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SOIL & CROP SCIENCES | RESEARCH ARTICLE

Determinants of the spatial distribution of enset (*Ensete ventricosum* Welw. Cheesman) wilt disease: Evidence from Yem special district, Southern Ethiopia

Sintayehu Legesse Gebre^{1,2*}, Ashenafi Woldeyohannes³, Kefelegn Getahun³ and Alemayehu Regassa²

Abstract: Enset (*Ensete ventricosum* Welw. Cheesman) is a perennial crop, cultivated by millions of smallholder farmers in the south, central, and southwestern Ethiopia. However, its production has been endangered by one of the overwhelming enset bacterial wilt (EXW) disease caused by *Xanthomonas campestris* pv. *musacearum* (Xcm). The burden of the disease and the geographical distribution and the main contributing environmental factors are not precisely known. Therefore this study was aimed at determining the magnitude of enset bacterial wilt and identification of biophysical factors that influences the spatial distribution of the disease using spatial statistical analysis techniques in Yem special district, southwest Ethiopia. Different data on EXW prevalence and incidence were collected by applying purposive and spatial random sampling methods. The logistic regression method was used to model the relationship between EXW prevalence and response variables. And a generalized linear model was employed to analyze the relationship between EXW incidence and response variables. The results show that EXW disease is widely distributed at different degrees of intensity. The overall average EXW prevalence and incidence rates are 64.4% and 20.11%, respectively. The predicting variables such as annual relative

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PUBLIC INTEREST STATEMENT

Enset is a perennial and monocarpic herb belonging to the banana family and originated in Ethiopia. Enset is commonly used in the south and southwest part of the country. More than 20 million people rely on it as food security and livelihood income. The part of the plant is used for many purposes like animal feed, medicine, fuel, construction, and ornamental in the rural community. However, the production has been magnificently affected by enset bacterial wilt (EXW) disease. Hence, identifying the environmental determinants and EXW disease hot spot areas is important for intervention measures to control and reduce the distribution of the diseases and boost enset crop production in the study area.

humidity (RH), total precipitation, altitude, silty soil texture, are positively correlated with EXW prevalence. Similarly, in the case of EXW incidence, RH, total annual precipitation, altitude, silty soil texture, soil pH, and insect vector (leaf-hopper) are positively correlated. This finding can be used as guidelines to control the spread of the disease on hot spot areas and further contributes to the growing research on the etiology of EXW.

Subjects: Agriculture & Environmental Sciences; Environmental Management; Environmental Issues

Keywords: Enset; enset bacterial wilt (EXW); incidence; prevalence; regression analysis

1. Introduction

Enset (*Ensete ventricosum* (Welw.) Chessman) is a perennial and monocarpic herb belonging to the banana family and originated in Ethiopia (Vavilov, 1951). Enset is a wonder food and income security crop for more than 20 million people, cultivated by millions of smallholder farmers in south, central and southwestern Ethiopia (Borrell et al., 2020). It is a source of food, cash, animal feed, medicine, fuelwood, construction, and ornament for smallholder farmers in Ethiopia (Jacobsen et al., 2018; Jones, 2000; Zerihun Yemataw et al., 2015). It is the most important traditional staple and co-staple food crop contributing to food security and rural livelihoods for over 20% of people in the south and southwest Ethiopia (Hunduma et al., 2015; Zippel, 2002). It is estimated that about 224,400 hectares of land in Ethiopia is covered with enset, whereas 145,800 and 78,600 hectares of land found in Southern Nations Nationalities and Peoples' Regional State (SNNPRS) and Oromia Regional State, respectively (CSA, 2007).

However, the productivity and area coverage of the crop are continuously declining due to various environmental and management factors (Birmeta et al., 2004). Enset bacterial wilt disease is a prior threat or problem to the enset production system in Ethiopia (Zerfu et al., 2018). Enset bacterial wilt disease, which is commonly known as "Banana *Xanthomonas* Wilt (BXW)", "Enset *Xanthomonas* Wilt (EXW)" or "Enset wilt" is a devastating disease caused by the bacterium *Xanthomonas campestris* pv. *musacearum* (Xcm) (Mekuria et al., 2016; Zerfu et al., 2018). This bacterium dominantly affects enset and banana plants. According to (Welde-Michael et al., 2010) study, enset wilt disease makes the edge of enset leaf yellow and then wilting the leaves, and progressively all the leaves wilt, bend over, and decline, finally it kills the plant (Blomme et al., 2017). The bacterial pathogen is very critical as it kills the plants at all growth stages and regularly causes total fatalities (Blomme et al., 2017; Tesfaye, 2008).

The disease is widely distributed and presently found in almost all enset growing regions (Welde-Michael et al., 2010; Zerfu et al., 2018). Currently, it is reported that up to 80% of enset farms in enset growing areas of Ethiopia are infected by EXW, which directly affects the livelihood of more than 20 million enset farmers in the country (Borrell et al., 2020; Z. Yemataw et al., 2017). This leads to food insecurity among the rural community. Hence, there should be a research study that clearly understands the distribution of EXW disease and its association with biophysical factors. This helps to develop a control mechanism to alleviate the anticipated food insecurity problem in enset growing regions. There have been some attempts to control and minimize the impacts of the EXW disease on enset production by introducing disease tolerant clones and adopting traditional enset crop management practices. However, the impacts of the disease are growing and affecting production (Haile et al., 2020).

Therefore, there is an urgent need to determine and identify the spatial distribution, spatial correlation between the spread of disease, and biophysical factors. The result of this study is important by providing tangible information with regards to disease hot spot areas, and determinant factors that influence the rate of the EXW disease prevalence and incidence in Yem special

district, southwest Ethiopia. The study report will be useful to control and manage the spread of disease to boost enset production and improve food security, particularly in the rural community.

2. Materials and methods

2.1. Description of the study area

Yem is a special district in the Southern Nations, Nationalities and Peoples' Regional States (SNNPRS), Ethiopia. The total area of Yem special district is about 724.5 km² (Kassahun, 2011). Geographically, the Yem special district is located between 7° 35' N to 8°02' N and 37° 24' E to 37°37' E (Figure 1). According to the population and housing census report, the total population of the Yem special district is 80,687(CSA, 2007). The district has a population density of 124.54 persons per square kilometer.

The Yem Special district has a different landscape, which varies considerably from one part of the area to another. The topography is characterized by rolling mountains, steeply sloppy areas, and flat to undulating plateaus (CSA, 2007; Zerfu et al., 2018). The lowest point of elevation is 817 m.a.s.l, which is located in the northeast (Gibe lowland) and the highest peak is 2940 m.a.s.l (mountain Bora) which is located in the central part of the study area (Figure 2 right). The area has two agro-ecological zones, namely, warm sub-humid lowlands which cover the central apex, and the southwestern part, and tepid sub-humid highlands which cover the eastern and the north-western part of the district (Figure 2 left). The mean annual temperature is between 20°C and 30°C in the lowlands (Kola) and between 16°C and 20°C in the middle highlands or temperate area (Woyina Dega) and between 12°C and 16°C in the highlands (Dega) area (Zerfu et al., 2018). The annual rainfall ranges from 800 mm—2200 mm (Zerfu et al., 2018).

2.2. Methods

This research implemented the cross-sectional survey design to collect both qualitative and quantitative data since such type of research demands both types of data (Creswell, 2009). The quantitative or technical approach was used to assess the spatial distribution of EXW prevalence and incidence and to model the relationship between the dependent and predicting variables. Whereas, the qualitative approach was used to check and interpret the results of the quantitative analysis.

Figure 1. Map of the study area.

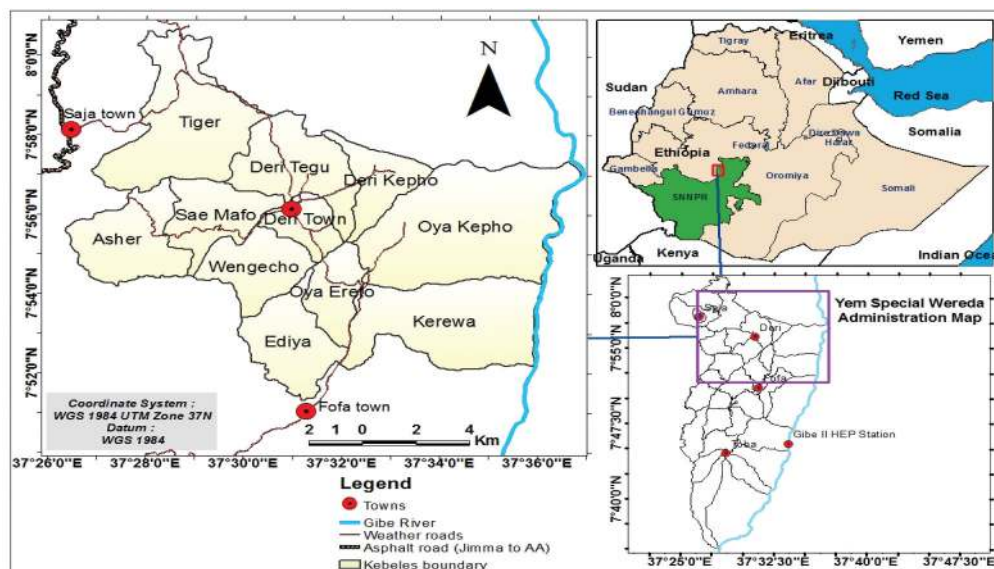
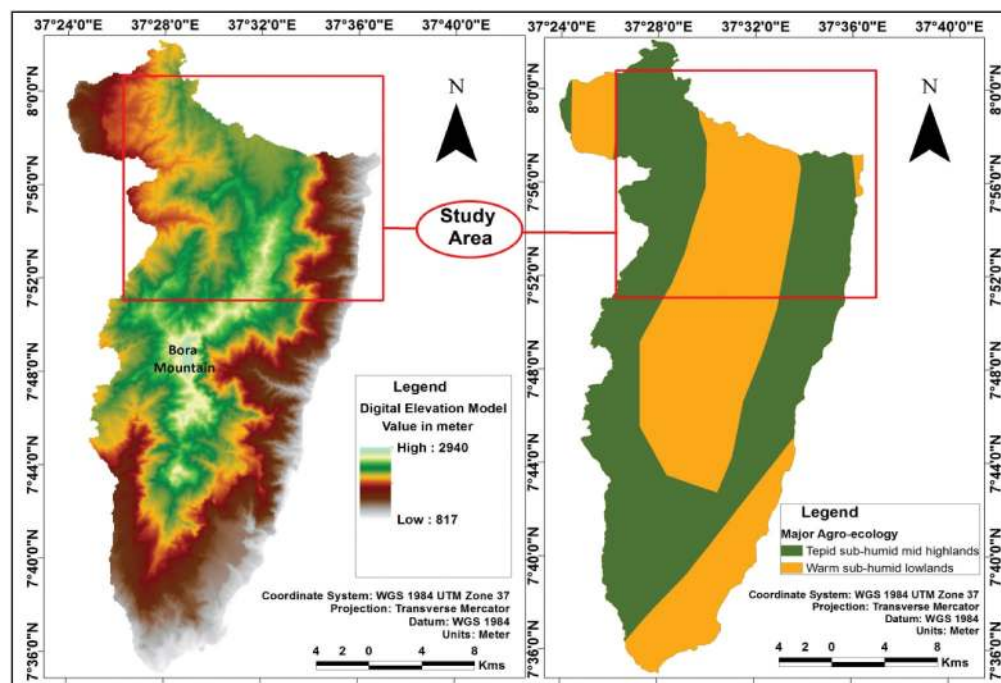


Figure 2. (a) Map of digital elevation model (left) (b) Map of agro-ecology (right).



2.2.1. Sources of data

The study data were collected from both primary and secondary sources. The primary source of data was collected from sampled respondents (farmers and experts) through semi-structured questionnaires and interviews. Further, the primary data collection also included field observations such as insect vector-like leafhopper presence and absence on the field farm plots. Since leafhopper serves as an EXW disease transmitter. According to Yirgou and Bradbury (1968), the EXW disease is transmitted from infected to healthy plants by mechanical means like contaminated agricultural operation hand tools. In addition, birds, sap-sucking insects, and nematodes are the main transmitter. Wondimagne (1981) indicated that among the commonly observed insects in enset fields leafhopper (*poecilocarda nigrinervis* stal) is the potential vector due to its active flying ability.

The secondary sources of data were retrieved from published and unpublished documents, articles, books, spatial data provider agencies, and different webpages (Table 1).

2.2.2. Sampling techniques

Before carrying out the sampling, a piece of base-line information about the study area was collected from the agriculture and natural resource development office of the study district. Broad discussions were made with experts regarding the selection of the representative study kebeles (the so-called smallest administrative units or villages). Then, the purposive sampling method was used to determine the sampling of farm plots in each kebele. This was followed by a reconnaissance field visit and then a spatial sampling (grid system) method was employed to determine the sample farm households. The method was employed because it would give us important data for our intended objectives. If we could implement random sampling we might loss many data and it requires huge amount of cost and time to fill the missed data due to spatial variability. Though every sampling method has its draw backs. In this case, despite its inherent bias, purposive sampling can provide reliable and robust data. The strength of the method actually lies in its intentional bias (Bernard, 2002; Lewis & Sheppard, 2006; Poggie, 1972). The inherent bias of the method contributes to its efficiency, and the method stays robust even when tested against random probability sampling. However this can be improved by the fundamental quality of data gathered from reliable informant sources that ensures good quality of data is collected. In our

Table 1. Sources and characteristics of spatial data used in the study

Variables	Data format		Resolution	Data sources & acquisition date
	Original	Converted	Original	
EXW	Point	-	-	Field/own
Altitude	DEM	DEM	30 m	SRTM (http://www.usgs.gov/)
Slope	DEM	DEM	30 m	
Temperature	Raster	Raster	30 second	WorldClim (1970–2000) (http://www.worldclim.org/)
Precipitation	Raster	Raster	30 second	
Precipitation	Raster	Raster	0.050	CHIRPS (2016–2017) (http://earlywarning.usgs.gov)
Temperature*	Point	-	-	National Meteorology Agency (NMA) of Ethiopia
Precipitation*	Point	-	-	
RH	Point	Raster	250 m	ISRIC-World Soil Information (http://www.isric.org/)
Soil texture	Raster	Raster	250 m	
Soil PH	Raster	Raster	250 m	
Soil type	Polygon	Raster	250 m	
AEZ	Polygon	Raster	250 m	
Boundary line	Polygon	-	-	Ethio-GIS (2004)

* (the climate data used to validate). RH (Relative Humidity), AEZ (Agroecology zone)

study we checked and rechecked by cross sectional method of the data gathered from farmers, experts and agricultural bureau prior to kebele selection.

From a total of 35 kebeles, 11 kebeles were purposively selected based on different factors like Enset growing potential, EXW prevalence or incidence, agroecological conditions, and geographical adjacency of kebeles. The area coverage of the selected kebeles is about 31.4% of the total area of the district. The sample size of the households was determined based on point features that were generated randomly by using the ArcGIS tool (create random points). Before generating a random point feature index was created at a 1 km² grid from the sampled kebeles using (Grid Index Features). The area in which the random points generated as defined by the constraining index was one for each 1 km² grid. Then, 207 random point features were generated for the sampled kebeles. In order to confirm whether the point features represent households with enset farm plots or not, the following techniques were used. First, the boundary line of the study area, grids (1 km²), and generated points were changed from their original shapefile (shp) format (ArcGIS) to keyhole markup language (KML) format of Google Earth by using ArcGIS conversion tool. Secondly, all converted point features were retrieved in Google Earth™ to evaluate whether they are placed on households with enset plots or not. Thirdly, point features, which have fallen on enset growing households were considered part of the study unit. Whereas, those point features, which were placed on non-enset households, were considered to be part of the sample by placing them to the next nearby enset growing household. On the other hand, some point features were ignored due to the total absence of enset farm plots within a 1 km² grid. Finally, from 207 randomly generated point features, 135 (households) were selected, and the remaining 73 were ignored due to the absence of enset farm plots.

2.2.3. Data collection

The assessment of the enset wilt disease was collected via semi-structured questionnaires, key informants interview/KIIs, GPS survey (GPS recorder), digital camera, and field observations. Besides, open questions and free-listing approaches were used. This helps to collect supplementary data on enset wilt disease, particularly to assess farmer's perception (indigenous knowledge) about the disease and its correlation with the environment. Informal discussions with pioneer pathologists were also carried out to validate the analysis result. A handheld GPS receiver was

used to tag the geographic coordinate of each of the sample enset plots. A digital camera was used to capture the scene of the disease events during the field observations.

Field survey of EXW disease was carried out in the rainy season between mid of March and June 2017. According to experts, the rainy season is a favorable time to identify the symptoms of the disease because, during the rainy season, the leaves of enset plants become green except the leaf of diseased or wounded enset plants. The characteristics of EXW symptoms were grasped based on the information obtained from previous research results on a similar subject and experts' and farmers' indigenous knowledge to identify and count a diseased and non-diseased enset plant on in-situ enset farm plots. The enset crop stands were counted and recorded from each survey farm plots.

Enset farm plots with and without EXW symptoms were counted and recorded at each enset sample plot. Therefore, the following equation by (Bhopal, 2002), was applied to calculate the EXW prevalence and incidence.

$$\text{EXW Prevalence} = (\text{SP/TP}) \times 100 \quad (1)$$

where,

SP (symptomatic plot) = the number of enset farm plots with EXW symptoms.

TP (total plots) = the total number of enset farm plots assessed at kebele level or in the study area.

$$\text{EXW Incidence} = (\text{SEP/TEP}) \times 100 \quad (2)$$

where,

SEP (symptomatic enset plants) = the number of enset plants with bacterial wilt symptoms in the sampled enset farm plot,

TEP (total enset plants) = the total number of enset plants assessed in the sampled enset farm plot.

2.2.4. Spatial analysis

Detecting and identifying the locations of clusters, hot spots, cold spots, and outliers, and further assessing why clusters, hot spots, cold spots, and outliers exist is very crucial for designing an intervention measure (Wilson & Fotheringham, 2008).

The kriging geostatistical technique was used because it can describe and model spatial patterns using (variography or semivariogram), predict values at unmeasured locations, and assess the uncertainty associated with a predicted value at the unmeasured locations. Besides, this tool uses mathematical forms to express autocorrelation (strength of statistical correlation as a function of distance) such as semivariogram or covariance. Further, it uses a transformation and allows us to estimate measurement error.

2.2.5. Mapping EXW disease distribution, prevalence and incidence

To visualize the actual potential of enset crop productions a spatial analyst tool i.e inverse distance weighted (IDW) interpolation technique was applied. IDW method determines a cell value using a linear weighted combination (LWC) of a set of sample points. The weight is a function of inverse distance. As this method assumes that the variable being mapped decreases as it is influenced by distance from its sampled location, the search radius variable is specified with only 4 points to increase the accuracy of prediction. To control the significance of known points on the interpolated values based on their distance from the output point, the default value was used in the power

parameter. The interpolation model was derived from 207-point data, which was collected during the field survey. All the point features that were randomly generated were used. The value of the total number of enset plants counted for the assigned 135 point features where enset plant was present. While the value of zero was assigned for the remaining 72 point features (randomly created but omitted due to the absence of enset plants around there). The absence of enset plants at those farms were approved during the field observation.

2.2.6. Spatial distribution of EXW prevalence and EXW incidence

EXW distribution was indicated in point patterns as absent and present of disease while a prevalence map was computed with the aggregate occurrences of disease at kebele level based on observed field survey. The EXW incidence map was generated based on the degree of incident rate or strength recorded at each surveyed enset farm plot by using the ArcGIS Geostatistical Analyst (simple kriging) tool. Kriging is one of the most common methods that use a weighted linear combination of nearby observations to obtain an exact best linear unbiased predictor (Goovaerts, 1997). Such a kind of interpolation method is ideal in the presence of a sufficient number of observations and a small-scale spatial inconsistency (Auchincloss et al., 2012).

2.2.7. Analyzing patterns of EXW prevalence and incidence

In spatial data analysis, it is frequently needed to determine whether or not identifiable spatial patterns exist (Ord & Getis, 1995). A spatial statistic test was used to quantify each unit's spatial pattern and compare that value to the one predicted by the null hypothesis (Goovaerts & Jacquez, 2004). Some of the most commonly used spatial statistics analysis techniques to detect spatial patterns of disease distribution in a certain area are Global Moran's I statistics, Getis-Ord G_i^* statistics, and Reply's K function (Pfeiffer et al., 2008). Areas with a positive or negative clustering can be identified when their values deviate from the null hypothesis by showing increased variability in disease rates (Elliott et al., 2009). If the null hypothesis is rejected, the variable is said to be spatially autocorrelated (Ord & Getis, 1995). Therefore, the result is the identification of how unlikely an observed spatial pattern is under the null hypothesis (Gustafson, 1998).

In this study, spatial autocorrelation analysis (Global Moran's I) and Getis-Ord G_i^* statistics were used to determine the clustering of EXW prevalence and incidence in the study area. Both of them are inferential statistics with a null hypothesis of complete spatial randomness (CSR). Global Moran's I statistics were used to examine the spatial pattern of EXW prevalence and incidence while Getis-Ord G_i^* statistics were undertaken to determine where significant spatial clustering of EXW prevalence and incidence occurred in the study area. In the case of spatial statistical analysis, the EXW prevalence refers to the presence or absence of disease at surveyed enset farm plots, while incidence refers to the ratio between symptomatic and asymptomatic plants at each surveyed enset farm plot. The hot spot analysis (Getis-Ord G_i^* statistics) was used to determine the spatial clustering event with respect to each other within a pre-defined distance threshold (Getis et al., 2010). A fixed distance band with a defined threshold distance was used to specify how spatial relationships among features are defined. The distance threshold was identified by using incremental spatial autocorrelation tools in ArcGIS.

The global Moran's I statistic measure the degree of spatial association between features across the study region as a whole by evaluating whether the pattern expressed is clustered, dispersed, or random. A global Moran's Index value close to -1 indicates the presence of strong negative spatial autocorrelation (dispersion) between the features in the study area. A value close to $+1$ indicates strong positive spatial autocorrelation between features and a value near 0 indicates spatial randomness between features (Anselin et al., 2006).

A Z-score and P-value calculated through a global Moran's I, indicate whether or not to reject the null hypotheses. In this case, the null hypothesis states that EXW prevalence and incidence are randomly distributed across the study area. The overall pattern and trend of EXW prevalence and incidence were measured with the global Moran's I statistic whether or not to reject the null

hypothesis. It was first developed by (Anselin, 1995). The Moran's I statistic for spatial autocorrelation is calculated as:

The Moran's I statistic

$$I = \frac{n}{s_0} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} Z_i Z_j}{\sum_{i=1}^n Z_i^2} \quad (3)$$

Where,

z_i is the deviation of an attribute for feature i from its mean ($x_i - \bar{X}$),

w_{ij} is the spatial weight between feature i and j ,

n is equal to the total number of features,

S_0 is the aggregate of all the spatial weights.

However, global Moran's I statistic does not indicate exactly where the clustering is located or found. Therefore, hot spot analysis (local or regional statistic) was used to know where the clusters are found in the study area. Local statistics like hot spot analysis tools assess each feature within the context of neighboring features and compare the local situation to the global situation. The hot spot analysis tool assesses whether there is a high or low-value spatial cluster. It tests not only tests for regional clustering. It can also show the presence of significant spatial clusters or dispersion. Identification of significant spatial pattern serves as the starting point for further investigation and the creation of hypothesized relations between the environment and health outcomes. Therefore, the patterns of EXW prevalence and incidence were analyzed to know where the spatial clusters are located.

The Getis-Ord local statistic was defined by (Ord & Getis, 1995) given as:

$$G_i^*(d) = \frac{\sum_j w_{ij}(d) X_j - W_i * \bar{X}}{S \{ [NS1i * -Wi * 2] / (N - 1) \}^{1/2}} \quad (4)$$

Where;

W a weights matrix used to determine spatial structure and association among locations in a data set,

i is the cell of analysis in which all other cells (j) must fall within a distance (d) to be included,

x is number of EXW cases,

N is the total number of locations,

S is the standard deviation,

$\bar{x}$ is the mean of all EXW cases.

Finally, to know where the clusters are formed, from the hot spots statistic analysis result G_i -Bin values were interpolated through ArcGIS Geostatistical analyst tool (simple kriging) was used to interpolate the observed EXW prevalence and incidence for the study area.

2.3. Modeling spatial relationships

After determining the patterns of disease, the next question should be assessing the main factors that affect the distribution and spread of the disease. Statistical approaches like simple or multiple

linear regressions and logistic regression allow us to look at relationships between independent and response variables. In this study, the statistical relationship was determined using STATA. The EXW prevalence was analyzed using a logistic regression analysis method since prevalence is expressed as in the form of absent or present. On the other hand, the EXW incidence was computed using a generalized linear model (GLM).

2.3.1. Correlation and regression analysis

The association between EXW prevalence or incidence and environmental variables were examined using the nonparametric Spearman's correlation coefficient (p -value ≤ 0.05) using STATA 14.0. Variables found to be significantly associated with EXW prevalence and incidence in the bivariate analysis were included in regression analysis.

Regression analysis allows us to model, examine, and explore spatial relationships and can help explain the factors behind observed spatial patterns. Spatial regression adds spatial weights into a regression analysis to include space in the model. In this analysis, logistic and general linear regression analysis techniques were used for EXW prevalence and incidence, respectively.

Logistic regression has been widely used to predict the geographic distribution of plant diseases (Yuen & Mila, 2015). It can be used to predict the probability of occurrence of an event as a function of the explanatory variables (Hosmer & Lemeshow, 2005). The logistic regression model also allows evaluating the importance of multiple independent variables that affect the response variable (Hosmer & Lemeshow, 2005). The logistic regression model was chosen for EXW prevalence (presence or absence) analysis because it has the capacity in predicting binary variables by nominal and ratio variables at the same.

Logistic regression generates model statistics and coefficients that predict a logit transformation of the probability that the dependent variable is 1 (probability of occurrence of an EXW event). Logistic regression involves fitting a dependent variable using the following equations:

$$Y = \text{logit}(p) = \ln(p/1 - p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_n X_n \quad (5)$$

Where;

p = the probability that the dependent variable (Y) is 1,

β_0 = intercept,

β_1 = coefficient,

X = predictors (environmental variables).

The other method is a general linear model. It usually refers to conventional linear regression models. The generalized linear models can handle more complicated situations and analyze the simultaneous effects of multiple variables, including mixtures of categorical and continuous variables (McCulloch, 2001). In this study, the relationship between EXW incidence and predicting environmental variables was explored by using a statistical application software called STATA. In general, a linear regression involves fitting a dependent variable using the following equations:

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (6)$$

where;

γ is dependent variable (EXW incidence),

β_0 is the intercept,

β_1 , β_2 , and β_n are regression coefficients of independent variables,

χ_1 , χ_2 , and χ_n are independent variables,

ε is residual/random error.

Each independent variable was associated with a regression coefficient describing the strength and the sign of that variable's relationship to the dependent variable. The potential relevant variable for EXW incidence prediction first was screened through the process of collinearity analysis.

3. Results

3.1. Spatial distribution of enset production

The distribution of enset production results is presented in (Figure 3). The high value 1725 shows the maximum number of enset stands counted in the farm plot, while a value zero indicates there is no enset crop stand in the representative farm plot. There is high enset production in the south, central, and north part of the study area. Low enset production is recorded in the eastern and western parts. The variability of the enset crop production is mainly due to the variation in elevation and farming systems. Most of the enset cultivation is practiced at a small scale particularly in the back yard of a farmer's house. This is also observed in a study conducted by Olango et al. (2014) at the enset farming system in Wolaita zone, Ethiopia.

3.2. EXW disease distribution, prevalence and incidence rate

3.2.1. Spatial distribution of the EXW disease

As indicated in (Figure 4) the bacterial wilt disease symptoms are observed in a large part of the study area. From our field survey of 135 enset plots, 87 plots have EXW disease symptoms and 48 sample plots have no EXW disease symptoms (asymptomatic). According to the farmers' responses to the interviews, the occurrence of the EXW disease varies from time to time. The rate is high during the summer season (rainy season).

Figure 3. The inverse distance weighted interpolation of enset crop production in Yem special district.

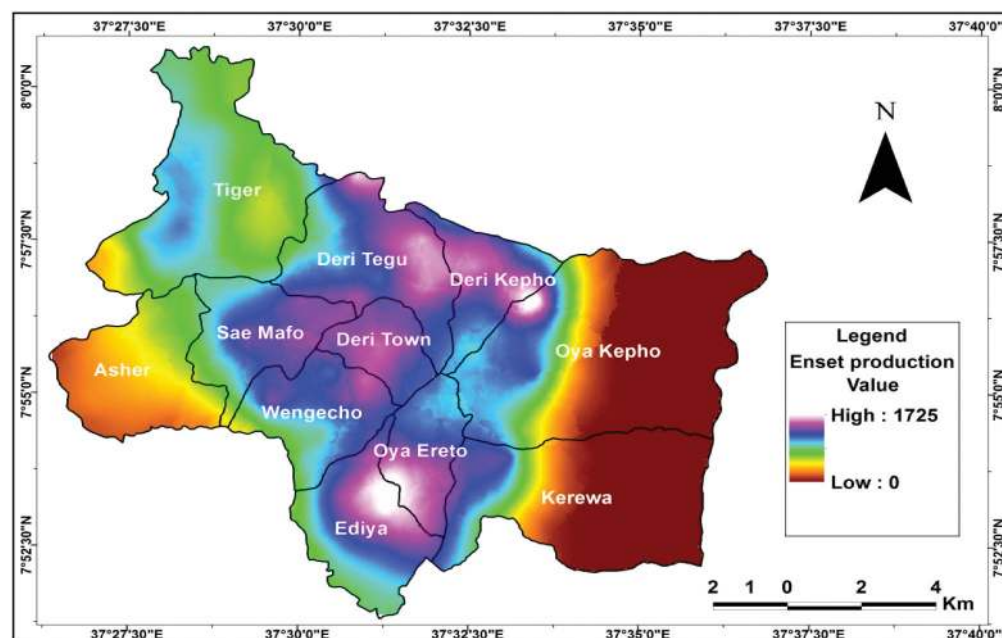


Figure 4. Spatial distribution of EXW disease in the study area.

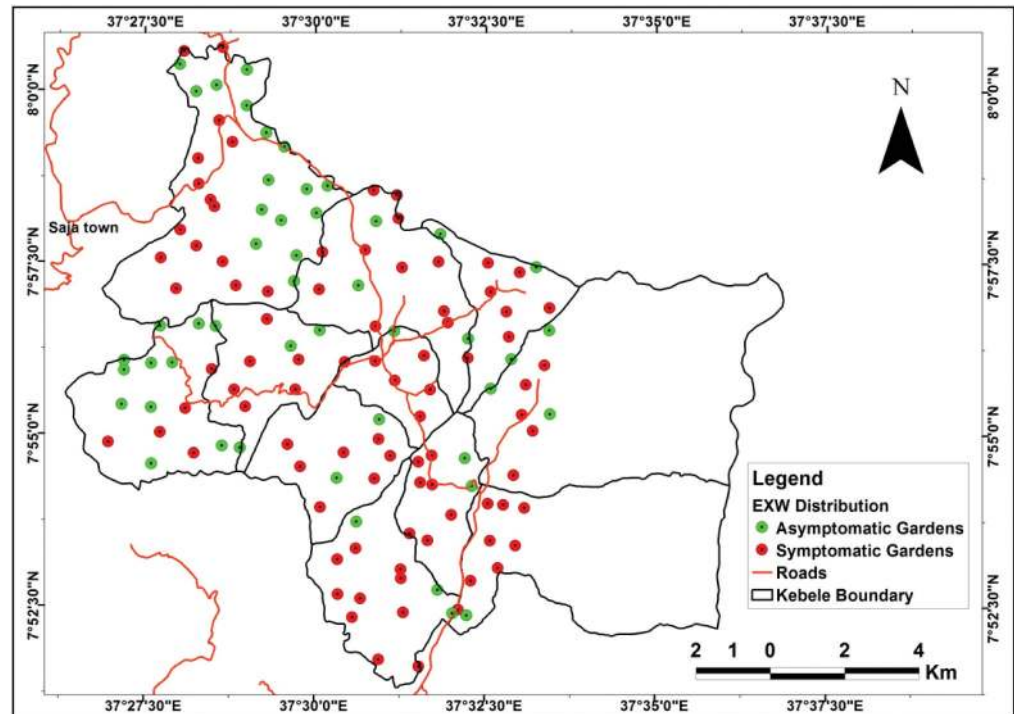
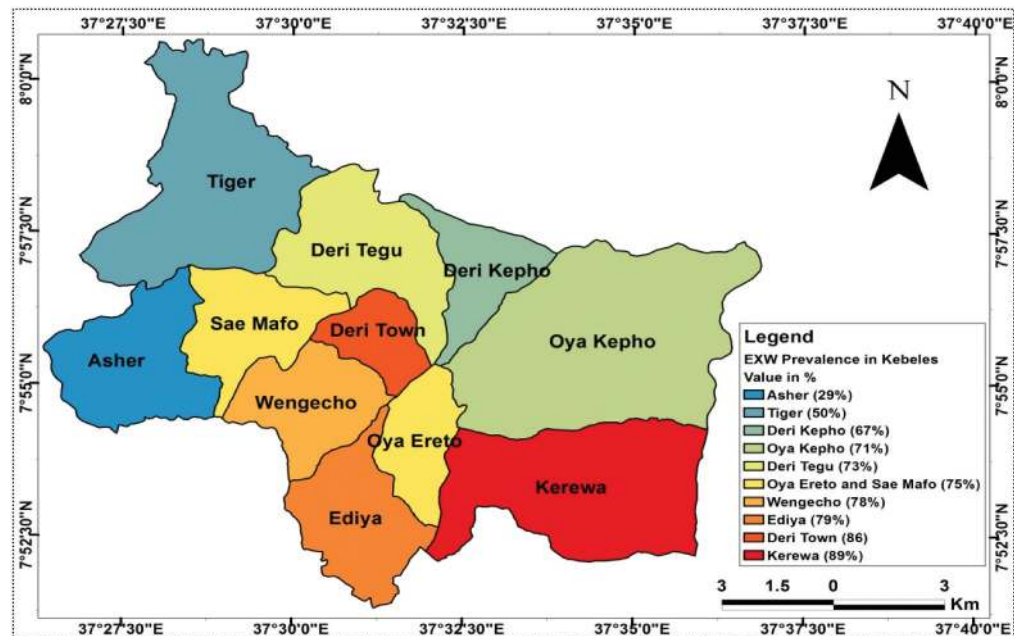


Figure 5. Enset Xanthomonas wilt (EXW) prevalence rate at kebele level.



3.2.2. EXW disease prevalence and incidence

In this section, Figure 5 shows only the degree of the spatial distribution of the EXW prevalence. It does not show the distribution or patterns of EXW prevalence. The high prevalence of EXW was recorded in the central and southern parts of the study area. The highest prevalence was recorded in Kerewa kebele (89%) and lowest in Asher kebele (29%). In summary, the over whole EXW prevalence is 64.4% (Table 2). On the other hand, the EXW incidence was also calculated as the

ratio of the number of positive (symptomatic) enset plants and the total number of enset plants observed at the sampled plot. The highest number of incidence was recorded in Oya Ereto kebele (38.86%) and lowest in Asher kebele (6.2%) (Table 2). The overall spatial distribution of EXW incidence per kebele level is presented in (Figure 6).

3.3. Analysis of pattern of EXW prevalence and incidence

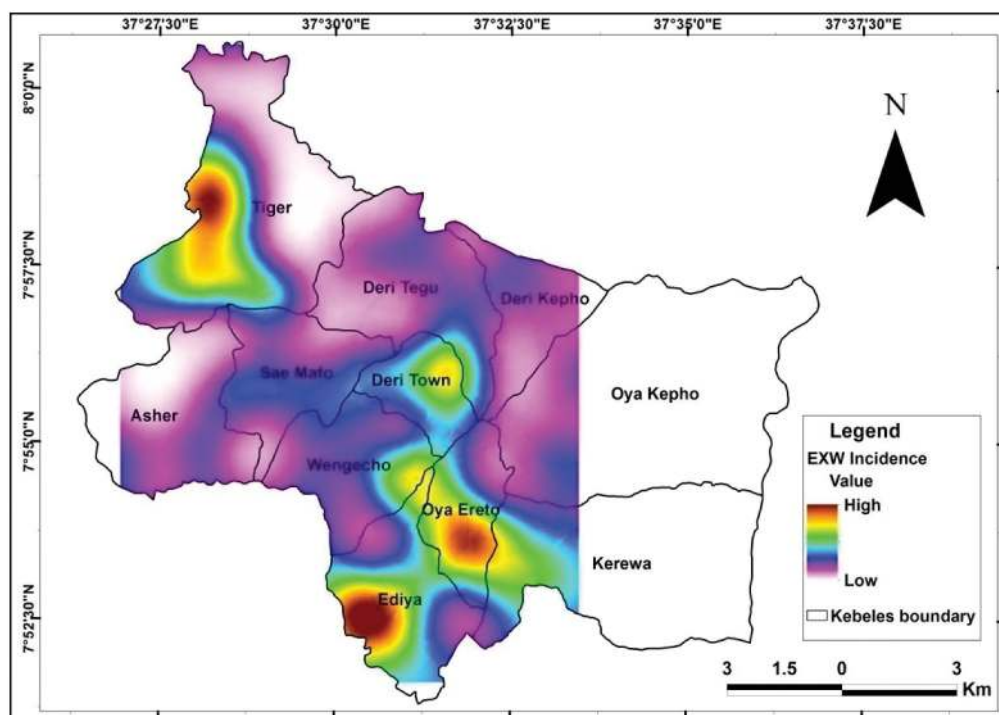
EXW prevalence and incidence rate were calculated by using Moran's I to test the spatial auto-correlation and hot spots analysis for the presence of clustering in both EXW prevalence and

Table 2. Intensity (prevalence and incidence) of EXW disease per kebele

Kebeles	OP	SEP	AEP	Prevalence in %	SE	AE	TEP	Incidence in %
Oya Ereto	8	6	2	75	1286	3309	4595	38.86
Kerewa	9	8	1	89	1077	4586	5663	23.48
Oya Kepho	7	5	2	71	291	4614	4905	6.31
Deri Kepho	9	6	3	67	365	3520	3885	10.37
Deri Tegu	15	11	4	73	918	8464	9382	10.85
Wengecho	9	7	2	78	1032	4997	6029	20.65
Asher	17	5	12	29	190	3064	3254	6.20
Deri Town	7	6	1	86	1176	3268	4444	35.99
Sae Mafo	8	6	2	75	411	3729	4140	11.02
Ediya	14	11	3	79	1890	7360	9250	25.68
Tiger	32	16	16	50	2823	10,058	12,881	28.07
CV				24.31				58.89
Total	135	87	48	64.44	11,459	56,969	68,428	20.11

OP (Observed Enset Farm Plots), SEP (Symptomatic Enset Farm Plots), AEP (Asymptomatic Enset Farm Plots), SE (Symptomatic Enset Plants), AE (Asymptomatic Enset Plants), TEP (Total Enset Plants in the Plots).

Figure 6. Enset Xanthomonas wilt (EXW) incidence distribution using Kriging interpolation.



incidence to understand the pattern of the disease distribution. By considering the threshold distance between two sample points i.e 1884.17 m in ArcGIS (Ord & Getis, 1995). Figure 7a and b show the spatial pattern of EXW prevalence and incidence rate.

As illustrated in Figure 8, the semivariogram model fits the empirical data, which passes through the center of the cloud of binned values, as close as possible to the average values (blue crosses). Hence, these indicate that the model performs and fits well for both spatial patterns of EXW prevalence and incidence rate.

In general, based on the hot spot analysis of the spatial pattern of EXW prevalence, significant clustering of hot spots was found in the south (Ediya kebele), west (Kerewa kebele), central (at Deri town and Wengecho kebele border), and north-west (west part of Tiger kebele) (Figure 7a). The EXW incidence result shows, hot spot areas are located in the south (Ediya and Oya Ereto kebeles) and northwest (west part of Tiger kebele), and cold spots found in the north (north part of Tiger kebele) and southwest (Asher kebele) (Figure 7b). EXW prevalence and incidence common hot spot areas observed in Ediya and west part of Tiger kebeles, while cold spot clustering in Asher and west part of Tiger kebeles.

3.4. Analysis of relationship between EXW disease and underlying determinant factors

3.4.1. Variables screening and collinearity test

It is important to screen and analyze which variable significantly affects the response variable. This helps to reduce and remove redundant variables. It is clear that not all the explored variables are not equally important to influences the distribution of EXW disease. In this study, with regard to EXW prevalence and incidence, individual predicting variables were investigated. Highly correlated predicting variables were determined and removed by performing pairwise Spearman's correlation tests to avoid multicollinearity. There should not be a high correlation between predicting variables. (Tabachnick & Fidell, 2007) suggest that correlation coefficient among independent variables should be less than 0.90, otherwise, if the correlation coefficient is greater than > 0.90 then the predictor has to be removed. Since in statistical modeling, it is important to avoid the inclusion of related variables that can reflect the same reality. This results in duplication of information or multicollinearity (Field, 2009). Therefore, the collinearity test has been done between all possible pairs of potential environmental variables. For example, temperature and altitude have a high correlation coefficient ≥ 0.95 with

Figure 7. (a) Enset Xanthomonas wilt (EXW) prevalence rate and (b) Enset Xanthomonas wilt (EXW) incidence rate in Yem special district.

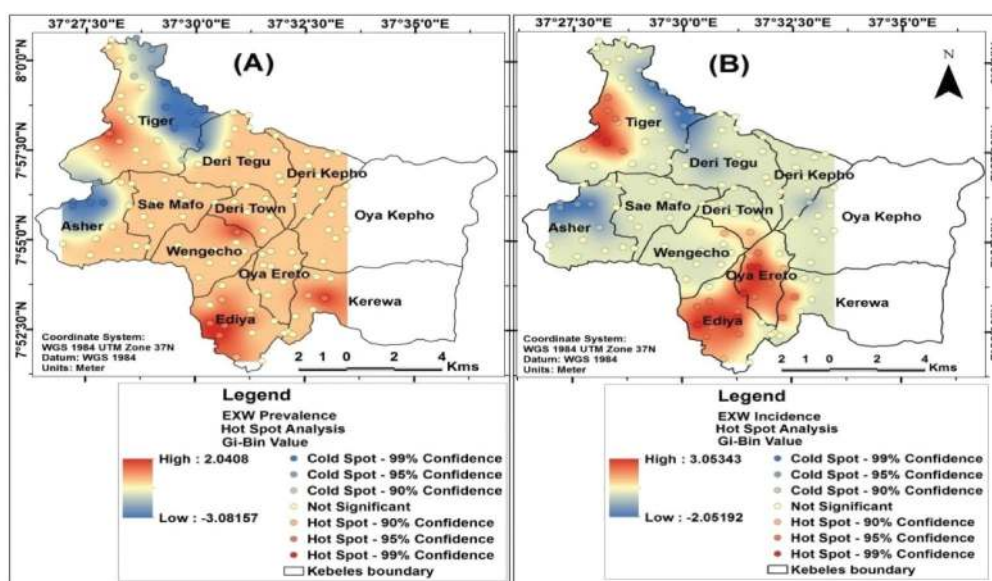
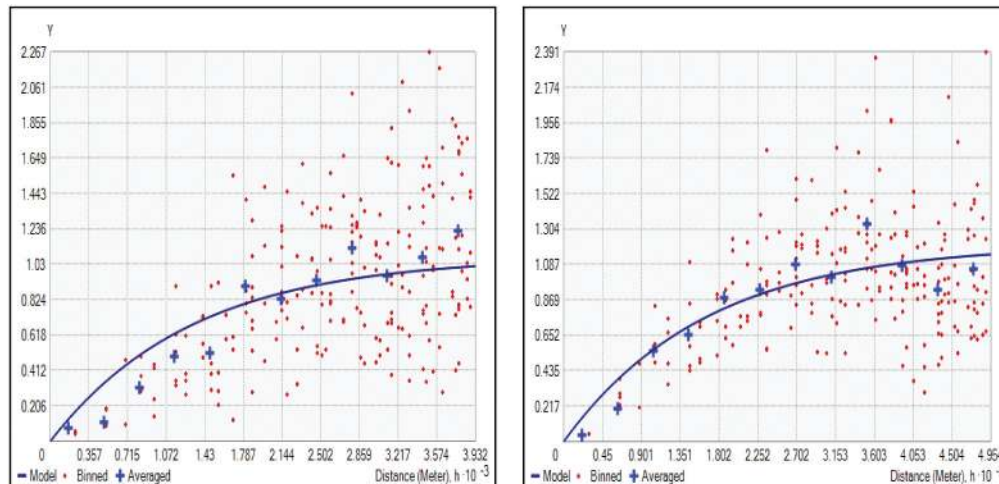


Figure 8. Semivariogram fitted with an exponential model for the hot spot cluster of Enset xanthomonas wilt (EXW) disease prevalence (left) and incidence (right) rate.



a significant $p = 0.000$, so the temperature was excluded from the model. Altitude was included because it has a strong correlation coefficient with both EXW prevalence and incidence and it would control the temperature. Similarly, all variables were checked using VIF (Variance inflation factor), all the variables have $VIF < 7.5$ and therefore collinearity is not a problem.

Predicting variables such as altitude, total annual precipitation, relative humidity, agroecology, soil pH values, soil textures, and soil types were screened for EXW prevalence. Whilst, altitude, total annual precipitation, relative humidity, slope, soil types, soil textures, soil pH values, and leafhopper were screened for EXW incidence. Leafhopper was not included in EXW prevalence analysis because there was no theoretical assumption that it could cause the EXW. However, it was included in the EXW incidence model since there is a possible assumption that insects could transmit bacterial disease from diseased plants to healthy plants.

3.4.2. Regression analysis

The associations between screened environmental variables and EXW prevalence and incidence were further assessed using logistic regression and general linear regression, respectively. Variables contributing to the model based on the statistical significance (probability) test and model performance were retained in the final model, for both EXW prevalence and incidence, specifically. P -values, 0.05 were considered significant.

The relationship between EXW prevalence and its underlying factors was analyzed through a stepwise regression where the Odd Ratio (OR) proved its significance. For each predictor, the Odd Ratio, 95% confidence interval (CI), and p -values were recorded.

From the screened predicting environmental variables, soil type, soil pH values, agro-ecology, and clay soil texture were not good EXW prevalence predictors ($p > 0.05$). So they were not included in the General Linear regression model (GLRM) for EXW prevalence factors analyses. Whereas predicting variables such as relative humidity, altitude, total annual precipitation, and silty soil texture were positively correlated and significantly contributed to EXW prevalence. In logistic regression, odds ratios are commonly employed to measure the strength of the partial relationship between one predictor and the dependent variable (in the context of the other predictor variables). Compared to all-important response variables, relative humidity was strongly related to EXW prevalence than the others such as altitude, total annual precipitation, and silty soil (Table 3).

Together, relative humidity, altitude, total annual precipitation, and silty soil texture account for 13.74 % of the variance in EXW prevalence. The final regression model show, a low predictive

Table 3. Results of logistic regression between the environmental predicting variables and EXW prevalence distribution

EXW predicting variables	OR	Std. Err	Z	P> z	[95% Conf. Interval]	
Relative Humidity	8.855	7.284	2.65	0.008*	1.766	4.401
Elevation	1.717	.4314	2.15	0.031*	1.049	2.809
Precipitation	1.024	.0123	2.03	0.043*	1.001	1.049
Silty Soil texture	1.283	.1285	2.49	0.013*	1.054	1.561
_cons	1.15e-70	6.61e-69	-2.81	0.005*	2.0e-119	6.62e-22

* Significant at $p < 0.05$; cons refers to constant in which the regression line intercepts the y axis

power ($R^2 = 13.74\%$). This explained the variables included in the model are not the only EXW prevalence underlying factors in the study area. There could be other variables, which can determine the EXW prevalence in the area.

3.4.3. General linear regression model

The relationships between environmental variables and incidence were assessed using the generalized linear regression model.

The statistical analysis results based on the generalized linear model (maximum likelihood estimation approach), which is illustrated in (Table 4). Based on GLM regression, total annual precipitation, altitude, relative humidity, slope, soil pH value, silty soil texture, and leafhopper correlates positively with EXW incidence and contributes significantly to the model, yet some variation in the analysis of variance. Other variables such as agro-ecology, clay soil textures, and soil type (99% CI, p -value > 0.05) were not significant predictors of EXW incidence.

4. Discussions

This study has focused on analyzing the spatial EXW prevalence and incidence and further includes the identification of environmental determinants that correlates with EXW disease distribution. Recently, different reports asserted that The production of onset is declining in most onset growing areas from time to time due to diseases and other detrimental factors such as climate change, low soil fertility, and so on (Brandt et al., 1997a; Endale et al., 2003; Tsegaye & Struik, 2001). EXW is the major disease in the study area with visible symptoms. The onset plant leaf becomes yellow at the margin and tip side of the leaf part, then it wilts. Wilting is a failure of turgidity and petiole wrinkling. This leads to dry leaf and after while the plant develops secretion of bacterial ooze from cut tissues of the plants (Alemayehu et al., 2016; Oli et al., 2014; Thwaites et al., 2000;

Table 4. The relationship between EXW incidence and predicting variables based on generalized linear models(GLM) with family(Gamma) link(log)

EXW predicting variables	Exp(Coef.)	Std. Err	z	P> z	[95% Conf. Interval]	
Relative humidity	3.160	1.503	2.42	0.016*	1.244	8.027
Precipitation	1.016	.006	2.69	0.007*	1.004	1.029
Altitude	1.465	.204	2.74	0.006*	1.115	1.926
Slope	1.455	.237	2.30	0.022*	1.057	2.003
Silty soil	1.162	.079	2.19	0.028*	1.016	1.330
Soil pH	1.164	.069	2.54	0.011*	1.035	1.309
Leafhopper	5.073	1.099	7.49	0.000*	3.317	7.759
_cons	2.31e-43	7.71e-42	-2.95	0.003*	9.94e-72	5.39e-15

* Significant at p -value < 0.05 ; cons refers to constant in which the regression line intercepts the y axis.

Tushemereirwe et al., 2001). According to farmers' interview responses, for a long period, the disease is known in the area. They indicated that the disease affects production. They tried to control the disease by implementing traditional farm management practices like burning and burying the infected plants from the field. However, the presence of the disease is increasing in the area.

About 64% of the surveyed farm plots have shown EXW symptoms. The EXW disease is spatially distributed and most of the symptoms are observed in the southern and central parts of the study area. It is likely that area with more enset production has more EXW symptoms. EXW prevalence in Yem special district is high compared to a study by (Regassa & Shiferaw, 2015) who reported 56% EXW prevalence in Borena, the southeastern part of Ethiopia. Oli et al. (2014) who studied EXW prevalence in Tikur Inchini and Jibat districts, reported more than 80% of the field survey farm plots have shown EXW symptoms. Likewise, the EXW prevalence, the incidence rate varies from place to place. The EXW incidence rate is between 6.20 and 38.86 % in the study area. A high incident rate is observed in the southern and central parts of the study area. In general, the EXW prevalence and incidence report show, EXW disease is a major problem that affects enset production. Some authors also indicated the chronic disease problem of EXW in Ethiopia (Oli et al., 2014; Zerfu et al., 2018).

Even if the EXW disease is widely distributed in the study area, the intensity of the disease is highly correlated to certain environmental predicting variables. When we observe the intensity of the disease distribution, there is a clear association with high altitude, precipitation, and relative humidity and vice versa. Therefore, it is important to study and analyze the correlation of environmental factors with regards to EXW prevalence and incidence rate. Different biophysical environmental factors based on literature and farmers and expert interviews were taken into considerations to identify the detrimental factors that influence the intensity of EXW disease distribution in the study area. Environmental factors influence the rate of spore germination, penetration, pathogen dispersal (in distance, and direction)(Conway & Agrios, 1989). From this point of view, there is a strong positive association between EXW prevalence and response variables such as relative humidity, altitude, precipitation, and silty soil texture in the study area. The result of this report is also similar to Anita et al. (1996), who discussed the high correlation of environmental variables with regards to the distribution of EXW disease in different parts of Ethiopia. Other authors (Ashagari, 1985; Brandt et al., 1997b; Mekuria et al., 2016; Mwangi et al., 2006) who studied the association of EXW disease intensity with environmental factors like elevation, they reported that high altitude influences the disease intensity. Normally, high altitude, relative humidity, and high moisture create a favorable condition for pathogens' multiplication and survival. The presence of high moisture abundant in the form of rain, dew or high humidity is the dominant factor in the development of most epidemic diseases caused by oomycetes, fungi, bacteria, and nematodes (Conway & Agrios, 1989).

In summary, the regression model show, altitude, precipitation, and relative humidity are the main factors that significantly contributed to both EXW prevalence and incidence. Whereas, the EXW incidence regression analysis revealed, insect vector (leafhopper) has a strong association compared to the other predicting variables. In fact, leafhopper is not directly affecting the EXW disease rate rather it worsens the spread of EXW incidence as a transmitter. They transmit the pathogens by obtaining and carrying and delivering into host plant pathogens. Different insects contribute to the entry of pathogens into their host through the wounds that the insects make on the plant organs. EXW disease caused by Xcm which is produced within or in between plant cells releases masses of sticky bacteria exudates through cracks and wounds in the infected areas. Then bacteria are likely to stick on the legs and bodies of all sorts of insects, such as leafhopper (Blomme et al., 2017; Heck, 2018). In conclusion, leafhopper is one of the dominant insects in the study area, in the future further investigation should be carried out to understand the association of insects with the distribution of EXW disease in enset growing regions.

5. Conclusions

This study analyzed the spatial distribution of EXW disease and identified major factors that influence the rate of EXW in Yem special district.

The result of the spatial interpolation analysis shows onset crop is spatially distributed in the whole district. More cultivation is observed in the south and central part of the study area. However, the production of the crop is decreasing from time to time, and different factors attribute to the decline of onset production. One of the major problems that farmers are facing in the Yem special district is the disease so-called EXW. There is a high rate of EXW prevalence and incidence that endanger the production of onset. EXW spatial distribution indicates, there is a high cluster of EXW presence in the central and southern parts of the study area. These are the area where dense onset production is occurring. This reveals that the existing and future stable source of food is at risk. It has a huge effect on the food security of the rural community, which has limited alternatives to food sources.

In the study area, there is a significant difference in the intensity and rate of the spatial distribution of EXW disease. Therefore it is very important to study and investigate the factors that contribute to the spatial variation. To understand the environmental variables and the EXW prevalence and incidence, the regression model was applied. Different predicting variables were used such as topography (altitude and slope), climatic conditions (relative humidity and precipitation), soil characteristics (silty soil texture and soil pH), insect (the most common insect in the study area is leafhopper). Other environmental factors were screened out using a multicollinearity test. Thus, relative humidity and elevation (altitude) are the dominant determinant factors that attribute to EXW prevalence. On the other hand, leafhopper and relative humidity are the main determinant factors for EXW incidence. The report of this study is important for the design of intervention strategies aimed at controlling the EXW diseases distribution on small holders farmers to sustain food security.

In the future, further study should be carried out that considers multiple seasons data, socio-economic factors, and different statistical models to compare and contrast the results for better understanding.

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Compliance with ethical standards

The authors declare that they have no conflict of interests.

General comments

It is a very good job and have grate contribution to researcher and users. I have grate appreciation.

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