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# Predicting stem borer density in maize using RapidEye data and generalized linear models

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ABSTRACT

Average maize yield in eastern Africa is 2.03 t ha$^{-1}$ as compared to global average of 6.06 t ha$^{-1}$ due to biotic and abiotic constraints. Amongst the biotic production constraints in Africa, stem borers are the most injurious. In eastern Africa, maize yield losses due to stem borers are currently estimated between 12% and 21% of the total production. The objective of the present study was to explore the possibility of RapidEye spectral data to assess stem borer larva densities in maize fields in two study sites in Kenya. RapidEye images were acquired for the Bomet (western Kenya) test site on the 9th of December 2014 and on 27th of January 2015, and for Machakos (eastern Kenya) a RapidEye image was acquired on the 3rd of January 2015. Five RapidEye spectral bands as well as 30 spectral vegetation indices (SVIs) were utilized to predict per field maize stem borer larva densities using generalized linear models (GLMs), assuming Poisson ('Po') and negative binomial ('NB') distributions. Root mean square error (RMSE) and ratio prediction to deviation (RPD) statistics were used to assess the models performance using a leave-one-out cross-validation approach. The Zero-inflated NB ('ZINB') models outperformed the 'NB' models and stem borer larva densities could only be predicted during the mid growing season in December and early January in both study sites, respectively (RMSE = 0.69–1.06 and RPD = 8.25–19.57). Overall, all models performed similar when all the 30 SVIs (non-nested) and only the significant (nested) SVIs were used. The models developed could improve decision making regarding controlling maize stem borers within integrated pest management (IPM) interventions.



## 1. Introduction

Maize (*Zea mays* L.) is a major staple food crop in Africa, particularly in the eastern region of the continent (Smale and Jayne, 2003; Tefera et al., 2011). The maize growing area in eastern Africa spans over 15 million ha with rural households cultivating the crop mainly as a means for human consumption and income generation (FAOSTAT, 2015; Kfir et al., 2002; Sileshi et al., 2010). Average maize yield in eastern Africa is 2.03 t ha$^{-1}$ as compared to global average of 6.06 t ha$^{-1}$ (FAOSTAT, 2015) due to biotic and abiotic production constraints (Mgoo et al., 2006; Mwalusepo et al., 2015). Among the biotic constraints in East Africa, stem borers are the most harmful (Kfir et al., 2002; Ong'amo et al., 2006a). In the region, maize yield losses due to stem borers were estimated between 12% and 21% of the total production (Ong'amo et al., 2006a). Losses largely depend on the pest density which is herein defined as the number of larvae per unit area, while the crop cycle and phenological stage at infestation as well as soil fertility and climatic (e.g. temperature and drought) factors (Dhaliwal et al., 2010; Mwalusepo et al., 2015) are key determinants for the propagation of the pest. In Kenya, for example, it is estimated that annual losses in maize yield due to the stem borers infestation can be 11% in the highlands and 21% in the lowlands (Odendo et al., 2003), however, in high stem borer occurrence areas, *Busseola fusca* can cause up to 82% maize yield losses annually (De Groote 2002).

Maize stem borers commonly cause yield losses through damaging almost all the plant parts (leaves, stems, tassels, cobs and kernels). The adult moth of some species (i.e. *B. fusca*) oviposits

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a large number of eggs behind the sheath of pre-tasseling maize crop and larvae hatch a week after to feed on the young leaves in the whorl for a while and then penetrate the stem in the lower part of the plant (Calatayud et al., 2014). However, some larvae may migrate away from the natal plants (Calatayud et al., 2014; Van Rensburg, 1997). Obviously, the larvae disturb the maize plant vascular system and affect the biological, physiological and morphological functions like water and metabolites translocations leading to stunted growth forms. Death of the growing point (chlorophyll-inactive growing point) often occurs during the first two months of attack (Kfir et al., 2002), whereas late stem borer attacks in the growing season can cause loss of crop stem vigor and direct cob damage (Bosque-Perez, 1995).

In line with other maize insect pests like maize leaf aphid, stem borers are commonly monitored using direct field survey methods like scouting and checking the plants for any damage symptoms. These methods are inherently time-consuming, tedious, expensive and subjective as only a few sites within the fields are sampled (e.g. Al-Hiary et al., 2011; Pinter et al., 2003). Therefore, complementary and synoptic maize stem borers monitoring methods that allow the implementation of site-specific practices are required. In this context, remote sensing is capable of offering synoptic, timely, accurate and relatively inexpensive data that can be utilized to provide explicit overview of maize stem borer damage or infestation. Also, remote sensing allows a wide-area insect pest monitoring approach thus less spotty (haphazard) and spatially more effective and coherent compared to point-specific field-based survey methods (Moran et al., 1997; Mulla, 2013). In small-scale maize farming systems, remote sensing can still be an encouraging option for monitoring maize stem borer densities, particularly in areas where labor is scarcely available and fields are highly scattered (Swinton and Lowenberg-DeBoer, 2001). Furthermore, a remote sensing-based stem borer monitoring approach allows selection of samples size and location in correspondence with the image pixels and extent, hence sampling time can be considerably reduced since a wider area can be consistently observed using bi-temporal or time-series data. Spatial stem borer damage or infestation information can be, furthermore, utilized to help in assessing the effects of climate, cropping systems and landscape matrices on the stem borer distribution and abundance in key maize growing areas.

In general, the successful use of remotely sensed data for crop pests damage detection is well documented in the literature. For instance, studies have used *in situ* (point-specific field measures) or laboratory (leaf specific) hyperspectral data to detect insects damage in sugarcane (Abdel-Rahman et al., 2010), wheat (Mirik et al., 2007), maize (Nansen et al., 2013), rice (Zhao et al., 2013), sorghum (Singh et al., 2007), and cotton (Sudbrink et al., 2003) crops using a quite wide range of statistical methods. Airborne and satellite-borne multispectral and hyperspectral data have also been utilized for detecting symptoms of insects attack in various field crops (e.g. Carroll et al., 2008; Elliott et al., 2015; Puig et al., 2015). These studies examined the possibility of detecting the visual symptoms of a pest attack, whereby the leaf or crop damage is visually categorized into different scales (e.g. low damage, moderate damage and severe damage). Visual categorization of insect symptoms in the field could be a biased approach due to differences in observers' skills (Harrington, 1987), particularly during the early pest damage stages. Hence, more objective and integrative and real-time insects infestation (number/density) estimation methods are needed to underpin early pest mitigation or intervention strategies. Essentially, insect density estimation early in the growing season can assist in developing a warning outbreak assessment system for cropland pests. Insect pest density estimates are also useful for determining the critical limits of control measures and hence minimizing the use of the insecticides (Sigvald, 2012). In other words, insecticides are applied when they are really needed whenever a critical insect density limit is reached and when the preventive methods are no longer effective or useful. Apparently, insect density dynamics are important information not only for setting a threshold for the deployment of insecticide treatment measures but also for integrated pest management (IPM) programs as such that aim to rather use biological control agents (i.e. natural pest enemies) to control pest numbers (Kfir, 1997).

To the best of our knowledge, the utility of remotely sensed data for estimating insect pest densities in field crops was only demonstrated using handheld sensors and airborne digital cameras at a localized scale (Mirik et al., 2006; Mirik et al., 2007; Sudbrink et al., 2003; Yang et al., 2005). Willers et al. (2005) mapped different cotton hapitat classes (resulted from various edaphic, environmental and phenological effects) using a 2-m airborne multispectral camera and found a positive relationship between the habitat classes and tarnished plant bug density. In another study, Abdel-Rahman et al. (2013) predicted the density of sugarcane thrips with relatively low prediction errors using leaf-level hyperspectral data. Most of the aforementioned studies employed hyperspectral data to model the insect densities. However, hyperspectral data are high dimensional, complex, expensive and their analysis is associated with a high computational cost. In addition, the narrow and contiguous wavebands of hyperspectral data are most probably correlated and cause a co-linearity problem when they are integrated in an empirical predictive model. Relatively newly launched multispectral satellite systems such as from the RapidEye constellation offer better spatial, spectral and temporal properties that are not yet fully linked to farm and plot level insects infestation rates in Africa.

Also, most of the previously reviewed studies examined the use of different parametric regression methods like correlation analysis and partial least square regression to predict insect pest numbers. Nonetheless, insect pest numbers could deviate from a Gaussian (normal) distribution due to excessive observations of low or even zero insect numbers and/or only having a few observations of high insect numbers or *vice versa* (skewed data). Hence, the assumptions of the regression parametric approaches could be violated when insect numbers are used as a response (dependent) variable. Therefore, studies advocated the use of non-parametric regression models that do not require any assumption on data distribution to model count data with excessive zeros (e.g. Xu et al., 2015). Specifically, observations on stem borer density are regarded as count data that should be modeled within the family of generalized linear models (GLMs) (Willers et al., 2005). In this regard, the Poisson ('Po'), negative binomial ('NB') and zero-inflated NB ('ZINB') count data regression models (Agresti, 2002; Kassahun et al., 2014) provide the required basis for deriving stem borer density predictive models using remotely sensed variables.

For maize stem borers, and to the best of our knowledge, no study has yet explored the use of remotely sensed data to predict stem borer densities. However, in a recent study Mwalusepo et al. (2015) sought the impact of climate change on the distribution and abundance of maize stem borers along eastern Afro-mountain gradient using an environmental niche modeling approach. In this study, we utilized three GLM approaches to predict maize stem borer larva densities in two test sites in Kenya using multispectral RapidEye data. Specifically, we aimed to explore the utility of RapidEye spectral variables for predicting larva densities of maize stem borer using 'Po', 'NB', and 'ZINB' count data regression models.

## 2. Study areas

The Bomet study site covers about 876.98 km$^2$ and is located between 34.97°E to 35.06°E and −0.76°S to −0.83°S (Fig. 1) with an elevation range of 1800–3000 m above sea level. The