Integrating land cover and terrain characteristics to explain plague risks in Western Usambara Mountains, Tanzania: a geospatial approach

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Abstract: Literature suggests that higher resolution remote sensing data integrated in Geographic Information System (GIS) can provide greater possibility to refine the analysis of land cover and terrain characteristics for explanation of abundance and distribution of plague hosts and vectors and hence of health risk hazards to humans. These technologies are not widely used in East Africa for studies on diseases including plague. The objective of this study was to refine the analysis of single and combined land cover and terrain characteristics in order to gain an insight into localized plague infection risks in the West Usambara Mountains in north-eastern Tanzania. The study used a geospatial approach to assess the influence of land cover and terrain factors on the abundance and spatial distribution of plague hosts (small mammals) and plague vectors (fleas). It considered different levels of scale and resolution. Boosted Regression Tree (BRT) statistical method was used to clarify the relationships between land cover and terrain variables with small mammals and fleas. Results indicate that elevation positively influenced the presence of small mammals. The presence of fleas was clearly influenced by land management features such as *miraba*. Medium to high resolution remotely sensed data integrated in a GIS have been found to be quite useful in this type of analysis. These findings contribute to efforts on plague surveillance and awareness creation among communities on the probable risks associated with various landscape factors during epidemics.

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Keywords: land cover, remote sensing, GIS, small mammals, fleas, plague, Tanzania

Introduction

Transmission of zoonotic vector-borne diseases forms complex systems in the landscape (Vanwambeke *et al.*, 2011). These systems are influenced by a broad spectrum of environmental factors operating at diverse scales, including climate (Debien *et al.,* 2009; Ben Ari *et al.*, 2011), land cover (Lambin *et al.*, 2010), soil, landscape and land use (Patz *et al.*, 2004; Neerinckx *et al.*, 2010; Vanwambeke *et al.*, 2011; Ben Ari *et al.*, 2011; Baumgardner *et al.*, 2012; Chammartin *et al.*, 2013). In Tanzania, plague (caused by *Yersinia pestis*) has occurred in West Usambara Mountains and in the Mbulu district since 1980 (Kilonzo & Mhina, 1982; Kilonzo *et al.*, 1997, 2005; Makundi *et al.*, 2003, 2007, 2008; Laudisoit *et al.,* 2009a,b; Neerinckx *et al.*, 2010). Most of the data and analytical techniques in these studies concentrated on biological and microbiological factors for which, unlike in the current study, little or no appeal was made to detailed terrain and land cover data involving remote sensing and geographical information systems (GIS).

Coarse resolution remote sensing and GIS techniques have been widely applied to understand the relation of regionally distributed environmental factors in relation to vector borne diseases including malaria (Ceccato *et al.*, 2005), dengue (Palaniyandi, 2012) and plague (Eisen *et al.*, 2011, 2012; MacMillan *et al.*, 2011). Debien *et al.* (2009) used Tropical Rainfall Measuring Mission (TRMM) at 0.25x0.25km resolution and MODIS monthly NDVI (1x1km) data to reconstruct rainfall patterns at 1x1km resolution for predicting occurrence of plague in north-eastern Tanzania. Neerinckx *et al.* (2010) used environmental dataset assembled from MODIS

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data at 250m resolution to predict potential risk areas of human plague in the Lushoto area of Tanzania and in larger parts of East and Southern Africa. Eisen *et al.* (2010) and MacMillan *et al.* (2011), attempted to identify elevated risk of human exposure to plague bacteria at sub-village level, using SRTM DEM (90m), and Landsat ETM+ (30x30m). Eisen *et al.* (2012) used 2-km resolution climate dataset derived from a suite of atmospheric simulations with the Weather Research and Forecasting Model (WRF) (Monoghan *et al.,* 2012) to compare host and flea abundance and diversity along an elevation gradient performed specifically for the West Nile region plague focus in Uganda.

Land cover is an important determinant of habitat suitability for disease vectors and hosts (Linard *et al.,* 2007) and hence of health risk hazards to humans. The abundance and spatial distribution of small mammals and fleas vary along the different land cover types and between landscape units (Vanwambeke *et al.,* 2011). Higher resolution remote sensing data are of increasing interest in disease studies (Ostfeld *et al.,* 2005); especially when land cover and landscape factors enter the picture. These factors also ask for spatial analytical tools and GIS. However, some factors including cost, access to equipment or insufficient skills in remote sensing and GIS have prohibited such approach (Le Sueur & Martin, 1996; Tanser & le Sueur, 2002; Ostfeld *et al.,* 2005; Zhang *et al.,* 2013). The objective of this study was therefore to refine the analysis of single and combined land cover and terrain characteristics in order to gain a better understanding of localised plague infection risks in the West Usambara Mountains in north-east Tanzania. It is expected to provide useful information for plague and other rodent borne disease control programmes as well as information for further in-depth research on the complex ecology of the plague system.

Materials and Methods

Study area

This study was carried out in the Western Usambara Mountains in Lushoto district of north-eastern Tanzania. The study area is located between Universal Transverse Mercator (UTM) coordinates 4000000 m E and 430000 m E and between 9480000 m N and 9500000 m N, Zone 37M, covering an area of about 34,000ha (Figure 1). The altitude ranges from 480 to 2,271m. In the Western Usambara Mountains, two rainy seasons exist: short rains *(vuli)* from October to December and long rains *(masika)* from March to May (Debien *et al.,* 2009). The rainy seasons are associated with the seasonal movement of the Intertropical Convergence Zone (ITCZ). Rainfall in the study area is influenced by topography (Debien *et al.,* 2009). The rainy seasons are associated with the seasonal movement of the Intertropical Convergence Zone (ITCZ). Rainfall in the study area is influenced by topography (Debien *et al.,* 2009). The area has mean annual precipitation ranging from 600 to 1200 mm. The study area shows large differences in relief dissection and intensity, vegetation and land use patterns, and human activities. Land use is dominated by mixed rainfed farming, followed by irrigated agriculture, livestock keeping and off farm activities including petty cash and carpentry (Msita *et al.,* 2010). These land uses are bordered or surrounded by natural forests, and plantation forest and utility woodlots.

Previous research on rodents, fleas and plague (Njunwa *et al.,* 1989; Kilonzo *et al.,* 1997; Davis *et al.,* 2006; Kamugisha *et al.,* 2007; Laudisoit *et al.,* 2007, 2009a, b; Neerinckx *et al.,* 2010) allowed defining the study area in such a way that it reflects a geographical gradient in the frequency of plague incidence. These authors concur in distinguishing high, medium, and low incidence zones. Within this gradient three representative landscapes were selected differing in terms of (i) the incidence of plague, (ii) diversity in land use and associated human activities, (iii) landform characteristics (relief intensity and level of dissection), and (iv) climatic conditions. The selected landscapes are named Shume (high plague incidence), Lukozi (medium plague incidence) and Mwangoi (low plague incidence) landscapes, after the name of their most important settlement.
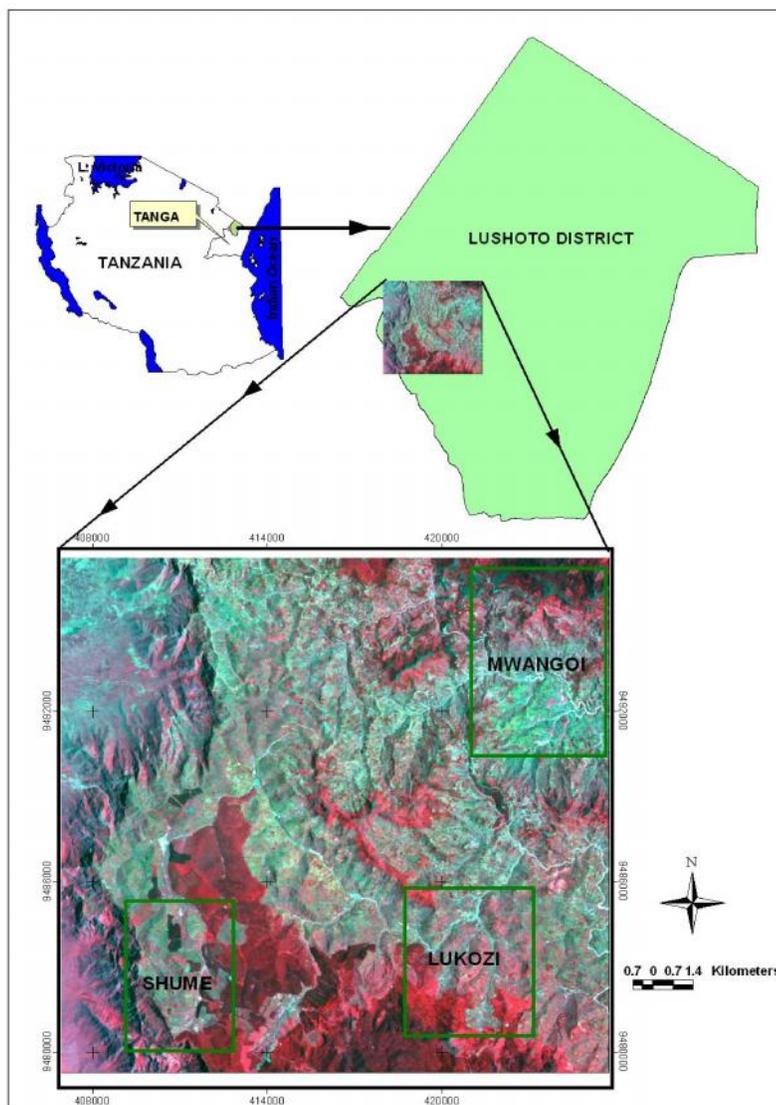
Figure 1: Selected study landscapes in West Usambara Mountains, Tanzania

Data collection and analysis

This study included the generation of terrain attributes from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Digital Elevation Model (DEM) with 30m resolution, a land cover map from three-band SPOT 5 image (nominal spatial resolution 2.5m) and the collection of small mammals and fleas. Boosted Regression Trees (BRT) was used to identify terrain and land cover predictors of abundance of small mammals and fleas. Both categories of organisms are seen as indicators of potential plague occurrence at landscape scale. The final layers were saved in raster (geotiff) format. Land cover was also defined in vector (shapefile) format. Data extraction and zonal statistics were carried out in ARCGIS 9.3 and QGIS respectively to generate spatial and attribute data for each 100x100m quadrat in which small mammals and fleas were collected. The developed spatial geodatabase associated with their attributes were used as independent variables in BRT analysis. Small mammal and flea data were used as dependent variables.

The developed geospatial database can be used in desktop GIS with ARCGIS, ARCVIEW, QGIS and other related GIS software. The methodological flow chart (Figure 2) summarises the steps followed in spatial geodata capturing, processing, integration, storage, and BRT modelling.
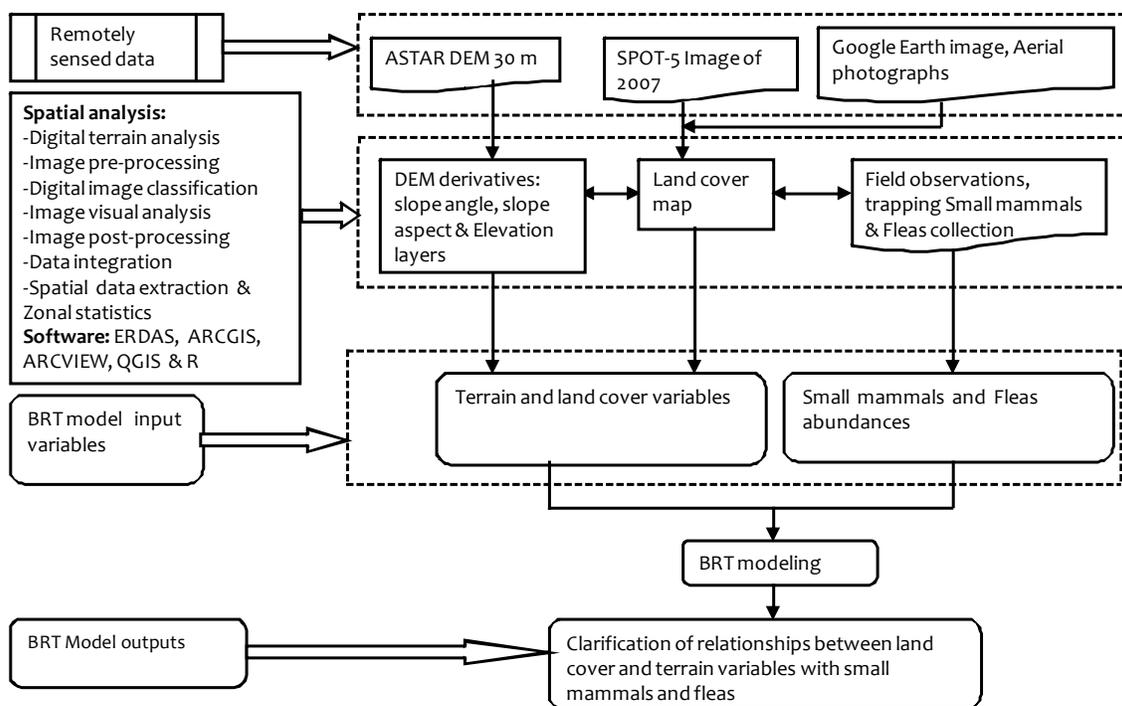
Figure 2: Methodological flow chart summarising the steps followed for data collection and analysis

Mapping of terrain variables

Three topographical variables (elevation, slope gradient and slope aspect) were derived from the ASTER DEM (30m) using ARCGIS 9.3 software. Elevation strongly determines climate in this area. Slope gradient strongly influences the choice of land management types, and is correlated with soil characteristics (Msita *et al.,* 2010). Slope aspect, measured clockwise in degrees from 0 (north) to 360, has been reported to influence rainfall in the West Usambara Mountains (Kajembe, 1994). Flat areas are given a slope aspect value of -1.

Generation of a land cover map

A cloud free three-band SPOT 5 image captured on 27 February 2007, nominal spatial resolution 2.5m, was used in this study. The image was orthorectified in ERDAS 2011 software. The initial classification of land cover was based on 20 spectral classes generated using the unsupervised ISODATA clustering technique in ERDAS2011. GPS supported field observation was conducted in August to September 2011, April to June 2012 and in August to October 2012, and allowed to define characteristic tone, texture and pattern of the land cover classes on the display of the SPOT 5 colour composite image. Also aerial photographs and Google Earth provided essential independent reference data to help in identifying land cover types within the SPOT 5 image.

The description of the different land cover categories was in the first instance based on Anderson *et al.* (1976) and then refined to match the terminology of the FAO Guidelines for Soil Description (FAO, 2006). Because of the occurrence of mixed pixels, similarity in spectral signatures of some land cover types, and heterogeneous illumination conditions in this undulating area, a hybrid image classification method was used (Wang *et al*., 2005; Horning, 2010a). This approach combines the advantages of the automated and manual methods to produce land cover maps (Horning, 2010a). Expert information and visual interpretation allowed refining and correcting the automated classification (Horning, 2010a). Also existing information, for example on the location and extent of plantation forest, was directly inserted in the land cover map, to avoid confusing recently harvested patches with bare land.

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Supervised classification was done using Random Forest (RF) algorithm (Breiman, 2001) in R software (R Development Core Team, 2006). Random Forest is known to be one of the most efficient classification methods (Akar & Gungor, 2012). A script written by Horning (2010b) was used. The script requires that training areas are digitized as polygons and saved as an ESRI shapefile. The training dataset is defined as multiple polygons for each class.

Post-processing of classified image included majority neighbourhood filter, clump and eliminate. The classified map was later compared with the original image and reference data used in this study. Classes which were not labelled correctly were spotted and edited. Five classes out of twelve were successfully generated: Cropland (Rainfed maize and beans), Agroforestry, Settlement, Woodlot and Shrub. Seven out of twelve classes were not sufficiently well classified by this algorithm due to similarity in spectral signatures: Cropland (perennials and furrow irrigated vegetables), Cropland (supplemental irrigated vegetables and potatoes), plantation forest, natural forest, grassland with emergent trees, bushland and woodland. Their initial classification was corrected through onscreen digitisation after visual interpretation of the SPOT 5 image. Software used during pre and post processing of the classified SPOT 5 image includes Arc View 3.3, ARCGIS 9.3 and ERDAS 2011.

Collection of data on small mammals and fleas

Based on the land cover and terrain attributes generated above, a total of 72 quadrats of 100x100 m were established. Twenty four quadrats were established at random for each landscape. At each observation site (quadrat) data on land cover, rodents and fleas from rodents were collected. Data collection was conducted in the dry season (August to October) of 2012.

Small mammals were trapped using Sherman LFA live traps (7.5x9.0x23 cm; HB Sherman Traps, Tallahassee, USA) baited with peanut butter and maize flour. A total of 49 Sherman live traps spaced 10 m apart were set in a grid per observation site (quadrat) and per trapping session. For the sites in natural forests, additionally two wire cages were used to capture somewhat larger mammals like squirrels. Each trapping session lasted 3 nights. Each trap was inspected every morning and traps with captured animals were replaced by empty traps (Zimba *et al.*, 2011). The captured animals were identified to genus level or species level where possible (Eisen *et al*., 2012) and carefully combed for fleas. Trap success (in percent) was calculated as the number of small mammals captured multiplied by 100 divided by the trap nights (i.e. number of traps x number of days) per quadrat (Mulungu *et al*., 2008; Laudisoit *et al*., 2009a). Fleas collected from each small mammal were counted. The flea index was calculated as the total number of fleas per total number of captured mammals in each quadrat (Laudisoit *et al*., 2009a). Trap success and flea index were used as dependent variables in the Boosted Regression Tree (BRT) modelling (to be explained later).

Boosted Regression Tree modelling

Exploring plague disease infection risk patterns requires a statistical technique that effectively addresses the complexity of the landscape systems and the disease ecology (Skolow *et al.*, 2009; Williams *et al.,* 2010; Aertsen *et al.*, 2012). The Boosted Regression Tree (BRT) model in R software (R Development Core Team, 2006) was used in this case. Models were fitted using the gbm.step function and a Gaussian response type, with most effective settings for learning rate (0.01–0.00001) and bag fraction (0.5–0.75) as found by repeated trial-and-error (Elith *et al.,* 2008). Tree complexity was set to 3, according to recommendations by Elith *et al.* (2008) for small datasets. The 10-fold cross-validation (CV) was used for model development and validation, with the benefit of still using the full data set to fit the final model (Elith et al., 2008). The measure of model performance was cv deviance and standard error (Elith *et al*., 2008; Williams *et al*., 2010). The combination of learning rate and bag fraction settings with the lowest cv deviance and standard error was the one selected to produce the final BRT model (Williams *et al*., 2010). Also during data exploration all predictor variables were tested for ecologically acceptable level of

collinearity (i.e. individual variance inflation factor (VIF) of <5) between predictor variables (Zuur *et al.*, 2010; Artsen *et al.*, 2012).

Ethical considerations

This study received approval from Directorate of Research and Post-Graduate Studies of Sokoine University of Agriculture, Tanzania and Flemish Inter-University Council (VLIR-UOS) of Belgium.

Results

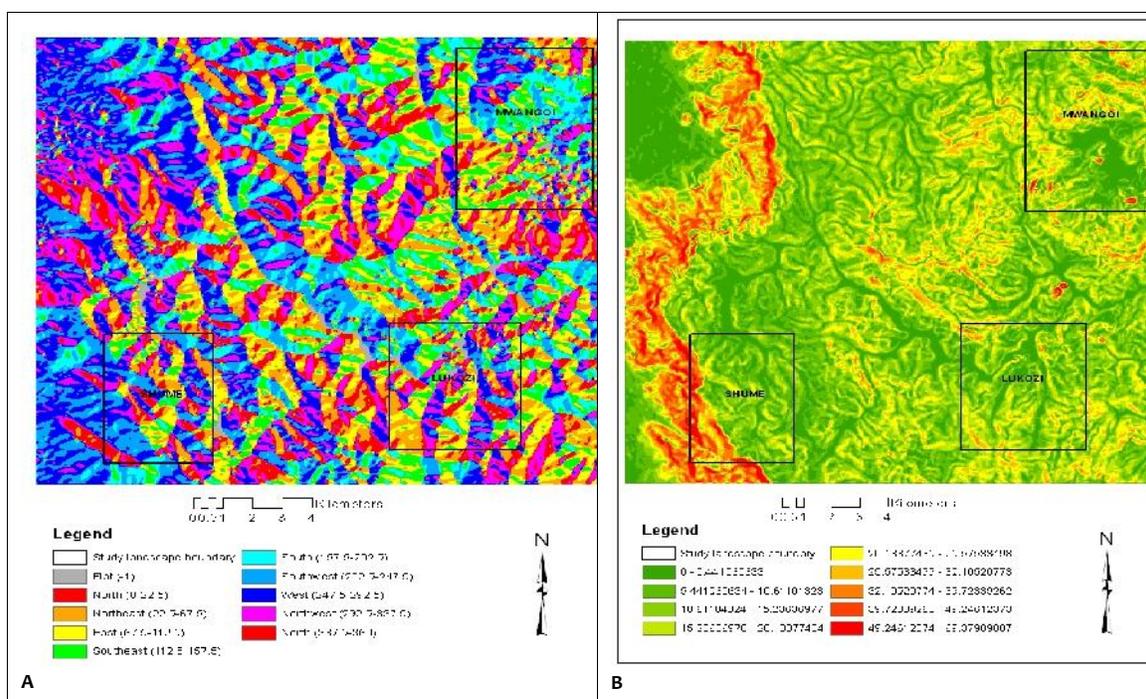### *Land cover, terrain variables and small mammals*

Figure 3A presents the land cover types of 2012 while in Table 1 their respective dominant coverage for the three studied landscapes are given. Figures 3B, 4A and 4B present elevation ranges, slope aspect and slope angle respectively, which are terrain attributes used as predictor variables along with land cover types for prediction of small mammal and flea abundance and spatial distribution. Table 2 provides the summary of the values for the terrain attributes extracted from the ASTER DEM and small mammal and flea abundances.
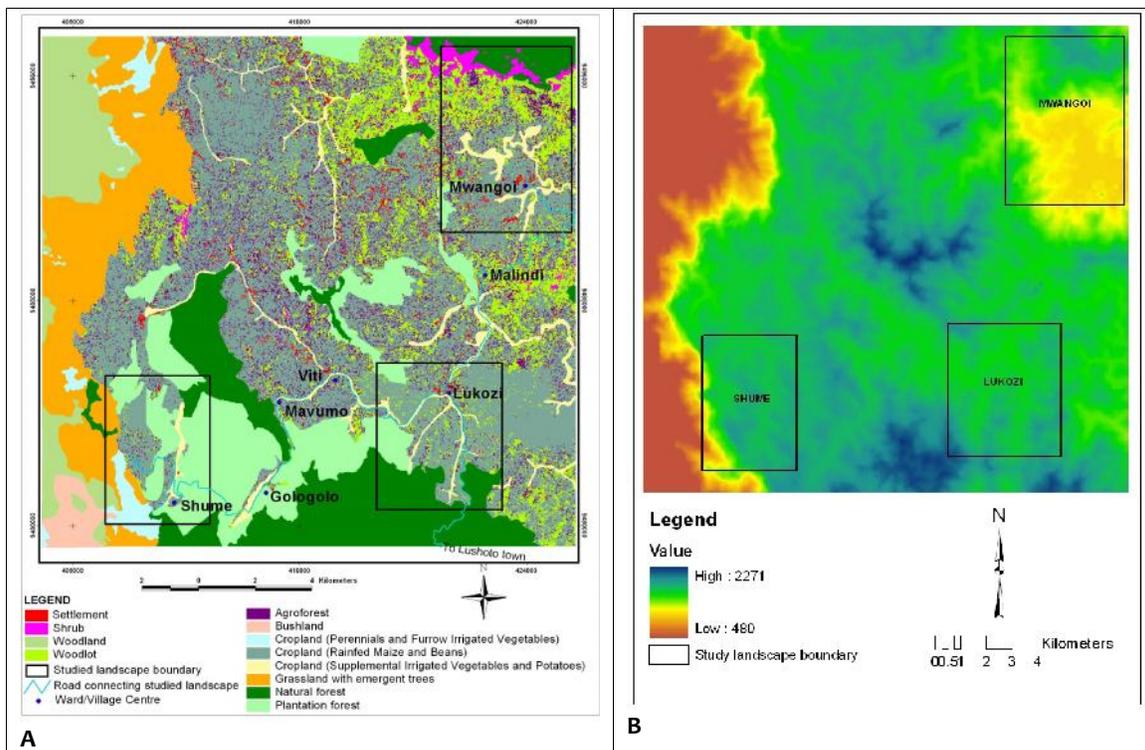
Figure 3 A: Land cover map covering the three studied landscapes (inside boxes); B: Elevation ranges used as terrain predictor variable for small mammal and flea abundance

Table 1: Land cover categories of the studied landscapes

| Land cover (ha)	Landscape		
	Mwangoi	Lukozi	Shume
Agroforest	277.1 (9.1%)	83.6 (3.6%)	35.9 (1.8%)
Cropland (Rainfed Maize and Beans)	1229.5 (40.3%)	1169.8 (50.9%)	445.5 (22.9%)
Cropland (Irrigated Vegetables and Potatoes)	207.9(6.8%)	122.6(5.3%)	59.9 (3.1%)
Natural forest	330.3 (10.8%)	509.4 (22.1%)	107.9 (5.6%)
Plantation forest	48.3 (1.6%)	233.3 (10.1%)	857.4 (44.2%)
Shrub	194.9 (6.4%)	3.2 (0.1%)	2.1 (0.1%)
Woodlot	684.2 (22.5%)	161.9 (7.0%)	32.7 (1.7%)
Settlement	74.8 (2.5%)	16.1 (0.7%)	4.4 (0.2%)
Woodland			30.6 (1.6%)
Cropland (Perennials and Furrow Irrigated Vegetables)			185.8 (9.6%)
Grassland with emergent trees			171.5 (8.8%)
Bushland			7.4 (0.4%)
Total	3,047.1	2,300.0	1,941.1

Figure 4 A: Slope aspects used as terrain predictor variable; and B: Slope angle in degrees used as predictor variable for small mammals and fleas abundance

Table 2: Summary of the terrain attributes values and small mammals and fleas

Landscape	Attribute	Attribute Mean	Small mammals	Fleas
Mwangoi	Elevation (m)	1589	79 (14%)	137 (20%)
	Slope angle (deg)	13.8		
	Slope aspect (deg)	163.3		
Lukozi	Elevation (m)	1855	232 (40%)	180 (27%)
	Slope angle (deg)	12.7		
	Slope aspect (deg)	169		
Shume	Elevation (m)	1819	265 (46%)	358 (53%)
	Slope angle (deg)	16.2		
	Slope aspect (deg)	192		

Boosted Regression Trees (BRT) model for explaining the relationship between land cover, terrain attributes and small mammals

Four predictor variables were retained by the BRT model as being influential on the observed spatial pattern of trap success (Figure 5). All four predictor variables had the ecologically acceptable level of individual variance inflation factor i.e. VIF<5. Elevation was the most important predictor with contribution of more than two thirds of the total (80.1%) and a strong positive effect. The elevation of 1,700 m appeared to be the threshold for a sharp increase in trap success. The second important predictor was slope aspect with contribution of 11.4% and a moderate positive effect. The location on 150 degree aspect (south east facing slope) appeared to be an important condition for increased trap success. The slope angle and land cover had weak positive effect although with small contributions. The abundance of small mammals (trap success) seemed to increase slightly on slopes of 10 degrees and above. The abundance also gradually increased as the land cover types varied from natural forest (coded 1) to other land cover types (coded from 2 to 7).
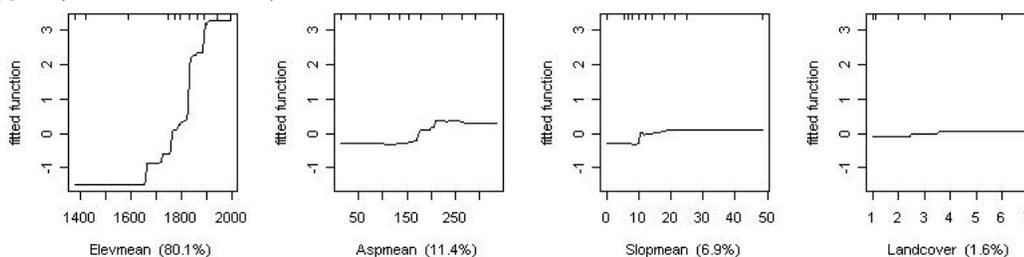
Figure 5: Partial dependence plots showing the effect of land cover & terrain variables on spatial pattern of small mammals. The relative contribution of each predictor is given in brackets. CV deviance=22.343, standard error=3.612, number of trees=1250. **Key:** Elevmean = Elevation, aspmean = Slope aspect, slopmean = Slope angle, Landcover = Land cover)

BRT model for explaining the relationship between land cover, terrain attributes and fleas

Four predictor variables were identified by the BRT model as having influence on the observed spatial pattern of flea index (Figure 6). All four predictor variables had the ecologically acceptable level of individual variance inflation factor i.e. VIF<5. Slope angle was the most important predictor with contribution of more than two thirds of the total (75.3%) and a strong positive effect. The presence of a slope angle of at least 10 degrees appeared to be an important condition for increased rodent flea abundance (flea index). The second important predictor was elevation with contribution of 17.3% and a moderate positive effect. The elevation of 1800 m appeared to be an important condition for increased flea index. Land cover and slope aspect had smaller contributions and showed weak effect. Land cover showed a slight negative effect as land cover types varied from that dominated by natural forest (coded 1) and plantation forest (coded 2) to the rest of the land cover types (coded from 3 to 7) (Figure 6).
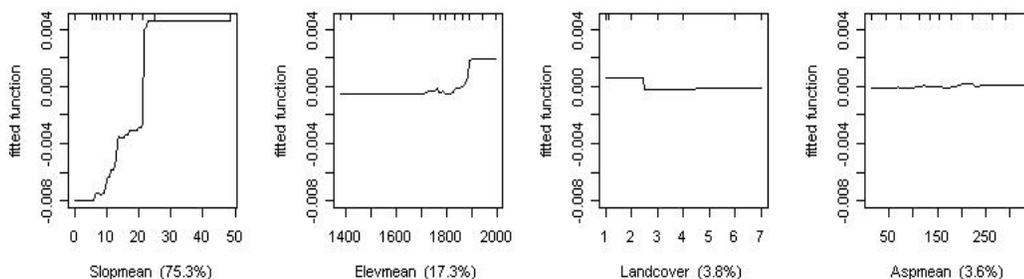
Figure 6: Partial dependence plots showing the effect of land cover and terrain variables on spatial pattern of flea index. The relative contribution of each predictor is given in brackets. **Key**=CV deviance=1.764, standard error=0.561, number of trees=1000. **Key:** Elevmean = Elevation, aspmean = Slope aspect, slopmean = Slope angle, Landcover = Land cover)

Discussion

Small mammals trap success seems to be greatly influenced by altitude. This finding is contrary to the observations by Mulungu *et al*. (2008) who found a decrease in small mammals trap success with altitude along Mount Kilimanjaro in Tanzania. This could be attributed to the increased resource availability (water and food) as one moves from low to high altitude in the studied landscapes compared to Mount Kilimanjaro, where resources availability decreases with increase in altitude. Furthermore, the results of our study clearly demonstrate that there is a positive influence of slope aspect on the small mammals trap success in the range 112-157 degrees i.e. south east facing slopes. This could be due to availability of water for small mammals as a result of orographic effect. High rainfall in West Usambara Mountains occurs in areas located to the east and south east which are the first to receive moisture-laden south-easterly trade winds from the Indian Ocean (Kajembe, 1994). The findings of this study are consistent with earlier studies which reported that food, water, rainfall and shelter are important factors for small mammals' abundance (Mwanjabe, 1993; Makundi *et al*., 2007; Mulungu *et al*., 2011).

The current study shows that slope gradient has strong positive influence on flea index. This relationship could be attributed to the different land management types and crops found on different geographic locations across the studied landscapes. The valley bottom areas and foot slopes characterized by flat or gentle slopes are mostly under irrigated vegetables. The application of insecticides and pesticides may explain the very low flea indices. As slope increases from lower parts to middle and upper slopes rainfed agriculture (i.e. the land cover type described in the current study as cropland (rainfed maize and beans) becomes the dominant land use. Also intensive land management practices including contour farming and indigenous land management system with grassy hedges called *miraba* increase. According to another study in the same area (Msita *et al.,* 2011), the density of *miraba* (total length of *miraba* segments per unit area) increases with slope gradient. Therefore, this strong positive influence of slope angle on flea index could be attributed to land management practices and mainly *miraba* cultivation which are associated with many rodent burrows (Kamugisha *et al.,* 2007; Brabers, 2012).

It should be noted that rodent burrows are also likely to harbour adult 'free flea population' which sometimes stay off host in the burrows (Eisen *et al*., 2012). According to Eisen *et al*. (2012), it is possible that off host adult flea populations of some infected species are able to survive for relatively long periods in burrows or nests, thus contributing to chances of plague persistence. Since the *miraba* in the study area provide suitable habitats for rodents, the possibility of rodents contacting high numbers of fleas inside burrows is most likely to be high (Hubbart *et al.,* 2011). The grasses grown along *miraba* can be a hiding place for pests like rats (Kamugisha *et al.,* 2007; Msita *et al.,* 2011). *Miraba* planted with Guatemala and elephant grass are frequently visited by humans during the dry season for fodder collection, a common practice for farmers practising zero grazing, hence high chances of flea bites (Vanwambeke *et al*., 2011). Also natural forests and shrubs on rocky slopes in the area mostly found on upper slopes and ridges also favour rodents' and fleas' abundance. These observations support earlier suggestions of potential plague infection risks being associated with land management and farming practices during epizootic periods in the plague risk area (MacMillan *et al*., 2011; Zimba *et al*., 2011).

In this study, flea index also tended to decrease as land cover types varied from natural forest and plantation forest to other classes. Results suggest that land cover dominated by natural forest and plantation forest tended to favour more fleas than other land cover types, though with weak effect. The effect of land cover type on flea abundance was reported in earlier studies in the study area (Laudisoit *et al.,* 2009a, b). In these studies shrubs which are also present in forested zones, were reported to have the highest flea abundance levels when compared to the other land cover types. Furthermore, elevation showed strong positive influence on flea index especially above 1800m. These findings are in line with previous studies in

the study area and elsewhere (Kilonzo *et al.,* 1992, 2005; Pham *et al.,* 2009; Winters *et al.,* 2009; Neerinckx *et al.,* 2010).

The middle and upper slopes of the study area dominated by *miraba* land management practices and contour farming favour the abundance of fleas. In addition, elevations above 1800 m have a strong positive influence on flea index. Furthermore, elevation has a strong positive relation with small mammals trap success, which can be explained by an increase of food and water availability with altitude. Land cover and terrain variables influence and predict the spatial distribution of small mammals and fleas abundance across the West Usambara Mountain landscapes.

The relationship between land cover and terrain attributes on one hand and small mammals and fleas as potential hosts and vectors of plague, hence as indicators of plague risks, on the other hand has been well elaborated by remote sensing and GIS integration of geodatabase at different spatial scales and resolutions. This has revealed that a geomatic approach using remote sensing data and GIS technologies is valuable in studying plague infection risks.

The developed spatial geodatabase is structured for easy access and use on desktop computer GIS. The framework developed by this study forms a useful tool for plague surveillance and to inform communities on the probable risks associated with various landscape factors during epidemics. The framework is also a powerful tool for land and pest management including management of rodents which are dominantly crop pests. The geodataset derived from the satellite data including land cover, and DEM derivatives integrated in the expert GIS engine provide future potential analysis and understanding of the association of plague risk indicators including climate and human behaviour variables. In addition the developed geodatabase is vital information for district land use planning and rural development programmes in the study area.

Acknowledgements

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