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Mapping of Tomatoes Pest Susceptibility in Zaria, Kaduna, Nigeria

Abdulmalik M. Olaniyi[a*], *Ekundayo A. Adesina*[b], *Gbenga Adeniyi*[c], *Albert I. Nwose*[d], *Lukman Abdulmumeen*[e]

Department of Surveying and Geoinformatics, Federal University of Technology, Minna Niger State
m.olaniyi@futminna.edu.ng

Abstract

This study aimed at analyzing the geospatial distribution of tomato farm pest susceptibility in Zaria using Geospatial techniques. The actual GPS positions of 153 tomato farms were observed and represented on a Landsat 8 image of Zaria. Their locations were then verified with a SPOT 5 imagery. Supervised classification was used to classify the image into Land use/ Land cover (LULC) by using Maximum likelihood classifier and subsequently used as a land utilization factor in the study. Other factors influencing tomato crop health and pest susceptibility such as the Normalized Difference Vegetation Index (NDVI), temperature, bioclimatic and solar radiation, soil moisture, proximity to drainage, water vapour, wind speed, elevation, slope and aspect of the study area were considered as parameters. These parameters were ranked and assigned weight by pairwise comparison for producing a weighted overlay in the Multi Criteria Evaluation (MCE) for susceptibility class of tomato crops to pest. The results were classified into four classes using the fuzzy set classification model. Result of the analysis shows that the majority of tomato farms have low susceptible to pest while few tomato farms have high susceptibility to pest. Findings depicts that out of 153 tomato farms studied susceptibility to pest while 20.26% with 31 tomato farms have high susceptibility to pest. The result of this study implies that the geographic space with favourable conditions for pest breeding suggest a very high tendency of pest development and spread to other farm locations with low or moderate susceptibility tendency overtime when adequate measures are not taken into consideration. It is therefore recommended that regular update of tomato farms location should be carried out and an effective information system should be established for monitoring infestation so as to effectively make informed decisions during pest outbreak.

Keywords: GPS, LULC, MCE, NDVI, SPOT

1. Introduction

Agriculture in Nigeria faces a number of different challenges, this includes how to increase productivity, guaranty sustainable food supply and security, transfer of information, technology and training the people involved in the sector (Matemilola, 2017). For a sustainable agriculture and increased productivity of agricultural goods to be achieved, farm products need to be monitored closely (Brodt *et al.*, 2011). Pest infestation on tomato farmland has destroyed tomato crops during cultivation. In 2016, 80% of tomato farms in Kaduna State was ravaged by Tuta absoluta which led to scarcity of the vegetable and high purchasing rates (Oso, 2016). Efforts and decisions to manage and control pest infestation on these farms in the study area involved using cultural and biological control methods. Currently, crop pest management practice in Zaria does not incorporate the spatial component for plant health information to provide scientific evidence to understand how this pest spread and patronize geographic regions for the intervention and control of the pest. The inefficiency of the current crop pest management practice represents a significant reduction of tomato production.

1.1 Study Area

The location for the study is Zaria Local Government Area (L.G.A) of Kaduna State. The state is located globally at the Northern part of Nigeria's high plains between latitudes 9° 03' and 11° 32' North of the Equator and longitudes 6° 05' and 8o 38' East of the Greenwich Meridian (Oshodi, 2018). Zaria Local Government Area is located in the Northern part of Kaduna State between latitudes 11° 09' and 11° 10' North of the Equator and longitudes 7° 38' and 7o 39' East of the Greenwich Meridian. Kaduna State is the 4th largest state in Nigeria, in terms of land area having a total area of 46,053km2 which is about 5% of the total land area of Nigeria and has a projected population of 7,976,735 people, based on the National Population Census of 2006 and growth rate of 3.4% (NPC, 2005).

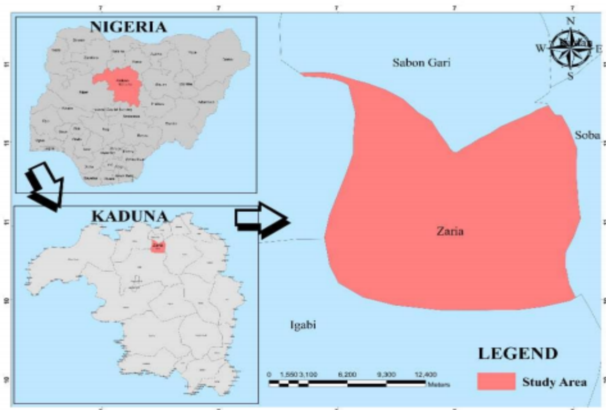

Figure 1: Map of study area

2. Materials and methods

2.1 Data acquisition

In order to effectively map tomato pest susceptibility, various data sets were collected and are categorized thus; 2-Dimensional geographic data obtained with a GPS, remotely sensed data (basically satellite imagery) and GIS datasets (NDVI, Climatic data, Land use/ Land cover images and Digital Elevation Models) as shown in Table 1. The satellite images used for mapping tomato pest susceptibility in the study is the Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) image consisting of nine shortwave spectral bands with a spatial resolution of 30 metres for all bands except the 15metres panchromatic band. The vectorized map of the Area of Interest used in the study was clipped and digitized from existing boundary of the administrative map of Kaduna State and was subsequently used to subsets all other datasets to fit within the study area. The vectorized map was used for graphical visualization of the topological features such as; routes, drainages, and point position of tomato farms. The map was related to the farm information on pest susceptibility which was handled separately for achieving a geospatial decision support system for tomato farms. The location and tomato pest susceptibility data were analyzed to produce decision supports for the key aspects of tomato cultivation. GIS operations mainly; overlay analysis, buffer analysis, network analysis was carried out using the ArcGIS desktop software version 10.4.1 and information for tomato disease support were generated.

Table 1: Summary of datasets used

Data	Data sources	Scale/Resolution	Acquisition date	Description	Purpose/Usage
Administrative Map	OSGOF		March, 2009	A geographic database of global administrative areas (boundaries).	Demarcation of AOI boundaries
Landsat 8 Satellite Imagery	USGS	30 metres	28th of August, 2018	Landsat 8 "OLI TIRS" satellite Image of Zaria, WRS PATH = 189 WRS ROW = 52.	Image processing and spatial analysis on NDVI, soil moisture, proximity to drainage and Land use/ Land cover.
Farm Location	Garmin Etrex 10 Handheld GPS	±3m (Accuracy)	2018	Northings and Eastings of tomato farmland	Showing location of farmlands on maps.
Spot 5	Space Agency of France	0.5 metres	2014	Spot Image of Kaduna State	Higher resolution image use for verifying tomato farms location

SRTM DEM	USGS	30 metres	2017	An image showing elevation of places in the area of study	Processed to extract some criteria to show farm susceptibility to pest
Climate	http://world clim.org. Global climate	2.5 minutes (~21km^2)	2019	Monthly average temperature, bioclimatic, solar radiation, relative humidity and wind speed data from 2010-2018.	Processed to extract some criteria to show farm susceptibility to pest.

2.2 Data processing

The image acquired is prepared and analyzed to perfectly fit for the spatial analysis of tomato farm information that covers the study area. ERDAS Imagine was employed for applying radiometric correction on the image. This process improves the quality of the satellite image and enhance its interpretation for quantitative data analysis that is used for tomato farms susceptibility. In classifying and interpreting vegetative status of crops from remotely sensed data, the quality of the interpretation is improved by the integration of ancillary data. The interpretation of features in the Landsat image covering the entire affected area was conducted based on the implicit and explicit use of collateral information which included maps, photographs, reports, site visit and personal experience of the study area so as to correctly represent features and application for a predefined classification system where Colour, Tone, Pattern, Texture, Association, Shape, Size, Shadows, and site clearly enabled Photo-morphic delineation of line and polygon features to produce the preliminary maps for the research. Fieldwork findings was incorporated to refine both the preliminary classification system and the preliminary image interpretation. Accuracy assessment between the laboratory and field classification and interpretation were also undertaken using ENVI software.

2.3 Modelling susceptibility of tomato farmlands to pests

In this study, developing a model to assess the susceptibility of tomato farmlands to pests is of utmost importance. This is needful to implement the multicriteria evaluation approach needed to map out susceptible tomato farm land too pest. It is deducible from reviewed literatures that presence of pests in tomato farmlands and its effects on the hosting farmlands are detectable from factors (having contributively influences of different magnitude on the susceptibility of tomato farmland to pests) generally grouped as vegetative property or healthiness (NDVI) of growing crops, temperature, bioclimatic elements, solar radiation, soil moisture, proximity to drainage, relative humidity, wind speed, slope angle, aspect, elevation and finally land utilization of the area of interests such as the cultivated land, uncultivated land, water body, bare land and built up area

For the purpose of evaluating and dividing tomato farmlands in the study area into different levels of their susceptibility to pests, different factors earlier identified were considered and to unanimously achieve the desired results, there is need to combine these factors together. Meanwhile, since these do not have the same or equal influence on susceptibility of tomato farms, there is need to determine and assign weight which will form a basis for discriminating among the factors, hence, the necessity of AHP. In evaluating the weight matrices or eigenvector used in the MCE of this study, the laid down steps (based on AHP) by Obeidat *et al.* (2018) was adopted. The normalized principal Eigen Vector is also called Priority Vector. As this is normalized, so, the sum of elements of priority vector is 1. Each element of priority vector shows the relative weight of its corresponding criteria.

It is also important, before implementing these values as the relative weight, that the consistency of W should be checked. In doing this, we firstly compute the principal Eugene value λ(max) which is done by finding the multiplicative addition of sum of each row are computed with their respective weight elements as shown in eq(1):

$$\lambda_{max} = 4.4(0.213) + 8(0.122) + 12(0.107) + 12.5(0.101) + 15(0.071) + 15(0.071) + 15(0.071) + 21(0.044) + 23(0.042) + 23(0.042) + 23(0.042) + 14(0.074) = 12.5053 \quad (1)$$

The Consistency Index is used by comparing with the Random Consistency Index (RI). The RI for twelve factors, according to Saaty (1987), is 1.54.

Finally, Saaty (1987) proposed Consistency Ratio (CR), which is a comparison between Consistency Index and Random Consistency Index. It can be shown with the following formula in eq(2) ;

$$CR = \frac{CI}{RI}$$

(2)

For this study, the CR is gotten as

$$CR = \frac{0.04591}{1.54} = 0.02981$$

With this formula we get CR = 0.029 (2.9%) in our twelve-factor example. Saaty suggested if the CR is less than or equal to 10%, then, the inconsistency is acceptable. Hence, the inconsistency for this pairwise comparison and weight deduction are acceptable.

To compute for susceptibility index based on considered criteria for tomato farms in the study area, the convex combination of the raster values containing the different fuzzy parameters were calculated by adopting the linear additive combination model equation by Malczewski (2004) as presented in eq(3).

$$SI = \sum_{j=1}^{k} \sum W * \mu i(x) \quad (3)$$

Where; SI is the susceptibility index, k is number of parameters, W is the weight of parameters and $\mu i(x)$ is the class value for the factors. Since the Weight (W) of NDVI is 0.213, temperature is 0.122, bioclimatic is 0.107, solar radiation weight is 0.101 etc. Hence, the susceptibility index based on the considered criteria for tomato farms will be;

$$SI = 0.213\,(NDVI) + 0.122(Temperature) + 0.107(Bioclimatic) + 0.101(Solar\ radiation) + 0.071(Soil\ Moisture) + 0.071(Proximity\ to\ drainage) + 0.071(Water\ Vapour) + 0.044(Wind\ speed) + 0.042(Slope) + 0.042(Aspect) + 0.042(Elevation) + 0.074(Land\ use) \quad (4)$$

The value of SI is between 0 and 1, where 0 represent very low susceptibility to pest and 1 represent very highly susceptibility to pest.

A perfectly evaluated weight for the AHP should have its consistency index of 0 (CI = 0) but small values of inconsistency may be tolerated. So far, the determined consistency ratio of such problem is less than 0.1. Since the CR for this study is 0.02 (value less than 0.1), it means inconsistencies are tolerable and a reliable result may be expected from the AHP.

During the multicriteria overlay using the weighted overlay tool in ArcGIS, weight elements in vector w above in eq(4) were employed in order to ensure an accurate output from the overlay. Each of the criteria considered are in their raster forms with classified pixel elements. The ArcGIS toolbox employed for the weighted overlay requires that each of the criteria's maps should be inherently distinguished in order to classify the varied pixel elements to their respective order of influencing susceptibility of tomato farmlands to pests. The value of SI is between 0 and 1, where 0 represent very lowly susceptible to pest and 1 represent very highly susceptible to pest.

Maps produced for the representation of each criterion has different pixel distribution and grouping and also have different raster size (cell sizes), overlaying these in ArcGIS using the 'weighted overlay' tool is impossible until they are brought to a uniform state of pixel groupings and also of the same raster cells. To this effect has the reclassification performed also in ArcGIS. Reclassified form of these criteria is still not well understood by the weighting tool until classes of each of the reclassified criteria maps are ranked. This output meanwhile is classified into four classes (using the symbology tool in ArcGIS) with numerical quantification. These classes were further expressed textually in the categories of i-Very low Susceptible, ii-Low Susceptible, iii-Highly Susceptible, iv-Very Highly Susceptible.

3. Mapping tomato farms pest susceptibility

The tomato farm susceptibility to pest were mapped based on weighted overlay of criteria maps. The criteria maps produced are the Normalized Difference Vegetation Index map as shown in Figure 2, the temperature map as represented in Figure 3, bioclimatic map (as shown in Figure 4), solar radiation map (in Figure 5), soil moisture map (as shown in Figure 6), proximity to drainage map (as represented in Figure 7), relative humidity map (as shown in Figure 8), wind speed map (as shown in Figure 9), gradient map, aspect map(as shown in Figure 10), elevation map (as shown in Figure 11) and land use/land cover map (as shown in Figure 12) to show pest susceptibility on tomato farms in the study area as represented in Figure 13.

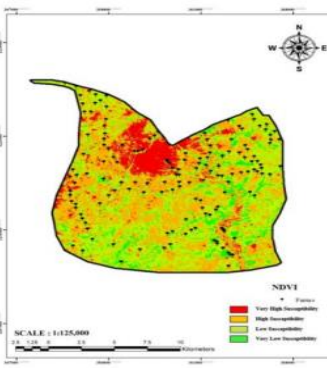

Figure. 2: The NDVI Map

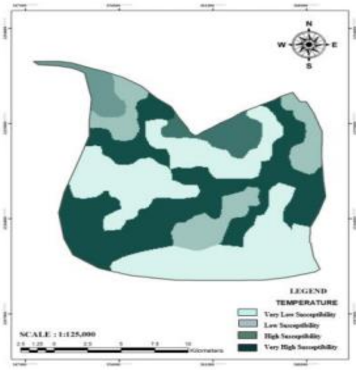

Figure. 3: Temperature Map

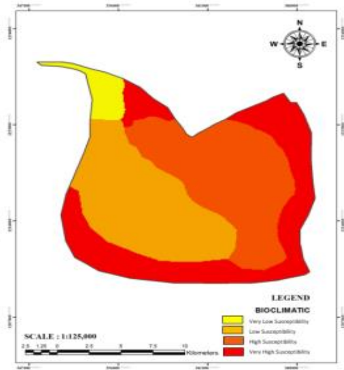

Figure. 4: Bioclimatic map

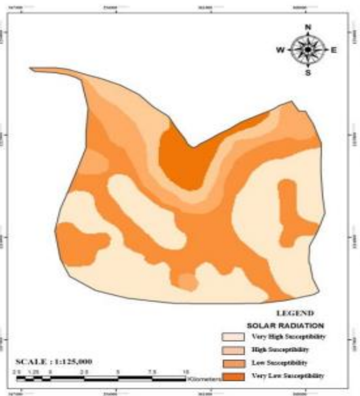

Figure. 5: Solar radiation map

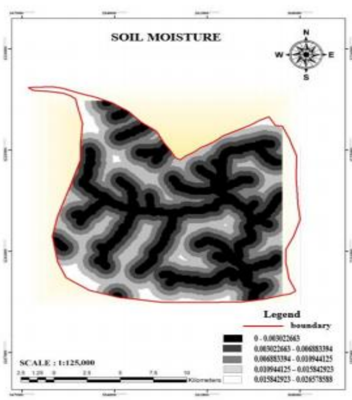

Figure. 6: Soil moisture map

Figure. 7: Proximity to drainage map

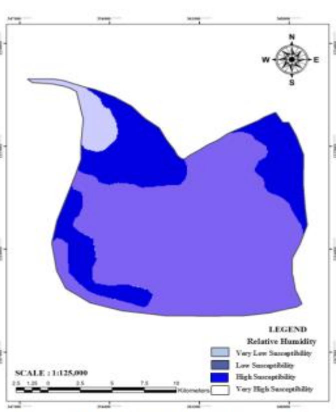

Figure. 8: , Relative humidity map

Figure. 9: Gradient map

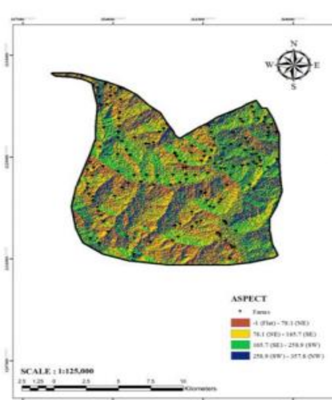

Figure. 10: Aspect map

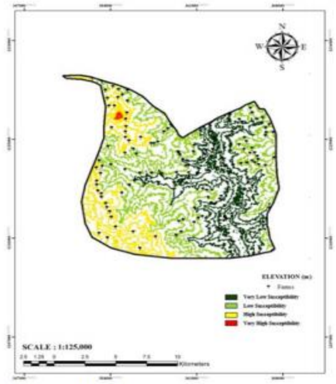

Figure. 11: Elevation map

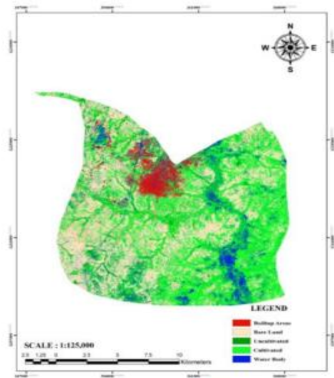

Figure. 12: Land use/land cover

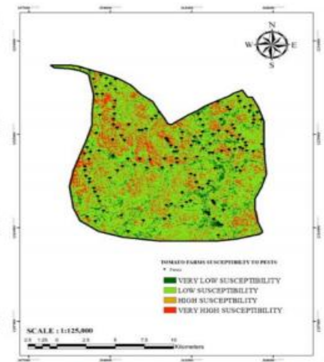

Figure. 13: Farms Susceptibility to Pest

The sampled farmlands (small black mushroom symbol in Figure 13) were overlay on the susceptibility map. Table 2 shows the number of farmlands falling on different levels of susceptibility of tomato farm to pest and also the area covered by each level both in square kilometres and in percentage of the entire study area. This coverage was derived from the pixel distributions (pixel counts) of each class in the study area.

Table 2: The distribution of tomato farms susceptibility to pest in the study area

Susceptibility Classes	Pixel count	Area (sq.km)	Percentage coverage (%)	No. of Tomato Farms	% Tomato farmland
Very Low	280	0.259	0.086	4	2.564
Low	83299	76.903	25.458	40	25.641
High	236187	218.052	72.183	108	69.231
Very High	7440	6.869	2.274	4	2.564
TOTAL		302.083	100	156	100

Table 2 indicates that less than 15% of the sampled tomato farmlands were found to have very low susceptibility to pests, over 56% exhibited low susceptibility, more than 20% were highly susceptible, and less than 10% were very highly susceptible to pest. For better understanding of the distribution of the different susceptibility of the tomato farmlands, a composite map showing a distinguishing representation of the tomato farmlands is shown in Figure 14. The sampled farmlands (small black, pink, red and green circular symbol in Figure 14) were overlaid on the susceptibility map.

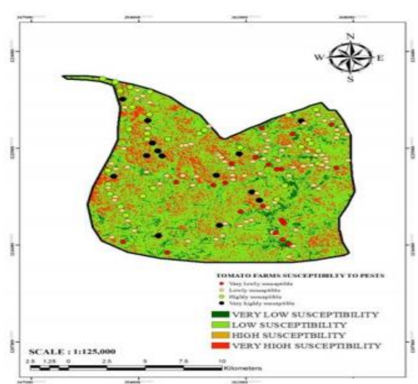

Figure 14: Susceptibility map of tomato farms to pests

4. Conclusion

This study successfully achieved its set objectives having successfully mapped tomato farms susceptibility to pests in the study area. A total of 6 sampled tomato farmlands in the study area. The farmland location was digitized on a clipped satellite image of the area of interest. Subsequently, the consideration of twelve (12) criteria which were further grouped into four main factors for the susceptibility of tomato farms to pest and disease in the study area. The factors were mapped and each reclassified and the classes ranked between 0 and 4 in an ascending order of their influence to tomato farms susceptibility to pests. Saaty's model of MCE was implemented in weighting individual factors in order to express their diverse influences on the susceptibility of tomato farmlands to pests. This model requires that weights be attached to each considered factor from (matrices) computations done to distinguish the considered factors in the order of their importance to the study, hence, factors were not equally weighted. These weighted factors were combined using the 'weighted overlay' tool in ArcGIS to produce map showing tomato farmlands susceptibility to pests in the study area. The produced map was categorized to four levels in textual form as very lowly, lowly, highly and very highly susceptible to distinguish the tomato farmlands according to their level of susceptibility to pests.

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