They used remotely sensed predictor variables to create these livestock distribution maps. Especially in extensive farming systems, the distribution of livestock is linked to the prevailing environmental conditions. These conditions can be measured from the satellite and therefore be used as main data source. These livestock distribution maps are currently being updated (Robinson et al, under revision). In Asia there is considerably focus on the distribution of ducks and geese, not only important for food security but also very relevant in the framework of highly pathogenic avian influenza (Prosser et al, 2011; Van Boekel et al, 2011). In Africa, Bryssinckx et al (2012) focused on the improved estimation of livestock in Uganda from survey data by adapting the sampling strategy and including RS data for the stratification.
Livestock distribution in Africa is closely related to vector-borne diseases. Tsetse-fly-transmitted trypanosomiasis is a major constraint to rural development in large parts of Africa (Swallow, 1998). The tsetse flies occur in about 10 million km^2 of sub-Saharan Africa and the trypanosomes they transmit can cause severe illness in livestock and people. Animal African Trypanosomiasis (AAT) in the Democratic Republic of Congo is transmitted by *Glossina tabaniformis* (Leak et al, 1991) and the prevalence is estimated at 4.5–9.5%. De Deken et al (2005) demonstrated that Human African Trypanosomiases (HAT) and AAT in Kinshasa are transmitted by *Glossina fuscipes quanzensis*. Simo et al (2006) indicated from bloodmeal analysis that transmission not only involves flies and humans but also pigs, hereby illustrating the complexity of transmission. Indeed, Sumbu et al (2009) established that pigs act as reservoir for HAT in Kinshasa. Because of the complexity and the limited availability of studies in Congo, the case study shown here is focusing on the Eastern Province in Zambia, where the seasonal distribution of the tsetse fly is correlated with the distribution of its main host, cattle (Van den Bossche and Staak, 1997). The case study demonstrates the use of remote sensing data to measure the impact of gradual forest clearance on the inherent apparent density of tsetse flies.

Case Study

In large parts of tsetse-infested sub-Saharan Africa the progressive clearing of the natural vegetation for cultivation, the introduction of domestic animals and the almost complete disappearance of large game animals have had important repercussions for the distribution and density of tsetse flies. It can be anticipated that in the years to come and with continued population growth and environmental change, a similar decline in the distribution and density of the tsetse population and the disease prevalence will be observed in Zambia as well. This process of gradual reduction may in certain areas ultimately lead to autonomous, anthropogenic clearing of tsetse and thus the disappearance of the disease (Bourn et al, 2000; Reid et al, 2000). Understanding this process may contribute to the development of focused trypanosomiasis control strategies that exploit this autonomous tsetse clearing.

To this end, Ducheyne et al (2009) used remote sensing to analyze the impact of land cover change on the abundance of tsetse flies. Whilst land cover change is often mapped and included in data analysis, incorporating the fragmentation level of different land cover types is less common. The arrival of software tools such as Fragstats does allow quantifying the fragmentation and, consequently, establishing the relationship between fragmentation and species distribution and abundance.

Inherent apparent density (IAD) of tsetse flies was calculated using survey results following the fly-round method along transects as described by Potts (1930) and Ford et al (1959). The fly-rounds were 6 km long and had about 30 sectors of roughly 200 m each. At the end of each sector was a stop. All transects were georeferenced to facilitate reallocation. The fly-rounds were surveyed twice in 2006: once in the rainy season and once in the hot dry season.

Two Landsat images, with a spatial resolution of 30 m, were preprocessed separately prior to mosaicking to reduce any effects of illumination differences and atmospheric absorption. The digital numbers (pixel values) were converted into near-surface reflectance taking into account atmospheric correction using a dark pixel subtraction method (Chavez, 1988). Subsequently, they were co-registered to remove any geometric distortions using a second-order polynomial followed by a nearest neighbor resampling method. Finally, the imagery was mosaicked using a grey level matching method (Richards and Jia, 1999). The images were then classified into four land cover types: i.e. munga, miombo, agriculture and villages. Two auxiliary categories were also included, i.e. cloud and shadow.

The fragmentation was calculated using the classified remote land cover maps. For each land cover type a moving hexagonal window was applied to determine the total class area, number of patches, mean patch size and patch size standard deviation. Based on these indices, the hexagons with similar fragmentation characteristics were grouped in classes using an unsupervised clustering method named Partitioning Around Medoids (PAM).

The outcome of this study shows that in the study area the destruction and fragmentation of the natural habitat of tsetse flies has significant repercussions for the density of those flies. Extensive clearing, mainly for cotton production in the southern part of the study area, has resulted in the disappearance of large parts of the tsetse habitat and in a significant reduction in the apparent density of tsetse compared to areas closer to the Luangwa escarpment where human density is much lower and the natural vegetation largely undisturbed. The results from this study suggest that the effect of habitat fragmentation on the apparent density of male and female tsetse flies is a gradual process with the inherent apparent density of tsetse decreasing with increasing levels of fragmentation. This relationship is not linear; the decrease in inherent apparent density only starts when a threshold in fragmentation is reached.

Conclusion

Remote sensing data offers the potential to closely monitor agricultural resources as early warning system for potential crop failure and to map livestock distribution. Given the anticipated global changes, remote sensing data are a valuable tool to estimate potential reduction in crop productivity or degradation in livestock zones.

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