Low Altitude Remote Sensing and its Application in Precision Agriculture: A Case of Nzathu Farm in Traditional Authority Somba in Blantyre District, Malawi

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Abstract

The practical application of Low Altitude Remote Sensing (LARS) in Precision Agriculture (PA) has tremendously gained ground recently. This is despite concerns about the viability of such systems for farmers related to the costs of both the system and the image processing software, technical expertise to operate the LARS and processing of the imagery itself, and timely delivery of information which is greatly compromised by not only the unstable and expensive internet facility but also local weather conditions such as wind and clouds. Using image analysis, this study illustrates the utilization of self-build unmanned aerial vehicle (UAV) in monitoring crop conditions in farmers' fields in the area of Traditional Authority Somba in Blantyre district of Southern Malawi. It demonstrates that both optical and near-infrared imageries obtained from LARS can be used to monitor fertilizer trials, conduct crop investigation and mapping of field surface drainage.

Keywords: Low Altitude Remote Sensing, Unmanned Aerial Vehicle (UAV), Global Positioning System (GPS), Geographic Information Systems (GIS), Precision Agriculture, Soil fertility, Maize, Crop Monitoring, Somba, Blantyre, Malawi

1. Introduction

The practical application of Low Altitude Remote Sensing (LARS) technologies in Precision Agriculture (PA) has tremendously gained grounds recently. Considering the quest to match agricultural practice with crop and soil conditions, PA technologies are considered as one major direction in modern agriculture development. Among the myriad benefits of PA include increased crop yield and efficiency achieved by lowering the costs associated with fertilizer, pesticides, herbicides, and fungicides (i.e. apply only what is needed, and at the required location and time). Socio-economically, PA is beneficial since it reduces the transport of agriculture inputs on the air, soil and water (Zhang & Kovacs, 2012). Environmentally, PA minimizes over-application of inputs hence reduces the risk of pesticide and fertilizer runoff or leaching into environmentally sensitive areas such as water.

Presently, there is substantial progress in using Variable Rate Technologies (VRT) and Global Positioning Systems (GPS) to reduce the application of fertilizer, insecticides and fungicides.

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

Nevertheless, obtaining up-to-date data for crop and soil conditions (e.g., nutrient deficiency, water stress, pests, disease) for VRT remains a challenge (Flowers, Weisz, & White, 2005). Historically, zonal maps for VRT machines have for so long been created by applying yield maps from yield monitors (Diker, Heermann & Bordahl, 2004). However, these maps are considered unreliable and limited. This is because they are generally acquired once a year and often display a huge variation when observed (Blackmore, Godwin & Fountas, 2003). Moreover, these types of yield maps are only available after the season, and many harvesters are still not equipped with yield monitors.

Currently, the alternative to the scenario above is the utilization of remotely sensed imagery acquired during the growing season. Apart from deriving yield maps from them, such imagery could as well be used to extract timely information about crop condition for management purposes (Yang, Everitt, Qian, Luo & Chanussor, 2013). Specifically, information about soil and crop condition can be obtained from high spatial resolution satellite imagery. For example, in their study on *Optimal geometric configuration and algorithms for LAI indirect estimates under row canopies of vineyards*, Lopez-Lozano, Baret, de Cortazar-Atauri, Bertrand & Casterad (2009) successfully applied a variety of satellite data, including data from IKONOS, QuickBird, GeoEye-1 and WorldView-2 in crop yield predictions. However, weather conditions coupled with the satellites' poor spatial and temporal resolution (i.e. highest spatial resolution for commercial satellite data e.g. WorldView-2 and GeoEye-1 is approximately 50 cm for the panchromatic band) restrict the image's availability for these sensors. While the spatial resolution might be quite good, the limited spectral resolution of the panchromatic band might not be adequate to examine within-field variations of crop condition and yield (Zhang & Kovacs, 2012).

This therefore makes the utilization of airborne multispectral and hyperspectral sensors eminent for monitoring crop condition and yield. These sensors have a finer spatial resolution and real-time monitoring capability (Yang, Everitt, Bradford and Escobar, 2000, 2004, & 2004). It is propounded that aerial imagery is as effective as high resolution satellite imagery in monitoring spatial variation of crop condition and yield. Moreover, the development of Low Altitude Remote Sensing Systems (LARS) over the recent past makes its application for PA possible. Plausible breakthroughs can be identified as from 2000 where Inoue, Morinaga, and Tomita collected crop images using a Charge-Coupled Device (CCD) camera mounted on a blimp to measure biomass and Leaf Area Index (LAI) variation within rice and soybean fields (Flowers, Weisz, & White, 2005). The results showed that studying crop biological parameters can best be accomplished through the use of LARS images. Hunt et al. (2005) used a colour digital camera mounted on a radio controlled model aircraft to collect images of a corn field in order to examine the relationships among Normalized Green Ratio Difference Index (NGRDI), biomass and corn nitrogen status. Likewise, in 2008 they also assessed the relationships between LAI and Green Normalized Difference Vegetation Index (GNDVI) for a wheat field. In their recent research in 2010, Hunt et al. used a customized digital camera on-board a LARS to take high-resolution (i.e. 2.7 and 5.1 cm) color-infrared pictures of two winter wheat fields. Through assessing the spectral information with ground collected biophysical data these researchers demonstrated the scientific feasibility of applying LARS to monitor within-field crop variations (Zhang & Kovacs, 2012). In a similar fashion, Primicerio et al. (2012) used an ADC-lite camera on-board a UAV to acquire photos of a vineyard. They managed to convert digital numbers to reflectance and then calculated NDVI to display vineyard vigour.

A number of sensors and cameras are available for LARS. However, optical or infrared sensors are the most commonly used for crop monitoring whereas thermal infrared sensors have been shown to be valuable for monitoring soil moisture or stress (Ryo et al, 2007; Berni et al, 2009;

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

Zarco-Tejada et al, 2012). Zarco-Tejada et al, (2013) further demonstrated that hyperspectral sensors on board a UAV could as well be used to examine leaf carotenoid content.

The aforementioned studies demonstrate the scientific feasibility of LARS applications for crop monitoring. The spatial resolution limitation of satellite imagery is seen to be resolved by LARS. In spite of all this, LARS has its own challenges too. The small spatial coverage and the image processing of the LARS data are the most apparent challenges. Transportation regulations of some countries restrict the operating height of LARS. This means that a large number of images need to be collected for each field. Most importantly, it is difficult to mosaic the images. Hunt et al. (2008) found it difficult to calculate NDVI from a mosaic of LARS. This was because the same crop feature in several images could have different digital numbers as a result of changes in the incident angles and/or the atmospheric transmittance. Therefore, instead of focusing on a mosaic of images, most LARS investigations concentrate on each image separately (Primicerio et al, 2012).

Arguably, there seems to be varied messages about the practical applications of LARS for PA. While scientific research praises LARS for the capability to measure relationships between crop biomass and water stress using the digital numbers (or reflectance values) obtained from LARS imagery, suggesting a typical practical use for crop monitoring, such analyses unfortunately are done on each image separately. This suggests that it would be impractical for farmers with vast fields who may consequently require many images to monitor their fields (Berni et al., 2009; Swain et al., 2010). The situation is compounded by limited literature on applications of LARS for crop monitoring.

2. Study Area

The study was conducted in Traditional Authority Somba, in the outskirts of Malawi's commercial city of Blantyre, on the trial farm of Nzathu Association, a GTZ funded project. The target crop was maize, Malawi's main staple crop. Located at 15°40ˈS, 34°58ˈE and at an average altitude of 1039m, Blantyre has an annual mean temperature of 22.4°C and annual mean rainfall of 834mm. Generally, Malawi is a characteristic of a tropical wet and dry savanna climate. As a country whose economy heavily relies on agriculture, it is essential to monitor the field crop conditions in a timely fashion to maximize production. Normal growing season in Malawi is from November to April (Ngongondo et. al. 2014). Permission to fly over the farm was granted by the association. The main objectives were to analyze fertilizer field trials, field tile drainage conditions, and crop damage from disease infestation. No permission was obtained from Malawi Government to fly the LARS over this area despite writing them for the same.

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

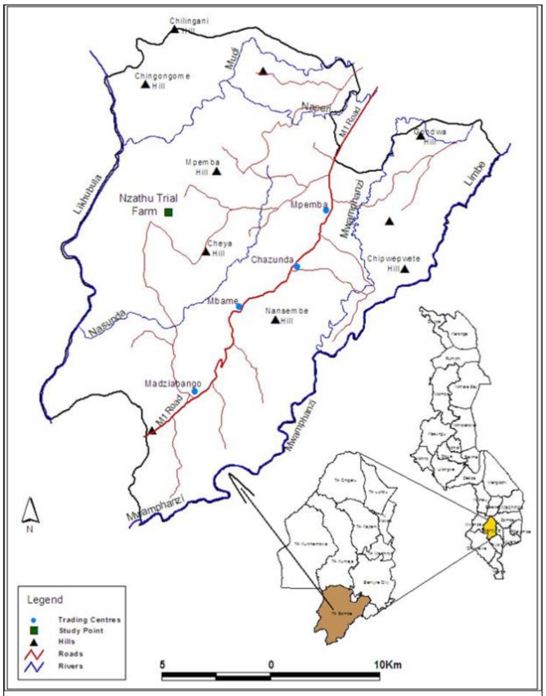

Fig. 1. Map of TA Somba showing study point

Figure 1

3. The Equipment and Methods employed

The UAV system used in this study weighed 3.4 kg and was developed by Manuel Kiewisch, a UAV technologist and research scientist of University of Technology, Germany. The Table below explains the component parts that the UAV consisted of.

Hexacopter Technical Overview		
Component (brand name)	**Function**	**Specifications**
Motors (AC 2836-358)	To provide lift and steering	Max. 880Kv (Rounds per minute per Volt)
Telemetry (Xbee Pro S1)	To enable wireless communication with PC	900 Mhz module, ca. 800m range
Frame (n.v.)	For stability and functional setup for the parts (anchorage)	Aluminium/glass fiber frame, ca. 50cm in diameter
Batteries (Turningy)	To provide power source for all energy consuming components	3S3P3 cells in series (3 cells in parallel), 3000 mAh (milli Ampere), 11.6 Volt
Chipset (Ardupilot Mega 2.0)	To enable communication between parts, steering, autopilot, and sensoric	Magentometer (stabilization in air), GPS (localization), Sonar (altitude measurement)
Remote Control (Spectrum DX7)	To enable manual control of the UAV	900 Mhz module, range ca. 800m, 7 channel setup
Camera (Canon PowerShot S95)	To record aerial optical ground information for remote mapping, study processes	10 Mega Pixels resolution, compact digital camera, ca. 260gr

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

Fig. 2. Self-made UAV and its control deck

Figure 2

The images, after capturing them using the PowerShot S95 camera, were stored directly on a flash card located in the camera. The PowerShot S95 camera has three bands: near infrared, red, and green. The flight altitude was set at 60 meters. Hence the camera had a spatial resolution of 5cm. Since the field had one crop only, the front overlap and side lap were 85% and 65% respectively. High overlapping flight path assists to improve the efficacy of post-flight mosaic processing.

Prior to each flight, a total of six Ground Control Points (GCP) were set up and dispersed throughout the field. The GCPs were mounted on a wood stake at a height of 1.5m. This was necessary for orthorectification and georeferencing of the final mosaic images. Locations of the GCPs were recorded using a Trimble GeoXH GPS. Each flight mission required a team of three people. One person operated the control unit for the planning and operation of the LARS, while the other two were responsible for flight observation (i.e. spotting potential hazards) and the distribution and collection of the GCPs. Each raw image was converted into a jpeg file and calibrated using *Pixelwrench2* software. Pix4d Mapper (*Pix4D, Switzerland*) software was used to orthorectify and mosaic the optical infrared imagery and also to generate NDVI images of fields. A stratified random sample was used to statistically examine the differences in NDVI among the three fertilizer treatments.

4. Study Results and Discussion

4.1 Assessing fertilizer treatments using UAV imagery

The benefits of organic manure on soil quality and crop production cannot be overemphasized. Several studies have shown that adding compost increases crop production and improve soil fertility (Keener, Dick, & Hoitink, 2000).

4.1.1 Mosaicked image of maize field as captured by the UAV (taken on 8th December, 2015)

Figure 3 shows two mosaicked images of a maize field as captured by the UAV. Image 1 is a mosaicked infrared color composite image (NIR, red, green-no enhancement applied) while image 2 is a mosaicked NDVI image. Area marked A is area treated with organic fertilizer (9.37 L/ha), while area B is treated with both organic and chemical fertilizer (9.37 L/ha) and chemical fertilizer (185.53 kg/ha), and area C is treated with chemical fertilizer only (371.25 kg/ha). Area marked D shows an error in fertilizer application. Calculated final yields for the areas A, B and C were calculated at 1.23, 1.77 and 2.47 tons/ha, respectively.

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

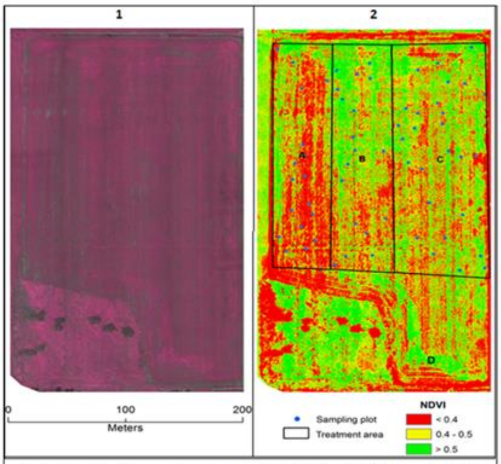

Fig. 3. Mosaicked image of maize as captured by the UAV (8 December 2015)

Figure 3

4.1.2 Mosaicked image of maize field as captured by the UAV (taken on 20th January, 2016)

Figure 4 are two mosaicked images of a maize field as captured by the UAV. Image 1 is a mosaicked infrared color composite image (NIR, red, green-no enhancement applied) while image 2 is a mosaicked NDVI image. Area marked A is area treated with organic fertilizer, while area B is treated with both organic and chemical fertilizer, and area C is treated with chemical fertilizer only. Area marked D shows an error in fertilizer application. Calculated final yields for the areas A, B and C were calculated at 1.23, 1.77 and 2.47 tons/ha, respectively.

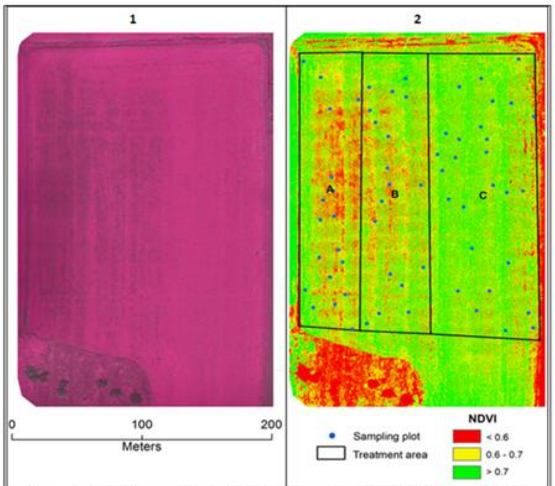

Fig. 4. Mosaicked image of maize field as captured by the UAV (20 January 2016)

Figure 4

The first flight took place on 8th December 2015 when maize crop was about 35cm high. Figure 3 shows a great contrast between the area treated with organic fertilizer and that treated with chemical fertilizer. The former had the weakest vegetation vigor hence appears much darker in the infrared image. Its NDVI values are considerably lower than those of the chemical fertilizer treatment (i.e. $P<0.001$). There is no much difference between areas **B** and **C** ($P=0.59$). The variability within each treatment area could be attributed to differences in soil types, soil moisture content, or other factors. The NDVI difference between areas **B** and **C** is very apparent in images taken on 20th January 2016 (Figure 3) when the crop was at a later growth stage than one taken earlier on 8th December 2015. Major differences (i.e. $P<0.001$) were observed between treatments A and C, and B and C. While the differences between treatment areas **A**

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

and **B** were not statistically significant (P=0.07), the P values is really close to the critical value of 0.05. Therefore, a flight taken between these two dates would have provided better discrimination of the treatment areas.

4.2 Identifying area of lodging and insect infestation using UAV imagery

One typical pest that attacks maize in tropical and subtropical regions is armyworm. A warm, humid weather and heavy rainfall favor the proliferation of armyworm in such regions. It is estimated that, on average, one caterpillar needs 140 cm^2 of leaf area to develop through 6 instars. However, the 6^{th} instar itself requires 77.2% of that leaf area (Sparks, 1979). Due to this scenario, Zhang & Kovacs (2012) explain that farmers may only recognize and report the armyworm infestation at this stage of growth. Following such infestation, the main midribs of the leaves remain intact while the succulent parts are completely consumed. This makes the leaf area of the field or parts of the field to drop considerably within a short period of time. With such damage, armyworm impacts can therefore be assessed using high resolution remotely sensed imagery. The expectation is that, due to the loss of flag leaves and increased exposure of the soil surface and shadows, there must be a decrease in reflectance in the NIR band while that of the red band should increase (Zhang & Kovacs 2012).

Fig 5. Armyworm infested maize plant | **A healthy maize plant**

Figure 5

Another important damage common to many cereal crops, maize inclusive, is lodging, or stem breakage. Mostly, this is a result of stormy weather conditions coupled with inadequate standing power of the crop during certain growth stages (i.e. heavy seed heads). High nitrogen fertilization too may cause plants to be more susceptible to lodging. A combination of armyworm infestation and stormy weather conditions rendered the maize crop more susceptible to lodging. Therefore, lodged areas appear as a bright red tone in the infrared image. Since the lodged maize crop covers the bare soil, stronger reflectance is observed from the leaves and stalks in the IR band giving a large contrast between the lodged and non-lodged areas (Zhang & Kovacs, 2012).

Fig. 6. Lodging maize plant

Figure 6

Figure 7 shows two images of the maize field. To the left is a mosaicked infrared color composite non-enhanced image (NIR, red, green) whose plants are infested with both armyworm and lodging. To the right is the corresponding NDVI derived image. Area **A** shows

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

a healthy non-infested maize field, **B** is a section of the maize crop attacked by armyworm whereas **C** and **D** indicates sections of lodging and rock outcrop, respectively.

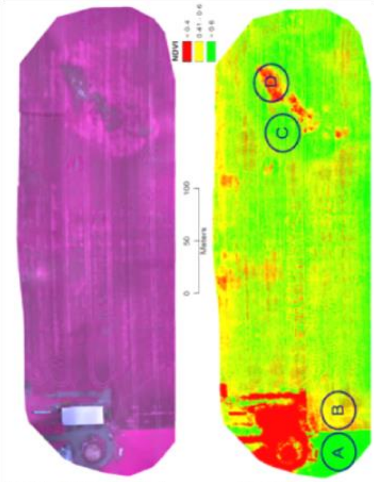

Fig.7. Mosaicked infrared color composite image (No enhancement)   NDVI derived image

Figure 7

From the same images in Figure 7, stressed areas of the crop field were also identified. During the field walk, it was discovered that the maize crop on shallow soils, for example on and around rock outcrop, were dead. In the NIR, these crops are shown in a dark tone. Information gathered from such interpretation may be used to determine whether a farmer should invest in equipment to lift the lodged heads during harvesting. Based on such information, a determination may further be made as to what mechanism should be put in place to improve the fertility of the shallow soils.

4.3 Identifying field tile network using UAV imageries

At an average altitude of about 1039m above sea level, Blantyre has an undulating topography with clay as the main soil type (UN-Habitat, 2011). The combination of these two factors leads to drainage problems for local farmers. In a bid to reduce risk of crop failure due to excess water and maintain uniform crop production amidst climate variability (Zhang & Kovacs 2012), the use of field tile drainage system were adopted. Good drainage also reduces the frequency of pests and disease outbreak while ensuring that a farmer gets a modest return (Zucker & Brown, 1998). Once installed these drainage systems need to be monitored and maintained hence it is necessary for the farmer to know the exact location of the tiles.

The images for this task were collected on 17th March 2016, immediately after harvest. They were processed by applying linear enhancement and mosaicked. After analyzing the mosaicked images, locations of some of the tiles in the image were identified. A brighter tone with a linear-like feature represented the locations of the tiles. At the same time, well drained areas were drier hence looked brighter (see Figure 8). Further, some drainage problems such as excessive wetness were also identified. Worth noting here is that, just like Zhang & Kovacs (2012), interpretation was possible in the section where the soil was bare as opposed to the western part of the field. This was as a result of presence of remains of maize stalks which covered the ground.

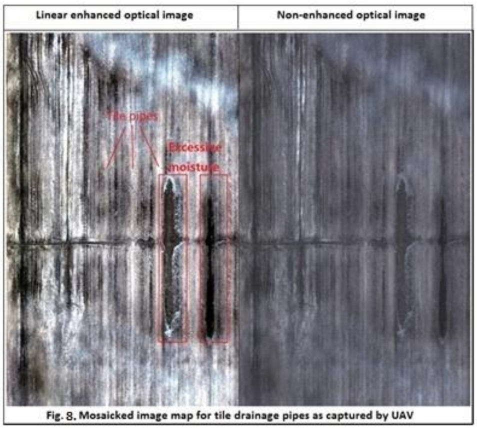

Fig. 8. Mosaicked image map for tile drainage pipes as captured by UAV

Figure 8

5. Conclusion

This paper demonstrated the feasibility of applying UAV acquired images, both in optical and near-infrared, for monitoring crop conditions in precision agriculture. The results suggest that it is possible to acquire images and process them in a timely fashion for PA applications. However, high current costs and operational logistics have compromised the assimilation of its application. Nevertheless, it is anticipated that as the costs of LARS decrease and more experienced personnel available to acquire and process the data, the adoption of UAV systems will skyrocket.

References

Berni, J.A.J., Zarco-Tejada, P.J., Suarez, L. & Fereres, E. (2009) ‘Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle’. *IEEE Geoscience and Remote Sensing*. 47 pp. 722–738.

Blackmore, S., Godwin, R.J. & Fountas S (2003) ‘The analysis of spatial and temporal trends in yield map data over six years’. *Journal of Biosystems Engineering*. 84(4) pp. 455-466.

Diker, K., Heermann, D.F. & Bordahl, M.K. (2004) ‘Frequency analysis of yield for delineating yield response zones’. *Journal of Precision Agriculture*. 5 pp. 435–444.

Flowers, M., Weisz, R. & White, J.G. (2005) ‘Yield-based management zones and grid sampling strategies: Describing soil test and nutrient variability’. *Agronomy Journal*. 97 (3) pp. 968–982.

Hunt, E.R., Cavigelli. M., Daughtry, C.S.T., McMurtrey, J. & Walthall, C.L. (2005) ‘Evaluation of digital photography from model aircraft for remote sensing of crop biomass and nitrogen status’. *Journal of Precision Agriculture*. 6(4) pp. 359–378.

Hunt, E.R., Hively, W.D., Daughtry, C.S.T., McCarty, G.W., Fujikawa, S.J., et al. (2008) ‘Remote sensing of crop leaf area index using unmanned airborne vehicles’. *In: Proceedings of the Pecora 17 Symposium, Denver, CO, November 18, 2008*. Bethesda, MD: American Society for Photogrammetry and Remote Sensing.

Hunt, E.R., Hively, W.D., Fujikawa, S.J., Linden, D.S., Daughtry, C.S.T., et al. (2010) ‘Acquisition of NIR-Green-Blue digital photographs from unmanned aircraft for crop monitoring’. *Journal of Remote Sensing*. 2(1) pp. 290–305.

Inoue, Y., Morinaga, S. & Tomita, A. (2000) ‘A blimp-based remote sensing system for low-altitude monitoring of plant variables: a preliminary experiment for agricultural and ecological applications’. *International Journal of Remote Sensing*. 21(2) pp. 379–385.

Keener, H.M., Dick, W.A. & Hoitink, H.A.J. (2000) ‘Composting and beneficial utilization of composted by-product materials’ In: Power, J.F., Dick, W.A. (Eds.), *Land Application of*

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

Agricultural, Industrial, and Municipal By-products. Madison, WI.: Soil Science Society of America, , pp: 315–341.

Lopez-Lozano. R., Baret, F., de Cortazar-Atauri, I.G., Bertrand, N. & Casterad, M.A. (2009) 'Optimal geometric configuration and algorithms for LAI indirect estimates under row canopies: The case of vineyards'. *Journal of Agriculture & Forest Meteorology*. 149 (8) pp 1307–1316.

Ngongondo, C., Tallaksen, L.M. & CHONG-YU XU (2014) 'Growing season length and rainfall extremes analysis in Malawi. Hydrology in a Changing World: Environmental and Human Dimensions' *In: Proceedings of FRIEND-Water 2014, Montpellier, France, Oct. 2014*. IAHS Publisher. pp. 363.

Primicerio, J., Gennaro, S.F., Fiorillo, E., Genesio, L., Lugato, E., et al. (2012) 'A flexible unmanned aerial vehicle for precision agriculture'. *Journal of Precision Agriculture*. 13(4) pp. 517–523.

Ryo, S., Noguchi, N., & Ishii, K. (2007) 'Correction of low-altitude thermal images applied to estimating of soil water status'. *Journal of Biosystems Engineering*. 96(3) pp. 301–313.

Sparks, A.N. (1979) *A review of the biology of the fall armyworm*. Florida: Florida Entomologist Publishers. pp. 82–87.

Swain, K.C., Thomson, S.J. & Jayasuriya, H.P.W. (2010) 'Adoption of an unmanned helicopter for low-altitude remote sensing to estimate yield and total biomass of a rice crop'. *Transactions of ASABE*. 53(1) pp. 21–27.

UN-Habitat (2011) 'Blantyre Urban Profile, Malawi. Nairobi, Kenya: *United Nations Human Settlements Programme,* p. 336.

Yang, C., Everitt, J.H., Bradford, J.M. & Escobar, D.E. (2000) 'Mapping grain sorghum growth and yield variations using airborne multispectral digital imagery'. *Transactions of ASABE*. 43(6) pp. 1927–1938.

Yang, C., Everitt, J.H. & Bradford, J.M. (2004) 'Airborne hyperspectral imagery and yield monitor data for estimating grain sorghum yield variability'. *Transactions of ASABE*. 47(3) pp. 915–924.

Yang, C., Everitt, J.H., Bradford, J.M. & Murden, D. (2004) 'Airborne hyperspectral imagery and yield monitor data for mapping cotton yield variability'. *Journal of Precision Agriculture*. 5(5) pp. 445–461.

Yang, C., Everitt, J.H, Qian, D., Luo, B. & Chanussor J (2013) 'Using High-Resolution Airborne and Satellite Imagery to Assess Crop Growth and Yield Variability for Precision Agriculture'. *Journal of Precision Agriculture*. 101 pp. 582–592.

Zarco-Tejada PJ, Gonzalez-Dugo V, Berni JAJ (2012) 'Fluorescence, temperature and narrowband indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera'. *Journal of Remote Sensing of Environment* 117 pp. 322–337.

Zarco-Tejada, P.J., Guillén-Climent, M.L., Hernández-Clemente, R., Catalina, A., González, M.R. et al. (2013) 'Estimating leaf carotenoid content in vineyards using high resolution hyperspectral imagery acquired from an unmanned aerial vehicle (UAV)'. *Journal of Agricultural and Forest Meteorology*. 171 pp. 281–294.

Zhang, C. & Kovacs, J.M. (2012) 'The application of small unmanned aerial systems for precision agriculture: A review'. *Journal of Precision Agriculture*. 13 pp. 693–712.

Zucker, L.A. & Brown, L.C. (1998) 'Agricultural drainage: Water quality impacts and subsurface drainage studies in the Midwest'. *Bulletin,* 871–98. St Paul, Minn.: University of Minnesota Extension,

ISSN 2223-7062 Proceedings and Report of the 9th UbuntuNet Alliance Annual Conference, 2016 pp 23-34

Biography

Donnex Chilonga is a research scientist cum geographer with specialty in the utilization of space-based technology in solving current social problems. He has been teaching at University level since 2012. Throughout his 4-year span Donnex has built a reputation for developing space-based scientific models tailored for disaster management. Together with his colleagues in the Geography and Earth Science department of Mzuzu University, Donnex is a lead on building a model for communication for first responders in times of flooding in Malawi. Donnex' academic background includes a PGD in Remote Sensing and GIS and BA (Geography) obtained from African Regional Centre for Space Science and Technology Education, Obafemi Awolowo University and Mzuzu University respectively. Currently he is an MSc student in GIS. His interest in environmental protection for equitable use saw Donnex obtaining a Diploma in Law from the University of Malawi.