The Journal of Basic and Applied Zoology

RESEARCH

Open Access

A meta-analysis of climatic conditions and whitefly *Bemisia tabaci* population: implications for tomato yellow leaf curl disease

Kanta Kumar Lobin[1], Vishal Chandr Jaunky[2*] and Nawsheen Taleb-Hossenkhan[3]

Abstract

Background: Tomato yellow leaf curl disease (TYLCD), which is caused by the genus *Begomovirus*, is basically transmitted by the vector whitefly, *Bemisia tabaci* (*B. tabaci*). It remains a destructive disease of tomato across the world. The disease is present in many tomato growing countries, and it has a broad geographical distribution. The population and distribution of the vector are therefore an important factor in disease spread. This study assesses the determinants of the relationship between climatic factors and whitefly population. A thorough search of relevant papers was first initiated, and eventually 16 articles with 142 estimates were selected. A meta-regression analysis, especially the random-effects model with a restricted maximum likelihood (REML) estimator, was applied.

Results: Summarization of effect sizes revealed a mean effect size for the study of $r = 0.15$. The forest plot suggested a significant amount of study heterogeneity. No evidence of significant publication bias was uncovered. The meta-analysis revealed that the population of whiteflies was significantly related to climatic independent variables such as maximum and minimum temperature and rainfall. Other factors such as altitude, number of symptoms, pesticide policy, type of soil, number of references, impact factor and publication status were found to significantly influence the effect sizes.

Conclusions: Whiteflies are playing a major role in spreading the TYLCD. Several factors were identified to have a significant impact on the climatic conditions-whitefly population nexus. Since climatic factors, altitude, existing pesticide laws and type of soil were found to have a significant impact on the effect sizes, agricultural management policies could be enacted by specifically considering those factors in a view to minimize the impact of whiteflies. In general, all the above factors could be considered in strategy to manage TYLCD.

Keywords: Climatic variables, Meta-analysis, Tomato yellow leaf curl disease, Whiteflies

Background

Tomato yellow leaf curl disease (TYLCD) is one of the most devastating emerging diseases of tomato in the warm and temperate regions of the world (Lefeuvre et al., 2010). TYLCD continues to spread to new regions in the Indian and Pacific Oceans in Australia, New Caledonia and Mauritius (Lobin et al., 2010; Mabvakure et al., 2016). Symptoms expressed on infected tomato plants include yellowing, curling, and cupping of leaves, severe stunting, abortion of flowers and fruits, leading to yield reduction of up to 100% (Abhary et al., 2007). The emergence and rapid global spread of *Tomato yellow leaf curl virus* (TYLCV), which is one of the six species that cause TYLCD, are through the whitefly *Bemisia tabaci* (*B. tabaci*, Gennadius, Hemiptera: Aleyrodidae). The spread and distribution of *B. tabaci* worldwide" have increased due to occurrence of new and more virulent biotypes of

*Correspondence: vishal.jaunky@ltu.se

[2] Department of Business Administration, Technology and Social Sciences, Luleå University of Technology, SE-971 87, Luleå, Sweden
Full list of author information is available at the end of the article

the vector and which has spread to all continents except Antarctica (De Baro et al., 2005).

The vector exhibits high genetic diversity within the polyphagous species complex. The *B. tabaci* Mediterranean (MED or biotype Q) and Middle East-Asia Minor 1 (MEAM1 or biotype B) species are highly invasive and destructive (De Barro et al., 2000; Ning et al., 2015), and they transmit TYLCV in a persistent and circulative manner. The insect vector can infect several fields and thus propagate the virus rapidly (Pakkianathan et al., 2015). *B. tabaci* B and Q differ in host range, feeding behaviour, insecticide resistance and virus transmission efficiency. Both biotypes damage plants by feeding on phloem and by transmitting plant viruses (Ning et al., 2015). The *B. tabaci* cryptic species complex is agriculturally significant because members within this pest complex are important vectors for many plant viruses including begomoviruses (Sseruwagi et al., 2006). The B and Q biotypes have been the primary vector involved in the displacement of endemic begomoviruses such as TYLCV-mild and TYLCV throughout Asia, American tropics, Europe, Mediterranean region and the tropical Africa (Brown, 2000). Insecticide resistance by *B. tabaci* has been reported (Wang et al., 2017), and its management requires novel approaches that maximize non-chemical methods for pest control (Žanić et al., 2018). Due to pesticide resistance by *B. tabaci* and in a view to minimize application of pesticides, it is important to find other means of controlling the vector so as to minimize incidence and severity of TYLCV in tomato plantations. A solution that can be brought forward is to adjust planting dates when the whiteflies' population is low. It is therefore vital to have an insight of the distribution of whitefly population with respect to climatic variables such as minimum and maximum temperature, rainfall and humidity on whiteflies' population.

Predictors such as soil types, plant growth stage, availability of host plants and susceptibility of host plant to the virus along with farmers practices have to be considered in a holistic approach when monitoring whiteflies population. Many authors have studied the effect of climatic factors on whiteflies distribution on tomato (Mahajan, 2001; Jha and Kumar, 2017; Gupta et al., 2009; Meena, 2014; Patra et al., 2016). In a study on aphids behaviour at different temperature levels, Kambrekar et al. (2015) have demonstrated that at higher temperatures, aphids are less responsive to hormones secreted when attacked by predators, thus decreases their population. Jha and Kumar (2017) also report that temperature (daily maximum and minimum) and sunshine (in hours) have a negative significant correlation, while morning and evening relative humidity have a positive significant correlation, but wind speed has non-significant positive correlation with whiteflies population. Marabi et al., (2017) working on soybeans demonstrate that temperature, percentage relative humidity, sunshine and rainfall played limiting factors for the buildup of whitefly population in soybean agro-ecosystem.

Although there are many studies on the relationship of *B. tabaci* on TYLCV incidence severity and distribution, no systematic review of the literature has been done regarding how climatic variables jointly influence their population. In this study, a systematic synthesis of the empirical literature, also called meta-analyses, is carried out on the effect of climatic factors on whitefly population. The aim is to identify, critically evaluate and integrate the findings of all relevant studies and to obtain a clear summary based of evidence on the effect of climatic variables on whiteflies population. Understanding the effect of climate on whiteflies population is a critical factor in devising management strategies against the vector.

In this study, the implications of soil characteristics on whiteflies population was taken into account. Soil characteristics have an influence on plant growth and together with climatic variables prevailing in a region or locality will determine the population of insects or vectors. Plants with good growth and biomass are more prone to insect attack than plants with poor growth and having less biomass. According to Passioura (1991), soil structures have an impact on root and shoot development of plants. Plant growth is also affected by soil temperature which in turn is related to soil types and texture. Soil temperature determines micro and macro organism population, organic matter decomposition and nutrient availability (Onwuka and Mang, 2018). Studies have shown that plant resistance to insect pests and diseases is related to optimal physical, chemical and biological properties of soil (Zehnder, 2014). Soils which are high in organic matter support plant growth better than soils low in organic matter and soil microbial diversity. In addition to the plants which are better able to tolerate pest damage, healthy soils also contain many natural enemies of insect pests, including insect predators, pathogenic fungi and insect parasitic nematodes. These factors affect the population of insects, and eventually, plant growth is related to the insect populations. This systematic synthesis of empirical literature brings forward and confirms the findings of researchers who have studied the effect of climatic variables on whitefly population. Overall, the findings can be used to devise policies to manage whiteflies and decrease incidence and severity of TYLCV.

Literature review

In the field of plant pathology, three broad research questions have been addressed using meta-analysis: the comparative efficacy of chemical treatments for managing disease and reducing yield loss across environments; the quantification of relationships between disease intensity and yield or between different measures of disease across studies and to assess factors affecting pathogen–biocontrol agent interactions or biocontrol of plant disease and weeds (Ngugi et al., 2011).

Meta-analysis has been applied for epidemiology and disease management on pathogens such as *Phakopsora* species on soybean and *Erwinia* species on apple (Ngugi et al., 2011). Meta-analysis is not only used to validate general conclusions drawn from qualitative reviews, but it can also reveal new patterns and interpretations which is not mentioned from individual studies (Ngugi et al., 2011). Meta-analysis has also been used to aggregate experimental results in the case of assessing the effectiveness of fungicides in minimizing yield loss from the Yellow Spot—Septoria Nodorum Blotch disease complex on wheat. It has also been used to identify areas where further research need to be carried out, and as such it has potential to be applied to similar analyses in other crop diseases (Salam et al., 2013). The magnitude and significance of treatment effects in terms of disease control and yield response can be estimated, along with the effects of moderator variables on efficacy (Molina et al., 2019). These studies have carried out a quantitative synthesis to determine target spot disease control efficiency and yield response to several fungicides evaluated in the main soybean growing regions of Brazil. Other objectives of the meta-analysis were to identify factors affecting the efficacy of the tested products and estimate the probability of economic benefit for applying a fungicide under a wide range of grain price–application cost scenarios. Meta-analysis, using a random-effects model, was conducted to determine effect sizes of the anaerobic soil disinfestations effect on soil borne pathogens, plant parasitic nematodes and weeds compared with unamended controls (Shrestha et al., 2016).

For the purpose of this study, the effect size was captured by the correlation between climatic factors and whitefly population. The control variables applied were: year of publication, climatic factors (such as temperature, rainfall and humidity), altitude, number of reported symptoms, prevalence of pesticide law, soil type (such as alluvial soil, sloppy soil. laterite soil, loamy soil. sandy loamy soil and volcanic soil), number of references, impact factor and publication status.

Year of publication

Year of publication was first considered as an independent variable in the meta-analysis and could be expected to have an impact on the effect sizes. The estimated correlation between publication year and effect size was used as the outcome to quantify the temporal effect size trend (Rødgaard et al., 2019).

Climatic factors

Climatic factors[1] such as temperature, relative humidity, sunshine hours and wind speed (Sawan, 2018) were found to havehadan effect on whiteflies' development. Verma et al. (1990) reported that egg and adult development in whiteflies are a function of temperature. Studies showed that development of adults from pupae increased under a constant temperature of 29.5 ± 0.6 °C and a photoperiod of 14:10 light: dark cycles (Hoffmanand Byrne, 1986). Optimal temperature for *B. tabaci* reproduction was between 28 and 33 °C (Curnutte et al., 2014; Sohani et al., 2007). Other studies demonstrated that increase in humidity and rainfall negatively impacts on the population of whiteflies. Kumar et al. (2016) reported the correlation coefficient between whitefly population and other abiotic parameters like temperature, relative humidity, rainfall and wind speed was non-significant. Moreover, they found that the relative humidity (maximum and minimum), rainfall and wind speed had got negative impact on population outbreak of whitefly while the temperature (maximum and minimum) had got non-significantly positive impact on the population fluctuation. Hossain et al., (2010) also contributed to this finding and confirmed that temperature was significantly correlated with and had pronounced effect on whitefly population as compared to relative humidity.

Altitude

Climatic factors vary with altitude and have an impact on the activities and distribution of insects. The numbers of insect species increased when climatic conditions were found to be favourable for their reproduction, growth and activities (Aidoo et al., 2014). Wolda (1987) reported that species richness as well as sample size decreased gradually with increasing altitude over a 100–2200 m range.

Symptoms

Symptoms of TYLCV were mainly used in the study included reduction in leaf size, upward cupping/curling of leaves, chlorosis (yellowing) on leaves reduction in fruit production and severe stunting (Cohen and Antignus, 1994).

Pesticide law

Pesticide regulations or laws have been set up in many countries with the objective to use pesticide rationally.

[1] Online at: http://metservice.intnet.mu/climate-services/climate-info-and-data.php

Different countries have their own pesticide regulations and include limits for pesticide residues on food, product registration requirements and pesticide use restrictions. Because of these differences, pesticides in international trade can be subject to pesticide regulations from multiple countries. Many countries regulate the amount of pesticide residue allowed on a given crop. In this meta-analysis, a search is made on the countries from where the studies and publications are made in order to find out whether these particular countries have pesticide regulations or not. The objective is to determine if those countries with pesticide regulations have had an impact on the vector population.

Soil types and plant growth

The physical, chemical and biological properties of soil lead to a series of physiological, biological and chemical changes along with growth, yield and quality of the plant biomass and thus of fibres (Khalil et al., 2015). Soil characteristics and plant growth are reviewed below.

Alluvial soils

Alluvial soils are porous due to their loamy (equal proportion of sand and clay) nature. Porosity and texture provide good drainage and other conditions favourable for agriculture. Alluvial soils are poor in nitrogen and potash, high in sands and tend to drain quickly. Alluvial soils are suitable for growing range of crops including vegetables under irrigation.[2] Alluvial soils which are present along rivers have the highest productivity (Dwevedi et al., 2017). Different types of crops such as rice, wheat, sugarcane, tobacco, maize, cotton, soybean, fruits, vegetables are grown under alluvial soil. Alluvial soil is one of the best soils, requiring the least water due to its high porosity.

Sloppy soils

Sloppy soils are soils found on sloppy terrains or lands. They are prone to soil erosion and lack fertility. To improve soil characteristics, farmers convert sloppy land into terraces (Allah et al., 2009). Sloppy soils are often marginal in nature and affects plant growth yield and growth and are unsuitable for high productivity.

Laterite soils

Laterite soils are generally acidic and have low cation exchange capacity. Other characteristics of these soils include poor inherent fertility, phosphorus fixation and aluminium toxicity (Singh et al., 2013). Laterite soils have lower content of nitrogen, phosphorus, potassium. Such soil lacks fertility due to a lower base-exchanging capacity and a lower content of nitrogen, phosphorus, and potassium. However, proper irrigation and use of fertilizers make it suitable for growing crops, such as tea, coffee, rubber, cinchona, coconut (Dwevedi et al., 2017).

Loamy soils

Loamy soils are naturally fertile soils with good water holding capacity and can be used for growing many types of crops or grassland farming. These soils have developed over a wide range of parent material; they are called medium-textured soils (Finch et al., 2014).

Sandy loamy soils

Sandy loamy soils cannot hold water, which can lead to insufficient nutrition in plants. They drain the excess water in them and as such require frequent fertilization and watering to boost plant growth. It also requires regular addition of nutrients.[3]

Black volcanic soils and others

Black volcanic soils have excellent physical properties chemically, but they may suffer from a high phosphate retention and may be limiting in nitrogen, potassium and some micronutrients. Nevertheless, these soils are among the most fertile lands in the world and are, therefore, very intensively cultivated (Neall, 2009). They are suitable to grow a wide range of crops.[4]

References

Number of references is taken from each paper used in the meta-analysis in order to explore whether this measure references is associated with reported results.

Impact factor

Journal impact factor is taken from the Google Scholar in order to explore whether this measure of journal quality is associated with reported results (Abdullah et al., 2015). The impact factor is a simple ratio of citations and articles and may not wholly represent the quality of all articles in the journal (Walter et al., 2003).

Publication status

The final set of meta-regression analysis variables relates to various dimensions of the publication process. Differences between published and unpublished studies are accounted for via the variable published (Nauzeer and Jaunky, 2021).

[2] https://www.pmfias.com/alluvial-soils-black-soils-soil-types-of-india-bhabar-terai-bhangar-khadar/

[3] https://gardenerdy.com/sandy-loam-soil-characteristics

[4] https://www.agrifarming.in/soil-types-suitable-crops-india

Methods

Meta-analysis involves combining summary information from related but independent studies (Crombie and Davies, 2009; Normand, 1999). Smith and Glass (1977) pioneered the application of meta-analysis in research related to psychological treatment and education, but this approach to research synthesis has now been extended to many scientific disciplines (Madden Paul, 2011). Meta-studies help to overcome the issue of small sample sizes because they review multiple studies across the same subject area. In a meta-analysis, the results are numerically pooled and a summary estimate is carried out in addition to a narrative summary (Basu, 2017). It is secondary data analysis and involves the re-analyses of existing original data from primary research studies carried out by other researchers (Boyle et al., 2016).

The meta-analysis aims for complete coverage of all relevant studies look for the presence of heterogeneity and explore the robustness of the main findings using sensitivity analysis. In other words, meta-analysis is used to increase statistical power, to deal with controversy when individual studies disagree, to improve estimates of size of effect and to answer new questions not previously posed in component studies (Hunter and Schmidt 1990). When the results from the individual studies are combined using meta-analysis, significant benefits of treatment may be shown (Crombieand Davies, 2009). The objective of meta-analysis offers an unbiased synthesis of the empirical data.

The following three types of bias should be avoided in a meta-analysis: publication, search and selection bias (Kristalyn Salters-Pedneault, 2018). The approach used in this study was based on the recommendations of the Meta-Analysis of Economics Research Network (Stanley et al., 2013) for meta-regression analysis.

Information search

A random and systematic search were first made using Google, Google Scholar and ResearchGate towards looking for published, unpublished articles, dissertations or in-press studies not yet indexed on the databases. Several variations in key words such as "*effect of climate, temperature, rainfall, relative humidity, correlation, tomato, TYLCV, virus, r values* were combined with variations in *B. tabaci population, whiteflies population.*" A systematic search of online databases such as EBSCO, JSTOR and Science Direct was afterwards conducted.

Inclusion and exclusion criteria

Publications were screened by first and second authors, and only full English versions were selected. Effect size measures include mean standardized mean differences, odds and risk ratios in addition to partial correlation coefficients. Partial correlation is the correlation of two variables while controlling for a third or more other variables. In this study, those studies reporting partial correlation coefficients were chosen as they are easily computed with only limited information.

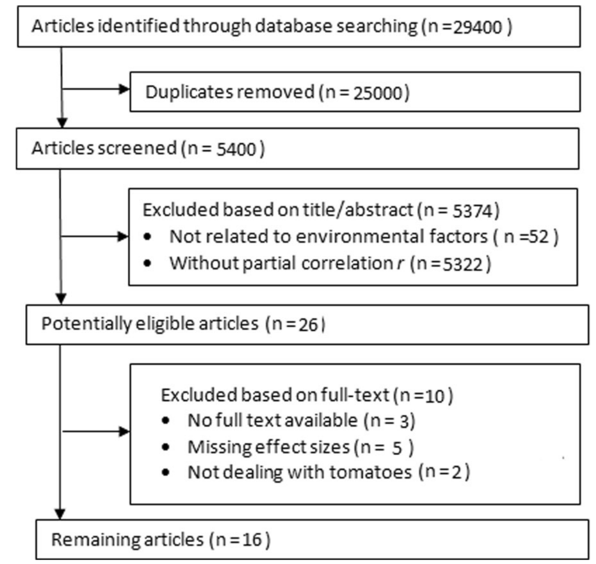

Fig. 1 Schematic selection process

Studies provided as reference were dated from 1999 to 2018.

The selection process was based on studies on effect of climate on *B. tabaci* population on tomatoes. Those studies in which the full text was not available, missing effect sizes, or with effect sizes not related to tomato crops were excluded and this narrowed the total number of studies selected to 16 articles. These articles were mostly from developing countries and no articles were obtained from developed countries. These articles consisted of correlation coefficient r and effect of climate on the whitefly populations, and all the 16 articles were chosen. There are prior meta-analyses that address very similar topics with comparable samples such as McNabb et al., (2019), where $n = 16$. The selection process is diagrammatically illustrated in Fig. 1.

Climatic factors

The climatic factors used in the study are maximum temperature, minimum temperature, maximum relative humidity, minimum relative humidity, rainfall, sunshine hour and wind speed. These factors were correlated with *B. tabaci* population .

Table 1 Variable Description for the Meta-Analysis

Variable name	Description
r	Correlation of the effect of climatic variables such as maximum relative humidity, maximum temperature, minimum relative humidity, minimum temperature, rainfall, sunshine, wind speed with whitefly (*B. tabaci*) population
SE	Standard error
Year	Year of publication
Climatic factors	
Minimum temperature	Minimum Temperature (in Celsius)
Maximum temperature	Maximum Temperature (in Celsius)
Rainfall	Rainfall (in millimeter)
Humidity	Relative humidity (in percentage)
Altitude	Altitude above sea level (in meter)
Symptom	Number of TYLCV symptoms described in the study (reduction in leaf size, upward cupping/curling of leaves, chlorosis (yellowing) on leaves reduction in fruit production and severe stunting)
Pesticide law	= 1, if the country in the study has a pesticide law and 0 otherwise
Type of soil	
Alluvial soil	= 0, if study deals with alluvial soil
Well-drained sloppy soil	= 1, if study deals with well-drained sloppy soil
Laterite soil	= 1, if study deals with laterite soil
Loamy soil	= 1, if study deals with loamy soil
Sandy loamy soil	= 1, if study deals with sandy loamy soil
Volcanic soil	= 1, if study deals with volcanic and black volcanic soil
References	Number of references in the study
Impact factor	Impact factor of the study
Published	= 1, if study was published in a peer-reviewed journal or 0 otherwise

Soil types

As per Fig. 1, 16 papers were identified. The type of soil was determined in the region where the study was carried out. Types of soil included in this study are alluvial soil, black volcanic soil, sandy loamy soil, well drained sloppy soil, laterite soil, loamy soil and volcanic soils.

Effect size coding

The effect sizes for the correlation results r were taken directly from these 16 studies. The variance of r is given by $V_r = \frac{(1-r^2)^2}{n-1}$, where n is the number of studies resulting to the effect sizes weighted by their inverse variance $G_{Zr} = n - 1$ and the standard error is $SE_r = \sqrt{V_r}$. As stated by Anderson et al. (2018), the partial correlation coefficient r is truncated at -1 and $+1$ and this can lead some issues. As such, meta-regressions can be run on the Fisher's Zr transformation (Hedgesand Olkins, 1985). But, the application of the Fisher's Zr transformation can yield negative bias with an upward one (Hunter andSchmidt, 2004). The Fisher's Zr is formulated as:$ES_{Zr} = 0.5 \log_e \left[\frac{1+r}{1-r}\right]$, where ES_{Zr} is the Fisher's z-transformed correlation and r is the reported correlation.

Heterogeneity of effect size

Heterogeneity of effect sizes was evaluated via the Q statistics. The I^2 statistics that point out the total variance attributable to between study were computed as: $I^2 = 100\% \frac{Q-df}{Q}$, where df was the degree freedom. The cut-offs percentages for low, medium and high heterogeneity were 25%, 50% and 75%, respectively (Higgins et al., 2003). Heterogeneity can result in Type I errors (Brockwell and Gordon, 2007), but any amount is satisfactory, as long as both the predefined eligibility criteria are appropriate. The restricted maximum likelihood (REML) estimator is usually downwardly biased in the presence of heterogeneity (Sidik and Jonkman, 2007).

Data coding

The description of the variables is described in Table 1

Table 2 Summary statistics

Authors (year)	Country	Region	Year	*N*	Frequency	Mean *r*	SD *r*
Appiagyei (2010)	Ghana	–	2010	48	6	−0.133	0.03
Chaudhuri et al. (2001)	India	West Bengal	2001	10	5	−0.121	0.023
Gupta (1999)	India	Himachal Pradesh	1999	20	6	0.375	0.022
Gupta et al. (2009)	India	Madhya Pradesh	2009	20	32	−0.37	0.027
Haider et al. (2017)	Pakistan	Faisalabad	2017	18	18	0.88	0.011
Jha and Kumar (2017)	India	Bihar	2017	75	6	0.007	0.03
Mahajan (2001)	India	Jammu	2001	100	5	0.084	0.081
Meena (2014)	India	Varanasi	2014	25	5	0.217	0.029
Mehmood et al. (2010)	Pakistan	Jammu	2018	120	12	0.884	0.001
Nagamandla et al. (2017)	India	West Bengal	2017	15	8	−0.072	0.023
Naveed et al. (2015)	Pakistan	Faisalabad	2015	7	16	−0.18	0.03
Patra et al. (2016)	India	West Bengal	2016	25	5	0.294	0.022
Razvi et al. (1999)	Oman	Sultanate	1999	25	2	0.24	0.095
Sharma et al. (2017)	India	Jammu Kashmir	2017	5	6	−0.028	0.044
Subba et al. (2017)	India	North East India	2017	15	5	−0.286	0.022
Yasin et al. (2017)	Pakistan	Faisalabad	2017	15	5	0.492	0.037
Overall					142	0.148	0.307

Results

Summary statistics

The descriptive statistics of the size effects per study are described in Table 2. Summarization of the mean effect size for the 16 papers is $r=0.148$ ($Zr=0.307$) with a range of $-0.95 \le r \le 0.99$ ($-1.83 \le Zr \le 2.93$).

B. tabaci is one of the most threatening pests to crop production in tropical and sub-tropical regions. Following Götz and Winter (2016), *B. tabaci* is a complex of at least 34 species, with Middle East-Asia Minor 1 and Mediterranean types being the most aggressive attributable to their broad host range and enhanced resistance to pesticides. Ramos et al. (2018) further report the occurrence of *B. tabaci* for regions on all continents. However, the combination of *B. tabaci* and tomato (*Solanum lycopersicum*) is more probable in tropical regions with high mean annual temperatures (including areas with wide variations in daily temperatures and a wider range in precipitation). Tropical climatic conditions were conducive for growing tomatoes in the open fields, and hence, a greater distribution and prevalence of whiteflies were found here. The meta-analysis was therefore more centred on developing countries which mostly had tropical climates and where most studies on whiteflies distribution had taken place as shown in Table 2.

Testing for publication selection bias

Publication bias refers to a situation where researchers report studies mainly published in peer-reviewed journals and ignore unpublished studies. Publication bias can distort the statistical inferences when smaller studies with non-significant conclusions are ignored in meta-analyses (Sun et al., 2018). To minimize the effect of publication bias, unpublished and grey studies can be included in the meta-analysis (Begg, 1994). In the absence of bias, the funnel plot will resemble a symmetrical funnel. Figure 2 suggests that the funnel plot seems to be rather symmetrical, but further test needs to be undertaken.

Sensitivity analysis

A sensitivity analysis was applied to determine the robustness of the results. The meta-regressions were re-run after detecting and excluding outliers from the study. No significant changes were observed after running the

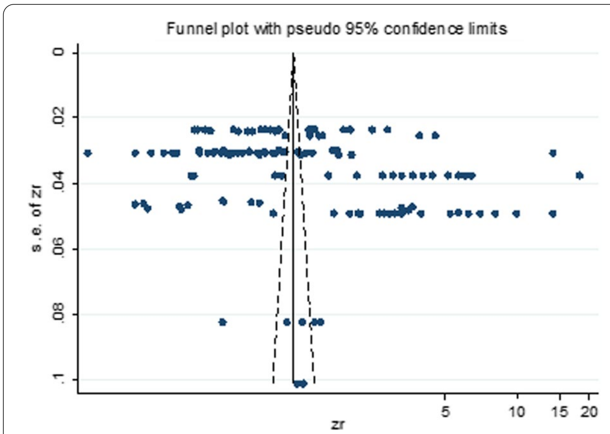

Fig. 2 Funnel plot. *Note* SE denotes standard error

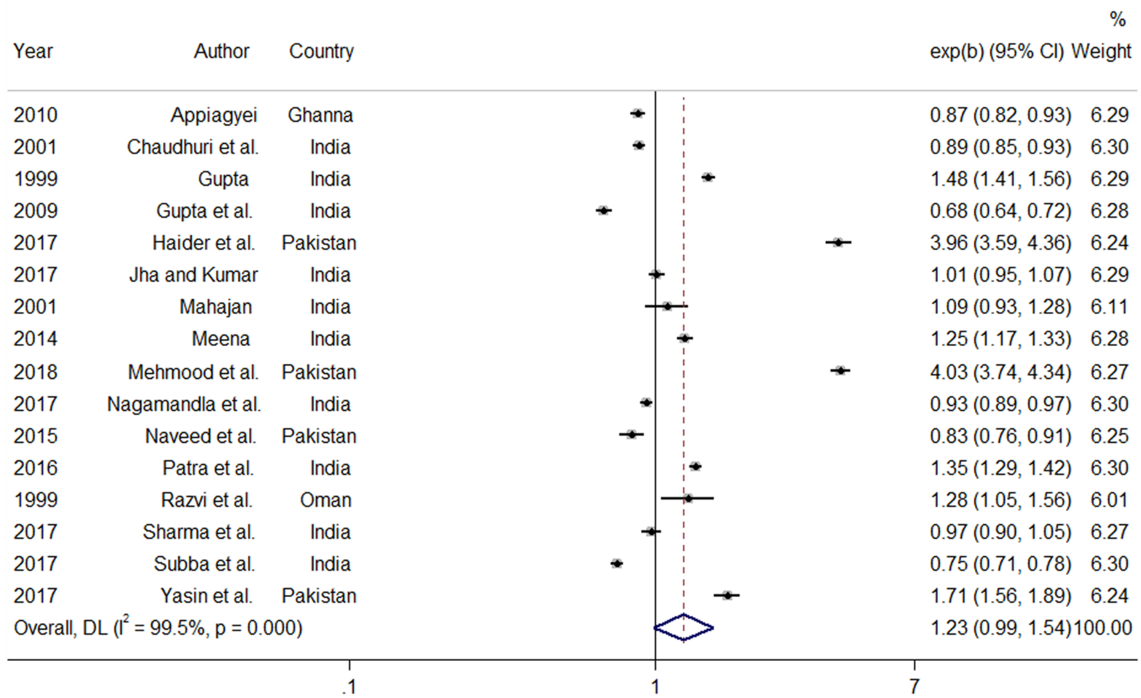

Fig. 3 Forest plot represented the *Zr*statistics. The diamond denoted the point estimate and confidence intervals when all the individual studies are combined and averaged together. If the horizontal tips of the diamond crossed the vertical line, the presence of heterogeneity would be rejected. However, the overall I Squared (I^2) was equal to 99.5% (p-value = 0.000), in which there was a high degree of heterogeneity between studies. The fixed-effects assumption of similar true effect in each study was strongly rejected. Weights were from random-effects model

model without unpublished articles. Similar to Nauzeer and Jaunky (2021), the meta-regression was re-run with Fisher's *Zr* transformation with dependent variable and little difference to our results, especially with regards to the major explanatory variables.

Testing for heterogeneity

Figure 3 shows the forest plot, which was used to look for heterogeneity in the study.

Meta-regression analysis

In the presence of between-study heterogeneity, the random-effects meta-regression model with REML estimator was applied. The model could be algebraically represented as follows:

$$r_{ij} = \beta_0 + \sum \beta_k X'_{ki} + \beta_1 SE_{ij} + \varepsilon_{ij} \tag{1}$$

where r_{ij} represented partial correlation between climatic factors and whiteflies population of the *i*th estimate and the *j*th study, β_0 was the true value of the effect size coefficient, X'_{ki} was the vector of moderator variables, β_k represented the meta-regression coefficients, SE_{ij} denoted the standard error of the coefficient of the *jth* study and ε_{ij} was the error term. The constant β_0 quantified the size of the effect as calculated by the partial correlation, holding all the other variables constant. In case $\beta_1 = 0$, then the literature would be free of publication selection bias (Stanley, 2008). This was known as the funnel asymmetry-precision effect test (FAT-PET). The results for the model are shown in Table 3.

As reported in Table 3, the null hypothesis that $\beta_1 = 0$ could be rejected. This implied no evidence of publication selection bias. Various variables were found to be important predictors such as climatic variables (minimum temperature, maximum temperature, rainfall and humidity), altitude, pesticide law, sloppy soil, laterite soil, loamy soil, sandy loamy soil, volcanic soil, references, impact factor and published. Variables like year, humidity and symptoms were found to have an insignificant impact on the effect size.

Discussion

Climatic factors effect on whiteflies population

Insects are very sensitive to changes in climatic conditions, and their effects on plant population dynamics will depend on climatic conditions (Dostálek et al., 2018). Factors such as temperature and rainfall were found to

Table 3 Estimates of the meta regression

Variable Name	Coefficients	Standard errors
SE	−24.01	117.67
Year	0.01	0.02
Climatic factors		
Minimum Temperature	−2.17	0.49***
Maximum Temperature	−2.23	0.59***
Rainfall	−0.02	0.00***
Humidity	−0.01	0.02
Altitude	0.01	0.00***
Symptoms	0.04	0.03
Pesticide law	4.79	1.85**
Type of soil		
Alluvial soil (reference)		
Sloppy soil	−30.04	7.13***
Laterite soil	30.24	7.48***
Loamy soil	−69.36	16.22***
Sandy loamy Soil	8.34	1.83***
Volcanic soil	23.4	6.03***
References	0.03	0.01***
Impact Factor	−0.06	0.03**
Published	−46.56	11.53***
Constant Term	120.02	50.69**
Number of observation	142	
tau2	0.18	
I-squared	100.00%	
Adj R-squared	51.80%	
F(23,118)	9.91	
Prob > F	0.00***	
Q_res (124 df)	6.30E+08	
Prob > Q_res	0.00***	
Likelihood ratio test of tau2 = 0: chibar2(01)	6.30E+08	
Prob > chibar2	0.00***	

***, ** and * are 1%, 5% and 10% Confidence intervals, respectively. The standard error is in brackets. REML estimate of between-study variance % residual variation due to heterogeneity proportion of between-study variance explained joint test for all covariates With Knapp–Hartung modification

be determinants on the population of whiteflies. From Table 3, the coefficients of temperatures such as maximum and minimum and rainfall were negative and statistically significant at the 1% level, asserting that these factors have negative impacts on the effect sizes. Temperature was important for growth, development, and reproduction of insects. It affected the internal and external conditions, including developmental stages, nutritional unbalance, pathogen intrusion, geographic habitats and other environmental stimuli (Denlinger and Lee, 2010; Denlinger and Yocum, 1998; Feder and Hofmann, 1999). Increasing temperature was favourable for activities and developmental processes of whiteflies due to which its population increase while the increasing relative humidity inhibited their activities (Aktar et al., 2008). Maximum whitefly infestation was observed in okra crop at high temperature and low relative humidity (Ali et al., 2005). Insects thrived best in a range of temperature. However, at extreme high and low temperatures the population could drop due to negative impacts on processes in the insects. In a study carried out by Chauduri et al. (2001), it was found that life cycle of whiteflies was negatively correlated with temperature, relative humidity, sunshine and rainfall and they were ranged from 17.07 to 22.13 °C, 65.29–72.78%, 7.79–8.89 h per day and 5 mm, respectively.

Climatic factors affect insects differently in different agro-ecological zones. As per Aidoo et al. (2014), there was a negative and highly significant ($p < 0.01$) correlation between insect abundance and rainfall. Furthermore, the correlation between mean temperature and insect abundance was negative and significant ($p < 0.05$). Marabi et al. (2017) report that minimum temperature and maximum temperature are positively correlated with whiteflies population ($r = 0.54$ and $r = 0.58$, respectively). Heat shock proteins (HSPs) are well known to respond to high temperature and other environmental stresses in a wide range of organisms. Typically, the genes encoding these proteins are not expressed under normal conditions but are quickly turned on in response to stress and again are quickly turned off when the stress is removed (Rinehart et al., 2006). This was also confirmed by Díaz et al. (2015), whereby the authors provided evidence that HSPs were unregulated by stress conditions in insects including whiteflies (*B. tabaci*). Hardening significantly increased fitness following heat stress, signifying that HSPs might contribute to hardening capacity in *B. tabaci*. According to Garg and Patel (2018), sunshine hours were positively correlated with whiteflies population ($r = 0.34$) while Patil et al. (2021) reported that rainfall and relative humidity had negative effects on whitefly activities ($r = -0.08$ and $r = -0.05$, respectively). Wide variation in temperature in different agronomic localities explained the difference in conformity observed by different authors.

Cooler weather, high relative humidity and rainfall could be detrimental to whitefly population and its spread. This was due to suppression in oviposition, increased the mortality of nymphs, adults and induced insect emigration (Sharma et al., 2017). The coefficients of rainfall and relative humidity were found to be negative and statistically significant at 1% level. Safdar et al. (2019) were working on the effect of abiotic factors on population dynamics of whiteflies and Jassid on Bacillus thuringiensis cotton and showed that relative humidity and rainfall negatively affected the population of whiteflies. The effect sizes were also affected by temperature.

However, the minimum and maximum temperatures were statistically proved to decrease the effect sizes. These varied with locations and countries and had to be determined under local condition when devising management strategies against the vector. For example, tomato cultivation could be adapted to seasons where whitefly population was low. Thus, combining practices such as tolerant varieties, planting season, timely application of pesticides and production of seedlings under insect proof conditions could provide a holistic approach to manage the disease.

Type of soil

The impact of climate on whiteflies' population was lower in sloppy and loamy soils relative to alluvial soil. The coefficients of sloppy and loamy soils were negative and are significantly different at 1%. However, the impact of climate on effect sizes was higher in laterite, sandy loamy and volcanic soils compared to alluvial soils. These soils show a positive coefficient and are significantly different at 1%. These values showed that soils type contributed to the population of whiteflies in and that climatic variables were not the only determinants of population of whiteflies, but it was also associated with other factors such as plant growth, soil type and cultural practices. Healthy crops, fertile soils and cultural practices such as pesticide application by farmers would determine the population of white flies. Chaudhuri et al. (2001) reported that temperature was not the only factor that determined insect population, but all the weather parameters and availability of host plants largely determined the size and fluctuation of any species. Sloppy soils were naturally poor in nutrients and lack water holding capacity and were easily eroded especially under high rainfall (Edem and Gideon, 2017). However, loamy soils which were naturally fertile had a negative coefficient also. This could be attributed to other determinants such as availability of host plants, variability in climatic variable and farmers practices in the localities with loamy thus impacting negatively on the population of whiteflies. According to Stanley et al. (1997), whitefly population dynamics were determined by environmental factors and crop phenology. The positive coefficient attributed to sandy loams and laterite soils was again attributed to other factors which contributed in fluctuations in the population of whiteflies. Regular addition of nutrients to promote plant growth would favour the development of insect pests due to increase in canopy. Mansour et al. (2012) demonstrated that a higher population of whiteflies was observed at the middle and younger stages of growth in tomato.

Altitude

Altitude had a positive coefficient and had a significant impact on whiteflies population at 1% causing an increase in the effect sizes. In a study on *Salvia nubicola* in altitudinal gradients, plant populations were observed to be affected from high altitudes in open habitats because of increased population of insect and damage (Dostálek et al., 2018). However, climatic factors extreme at high and low altitude not only altered whiteflies population but also the growth and development of hosts. Lawton et al. (1987) reported that increasing environmental harness is responsible for the decline in insect species richness that is observed with increasing altitude.

Pesticide law

In Table 3, it was reported that countries with pesticide laws had a significant positive impact on effect sizes at 5% level of significance. This might be associated with lesser or minimal use of pesticides in these countries and therefore contributing to the increase populations of the whiteflies. In many countries with pesticide laws, it could be difficult to maintain whiteflies population to a required threshold. Moreover, due to the ability of the whitefly vectors to develop insecticide resistance, there was a growing need to develop and deploy strategies that did not rely on insecticides (Lapidot, 2014). It was also difficult to manage TYLCV by solely spraying pesticides against whiteflies as even a low population of whiteflies might propagate the disease in neighbouring fields as they transmitted the whiteflies in a persistent manner (Pakkianathan et al., 2015).

Reference

The coefficient of the references variable was found to be positive and statistically significant at 1%. Studies with higher number of references tended to have a larger positive impact on the effect sizes.

Impact factor

The coefficient of impact factor variable was found to be statistically significant at 5%. Studies with a higher impact factor tended to have a negative impact on the effect sizes.

Published

The coefficient of published variable was found to be statistically significant at 1%. Studies with higher number of publication tended to have a negative impact on the effect sizes relative to unpublished studies.

Limitations and future research

We recognized possible limitations of our research. Regardless of the results from the FAT-PET, we could not fully exclude the risk of a publication bias. The keywords under climatic factors excluded indicators such as radiation, evaporation, atmospheric pressure, vapour pressure, soil temperature, upper air data and thunderstorm days. These could be considered in future studies.

For future research on effect of climatic factors on population of whiteflies, the effect of biotypes could be considered. The study was also limited by the information on whiteflies in the open field. Aspects of climatic factors on whiteflies population in protected cultures were not considered. Alternatively, the meta-analytic structural equation modelling could also be used to investigate the factors affecting climatic conditions and whiteflies population.

Conclusions

As stated by Hunter and Schmidt (1990), the meta-analysis helped to answer new questions not previously posed in component studies. New finding brought forward in this meta-analysis was that climatic variables were not the only impact on whiteflies population. Other factors such as soil type, altitude, host plant population and distribution and pesticide policy in a country were all determinants on the population of insects. All the factors were interrelated and were to be considered in a strategy to manage TYLCV.

Since whiteflies population had an important role in spreading the disease, it was imperative to consider all interrelated factors that determined the population level. Per se, climatic conditions, soil types, availability of host plants, stage of growth were among the determinant of whitefly populations. In general, government policy with regard to pesticide use and cultural practices adopted by farmers must be looked into as well as varieties grown and their susceptibility to the virus. It could be recommended that future studies be carried out to determine at what time of the year whitefly populations are lower and this has to be correlated with prevailing climatic variables. Studies should integrate soils characteristics in different regions and types and stages of growth of crops grown in these specific localities. Such findings would help build up a database that should facilitate policies in managing the disease in tomato plantation. For example, a grower could grow a susceptible variety that had high yields and culinary characteristics in certain localities and specific time of the year when the population of whiteflies was to be low.

Abbreviations

FAT-PET: Funnel asymmetry-precision effect test; HSPs: Heat shock proteins; REML: Restricted maximum likelihood; TYLCD: Tomato yellow leaf curl disease; TYLCV: Tomato yellow leaf curl Virus.

Acknowledgements

We would like to thank the staff member of Lulea University of Technology for their assistance in providing access to online research papers.

Author contributions

KKL analysed and discussed the findings of meta-regression. VCJ run the model and interpreted the results. NTH performed a thorough examination of the manuscript and contributed, especially in the introductory part. All authors read and approved the final manuscript.

Funding

This research received no external funding.

Availability of data and materials

The data can be available upon author's request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Approval for publication was obtained from the Food and Agricultural Research and Extension Institution.

Competing interests

All authors have no competing interests.

Author details

[1]Plant Pathology Division, Food and Agricultural Research and Extension Institute, Reduit, Mauritius. [2]Department of Business Administration, Technology and Social Sciences, Luleå University of Technology, SE-971 87, Luleå, Sweden. [3]Department of Biosciences and Ocean Studies, Faculty of Science, University of Mauritius, Reduit, Mauritius.

Received: 7 July 2020 Accepted: 30 November 2022
Published online: 21 December 2022

References

Abdullah, A., Doucouliagos, H., & Manning, E. (2015). Does education reduce income inequality? A meta-regression analysis. *Journal of Economic Surveys, 29*(2), 301–316.

Abhary, M., Patil, B. L., & Fauquet, C. M. (2007). Molecular biodiversity, taxonomy, and nomenclature of tomato yellow leaf curl-like viruses. In H. Czosnek (Ed.), *Tomato yellow leaf curl virus disease: management, molecular biology, breeding for resistance* (pp. 85–118). Springer.

Aidoo, O. F., Kyerematen, R., Akotsen-Mensah, C., & Afreh-Nuamah, K. (2014). Effect of some climatic factors on insects associated with citrus agro-ecosystems in Ghana. *J Biodiversity Environ Sci, 5*, 428–436.

Aktar, M. M., Akhter, M. S., & Akanda, A. M. (2008). Impact of insecticides and organic oil spray on the growth and yield of tomato under TYLCV infected condition. *Bangladesh Res. Publ. J, 1*, 199–205.

Ali, S. A. F. D. A. R., Khan, M. A., Habib, A., Rasheed, S., & Iftikhar, Y. (2005). Correlation of environmental conditions with okra yellow vein mosaic virus and *Bemisia tabaci* population density. *International Journal of Agriculture and Biology, 7*(1), 142–144.

Allah, R., Lone, M. I., Ali, S., & Hussain, S. (2009). Soil water variation under different cropping patterns on sloppy lands in Punjab, Pakistan. *Soil and Environment (pakistan), 28*(2), 156–161.

Anderson, E., d'Orey, M. A. J., Duvendack, M., & Esposito, L. (2018). Does government spending affect income poverty? A meta-regression analysis. *World Development, 103*, 60–71.

Basu, A., 2017. How to conduct meta-analysis: a basic tutorial.

Begg, C. B. (1994). Publication bias. *The Handbook of Research Synthesis, 25*, 299409.
Boyle, J., Connolly, M. & MacKay, T., (2016). Systematic review and meta analysis. *Educational and Child Psychology*, *33*(3).
Brockwell, S. E., & Gordon, I. R. (2007). A simple method for inference on an overall effect in meta-analysis. *Statistics in Medicine, 26*(25), 4531–4543.
Brown, J. K. (2000). Molecular markers for the identification and global tracking of whitefly vector–Begomovirus complexes. *Virus Research, 71*(1–2), 233–260.
Chaudhuri, N., Deb, D. C., & Senapati, S. K. (2001). Biology and fluctuation of white fly (*Bemisia tabaci* Genn.) population on tomato as influenced by abiotic factors under Terai region of West Bengal. *Indian Journal of Agricultural Research, 35*(3), 155–160.
Cohen, S., & Antignus, Y. (1994). Tomato yellow leaf curl virus, a whitefly-borne geminivirus of tomatoes. *Advances in disease vector research* (pp. 259–288). Springer.
Crombie, I.K. and Davies, H.T., 2009. What is meta-analysis. *What is*, pp.1–8.
Curnutte, L. B., Simmons, A. M., & Abd-Rabou, S. (2014). Climate change and *Bemisia tabaci* (Hemiptera: Aleyrodidae): Impacts of temperature and carbon dioxide on life history. *Annals of the Entomological Society of America, 107*(5), 933–943.
Díaz, F., Orobio, R. F., Chavarriaga, P., & Toro-Perea, N. (2015). Differential expression patterns among heat-shock protein genes and thermal responses in the whitefly *Bemisia tabaci* (MEAM 1). *Journal of Thermal Biology, 52*, 199–207.
De Barro, P. J., Driver, F., Trueman, J. W., & Curran, J. (2000). Phylogenetic relationships of world populations of *Bemisia tabaci*(Gennadius) using ribosomal ITS1. *Molecular Phylogenetics and Evolution, 16*, 29–36. https://doi.org/10.1006/mpev.1999.0768
De Barro, P. J., Trueman, J. W. H., & Frohlich, D. R. (2005). Bemisia argentifolii is a race of *B. tabaci* (Hemiptera: Aleyrodidae): the molecular genetic differentiation of *B. tabaci* populations around the world. *Bulletin of Entomological Research, 95*(3), 193–203.
Denlinger, D. L., & Lee, R. E., Jr. (Eds.). (2010). *Low temperature biology of insects*. Cambridge University Press.
Denlinger, D.L. & Yocum, G. D. (1998). Physiology of heat sensitivity. *Temperature sensitivity in insects and application in integrated pest management*, *29*.
Dostálek, T., Rokaya, M. B., & Münzbergová, Z. (2018). Altitude, habitat type and herbivore damage interact in their effects on plant population dynamics. *PLoS ONE, 13*(12), e0209149.
Dwevedi, A., Kumar, P., Kumar, P., Kumar, Y., Sharma, Y. K., & Kayastha, A. M. (2017). Soil sensors: Detailed insight into research updates, significance, and future prospects. *New pesticides and soil sensors* (pp. 561–594). UK: Academic Press.
Edem, D. & Gideon, I.K. (2017). Evaluation of soil changes resulting from application of vetiver (*Vetiveria nigritana*) grass technology on sloppy urban farm in Uyo, Akwa Ibom State.
Edwards Molina, J. P., Paul, P. A., Amorim, L., da Silva, L. H. C. P., Siqueri, F. V., Borges, E. P., Campos, H. D., Nunes Júnior, J., Meyer, M. C., Martins, M. C., & Balardin, R. S. (2019). Meta-analysis of fungicide efficacy on soybean target spot and cost–benefit assessment. *Plant Pathology, 68*(1), 94–106.
Feder, M. E., & Hofmann, G. E. (1999). Heat-shock proteins, molecular chaperones, and the stress response: Evolutionary and ecological physiology. *Annual Review of Physiology, 61*(1), 243–282.
Finch, S., Samuel, A., & Lane, G. P. (2014). *Lockhart and Wiseman's crop husbandry including grassland*. Elsevier.
Götz, M., & Winter, S. (2016). Diversity of *Bemisia tabaci* in Thailand and Vietnam and indications of species replacement. *Journal of Asia-Pacific Entomology, 19*(2), 537–543.
Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Academic Press.
Higgins, J. P., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analysis. *British Medical Journal, 327*, 557–560.
Hoffman, C. J., & Byrne, D. N. (1986). Effects of temperature and photoperiod upon adult eclosion of the sweetpotato whitefly, *Bemisia Tabaci*. *Entomologia Experimentalis Et Applicata, 42*(2), 139–143.
Hossain, M., Akanda, A., & Hossain, M. (2010). Environmental effect on tomatoyellow leaf curl virus and whitefly population in tomato varieties under field condition. *Annals of Bangladesh Agriculture, 14*(1&2), 8.
Hunter, J., & Schmidt, F. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Sage Publications.
Hunter, J. E., & Schmidt, F. L. (1990). *Methods of meta-analysis: Correcting error and bias in research findings*. Sage Publications Inc.
Jha, S. K., & Kumar, M. (2017). Effect of weather parameters on incidence of whitefly, *Bemisia tabaci* (Gennadius) on tomato. *Journal of Entomology and Zoology Studies, 5*(6), 304–306.
Kambrekar, D. N., Guledgudda, S. S., Anand, K., & Mohan, K. (2015). Impact of climate change on insect pests and their natural enemies. *Karnataka Journal of Agricultural Sciences, 28*(5), 814–816.
Khalil, H. A., Hossain, M. S., Rosamah, E., Azli, N. A., Saddon, N., Davoudpoura, Y., Islam, M. N., & Dungani, R. (2015). The role of soil properties and it's interaction towards quality plant fiber: A review. *Renewable and Sustainable Energy Reviews, 43*, 1006–1015.
Kristalyn Salters-Pedneault, P (2018). The role of meta-analysis in scientific studies.
Kumar, B., Uikey, B. L., Gharde, S. K., Gupta, S. D., & Pal, P. K. (2016). Seasonal incidence of white fly and jassids along with impact of weather parameter on their population build up in brinjal. *Environment and Ecology, 34*(4A), 1503–1507.
Lapidot, M., Legg, J. P., Wintermantel, W. M., & Polston, J. E. (2014). Management of whitefly-transmitted viruses in open-field production systems. *Advances in virus research* (pp. 147–206). Academic Press.
Lawton, J. H., MacGarvin, M., & Heads, P. A. (1987). Effects of altitude on the abundance and species richness of insect herbivores on bracken. *The Journal of Animal Ecology, 56*, 147–160.
Lefeuvre, P., Martin, D. P., Harkins, G., Lemey, P., Gray, A. J., Meredith, S., Lakay, F., Monjane, A., Lett, J. M., Varsani, A., & Heydarnejad, J. (2010). The spread of tomato yellow leaf curl virus from the Middle East to the world. *PLoS Pathogens, 6*(10), e1001164.
Lobin, K., Druffel, K. L., Pappu, H. R., & Benimadhu, S. P. (2010). First report of Tomato yellow leaf curl virus in Tomato in Mauritius. *Plant Disease, 94*(10), 1261–1261.
Mabvakure, B., Martin, D. P., Kraberger, S., Cloete, L., van Brunschot, S., Geering, A. D., Thomas, J. E., Bananej, K., Lett, J. M., Lefeuvre, P., & Varsani, A. (2016). Ongoing geographical spread of Tomato yellow leaf curl virus. *Virology, 498*, 257–264.
Madden, L. V., & Paul, P. A. (2011). Meta-analysis for evidence synthesis in plant pathology: An overview. *Phytopathology, 101*(1), 16–30.
Mansour, S.A.A., Roff, M.M., Mohd, H.Y., Abuzid, I. and Idris, A.B., 2012. Effects of plant growth on the population of Whitefly *Bemisia tabaci* under glasshouse conditions. *American-Eurasian Journal of Sustainable Agriculture*, pp. 299–304.
Marabi, R. S., Das, S. B., Bhowmick, A. K., Pachori, R., & Sharma, H. L. (2017). Seasonal population dynamics of whitefly (*Bemisia tabaci* Gennadius) in soybean. *Journal of Entomology and Zoology Studies, 5*(2), 169–173.
McNabb, S., Harrison, T. A., Albanes, D., Berndt, S. I., Brenner, H., Caan, B. J., Campbell, P. T., Cao, Y., Chang-Claude, J., Chan, A., & Chen, Z. (2020). Meta-analysis of 16 studies of the association of alcohol with colorectal cancer. *International Journal of Cancer, 146*(3), 861–873.
Nauzeer, S., & Jaunky, V. C. (2021). A meta-analysis of the combined effects of motivation, learning and personality traits on academic performance. *Pedagogical Research, 6*(3), em0097.
Neall, V. E. (2009). Volcanic soils. *Land Use, Land Cover and Soil Sciences, 7*, 23–45.
Ngugi, H. K., Esker, P. D., & Scherm, H. (2011). Meta-analysis to determine the effects of plant disease management measures: Review and case studies on soybean and apple. *Phytopathology, 101*(1), 31–41.
Ning, W., Shi, X., Liu, B., Pan, H., Wei, W., Zeng, Y., Sun, X., Xie, W., Wang, S., Wu, Q., & Cheng, J. (2015). Transmission of Tomato yellow leaf curl virus by *Bemisia tabaci* as affected by whitefly sex and biotype. *Scientific Reports, 5*, 10744.
Normand, S. L. T. (1999). Meta-analysis: Formulating, evaluating, combining, and reporting. *Statistics in Medicine, 18*(3), 321–359.
Onwuka, B., & Mang, B. (2018). Effects of soil temperature on some soil properties and plant growth. *Adv. Plants Agric. Res, 8*, 34–37.
Pakkianathan, B. C., Kontsedalov, S., Lebedev, G., Mahadav, A., Zeidan, M., Czosnek, H., & Ghanim, M. (2015). Replication of Tomato yellow leaf curl virus in its whitefly vector, *Bemisia tabaci*. *Journal of Virology, 89*(19), 9791–9803.
Passioura, J. B. (1991). Soil structure and plant growth. *Soil Research, 29*(6), 717–728.
Patil, V., Singh, P. P., Kumar, R., & Kumar, P. (2021). Population dynamics of whitefly and incidence of yellow mosaic virus disease on mung bean in relation to

abiotic factors in Bihar, India. *Journal of Experimental Zoology India, 24*(1), 475–479.

Ramos, R. S., Kumar, L., Shabani, F., & Picanço, M. C. (2018). Mapping global risk levels of *Bemisia tabaci* in areas of suitability for open field tomato cultivation under current and future climates. *PLoS ONE, 13*(6), e0198925.

Rinehart, J. P., Hayward, S. A., Elnitsky, M. A., Sandro, L. H., Lee, R. E., & Denlinger, D. L. (2006). Continuous up-regulation of heat shock proteins in larvae, but not adults, of a polar insect. *Proceedings of the National Academy of Sciences, 103*(38), 14223–14227.

Rødgaard, E. M., Jensen, K., Vergnes, J. N., Soulières, I., & Mottron, L. (2019). Temporal changes in effect sizes of studies comparing individuals with and without autism: A meta-analysis. *JAMA Psychiatry, 76*(11), 1124–1132.

Safdar, M. Z. (2019). Effect of abiotic factors on population dynamics of whitefly and Jassid on Bt-cotton. *Acta Scientific Agriculture, 3*, 118–121.

Salam, K. P., Thomas, G. J., Beard, C., Loughman, R., MacLeod, W. J., & Salam, M. U. (2013). Application of meta-analysis in plant pathology: a case study examining the impact of fungicides on wheat yield loss from the yellow spot—septoria nodorum blotch disease complex in Western Australia. *Food Security, 5*(3), 319–325.

Sawan, Z. M. (2018). Climatic variables: Evaporation, sunshine, relative humidity, soil and air temperature and its adverse effects on cotton production. *Information Processing in Agriculture, 5*(1), 134–148.

Sharma, D., Maqbool, A., Jamwal, V. V. S., Srivastava, K., & Sharma, A. (2017). Seasonal dynamics and management of whitefly (*Bemesia tabaci* Genn) in tomato (*Solanum esculentum* Mill). *Brazilian Archives of Biology and Technology*. https://doi.org/10.1590/1678-4324-2017160456

Shrestha, U., Augé, R. M., & Butler, D. M. (2016). A meta-analysis of the impact of anaerobic soil disinfestation on pest suppression and yield of horticultural crops. *Frontiers in Plant Science, 7*, 1254.

Sidik, K., & Jonkman, J. N. (2007). A comparison of heterogeneity variance estimators in combining results of studies. *Statistics in Medicine, 26*(9), 1964–1981.

Singh, B., Bishworjit, N., & Athokpam, H. S. (2013). Characterization, and evaluation for crop suitability in lateritic soils. *African Journal of Agricultural Research, 8*(37), 4628–4636.

Smith, M. L., & Glass, G. V. (1977). Meta-analysis of psychotherapy outcome studies. *American Psychologist, 32*(9), 752.

Sohani, N. Z., Shishehbor, P., & Kocheili, F. (2007). Thermal effect on the biology and life tables of *Bemisia tabaci* Gennadius (Homoptera: Aleyrodidae). *Pakistan J. Biol. Sci, 10*, 4057–4062.

Sseruwagi, P., Maruthi, M. N., Colvin, J., Rey, M. E. C., Brown, J. K., & Legg, J. P. (2006). Colonization of non-cassava plant species by cassava whiteflies (*Bemisia tabaci*) in Uganda. *Entomologia Experimentalis Et Applicata, 119*(2), 145–153.

Stanley, T. D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics, 70*(1), 103–127.

Stanley, T. D., Doucouliagos, H., Giles, M., Heckemeyer, J. H., Johnston, R. J., Laroche, P., Pugh, G., Nelson, J., Paldam, M., Poot, J., Rosenberger, R., & Rost, K. (2013). Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys, 27*(2), 390–394.

Stansly, P. A., Schuster, D. J., & Liu, T. X. (1997). Apparent parasitism of *Bemisia argentifolii* (Homoptera: Aleyrodidae) by Aphelinidae (Hymenoptera) on vegetable crops and associated weeds in south Florida. *Biological Control, 9*(1), 49–57.

Sun, J., Freeman, B. D., & Natanson, C. (2018). Meta-analysis of clinical trials. *Principles and practice of clinical research* (pp. 317–327). Academic Press.

Verma, A. K., Ghatak, S. S., & Mukhopadhyay, S. (1990). Effect of temperature on development of whitefly (*Bemisia tabaci*) (Homoptera: Aleyrodidae) in West Bengal. *Indian Journal of Agricultural Sciences, 60*(5), 332–336.

Walter, G., Bloch, S., Hunt, G., & Fisher, K. (2003). Counting on citations: A flawed way to measure quality. *Medical Journal of Australia, 178*(6), 280–281.

Wang, R., Zhang, W., Che, W. N., Qu, C., Li, F. Q., & Desneux, N. (2017). Lethal and sublethal effects of cyantraniliprole, a new anthranilic diamide insecticide, on *Bemisia tabaci* (Hemiptera: Aleyrodidae) MED. *Crop Protect., 91*, 108–113.

Wolda, H. (1987). Altitude, habitat and tropical insect diversity. *Biological Journal of the Linnean Society, 30*(4), 313–323.

Žanić, K., Dumičić, G., Mandušić, M., Vuletin Selak, G., Bočina, I., Urlić, B., Ljubenkov, I., Bučević Popović, V., & Goreta Ban, S. (2018). *Bemisia tabaci* MED population density as affected by rootstock-modified leaf anatomy and amino acid profiles in hydroponically grown tomato. *Frontiers in Plant Science, 9*, 86.

Zehnder, G. (2014). Managing the soil to reduce insect pests. *Extension: America's Research-based Learning Network*.

10 References used in the meta-analysis

Appiagyei, F. (2010). *Effects of two neem kernel extracts in the control of whitefly (Bemisia tabaci) on tomato* (Doctoral dissertation).

Chaudhuri, N., Deb, D. C., & Senapati, S. K. (2001). Biology and fluctuation of white fly (*Bemisia tabaci* Genn.) population on tomato as influenced by abiotic factors under Terai region of West Bengal. *Indian Journal of Agricultural Research, 35*(3), 155–160.

Gupta, D. (1999). *Characterization of viruses causing leaf curl disease of tomato in Himachal Pradesh*. Thesis Submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Mycology and Plant Pathology. College of Horticulture, University of Horticulture and Forestry Nauni-Solan -173 230 (HP) India.

Gupta, M. P., Nayak, M. K., & Srivastava, A. K. (2009). Studies on seasonal activity of white fly (*Bemisia tabaci* genn.) population and its association with weather parameters in Bundelkhand zone of Madhya Pradesh. *Journal of Agrometeorology, 11*(2), 175–179.

Haider, S., Khan, M. A., & Jahanzaib, M. (2017). Characterization of epidemiological factors for the whitefly (*Bemisia tabaci* Genn.) population and tomato leaf curl virus disease (TLCVD) incidence on tomato genotypes in Faisalabad. *Pakistan. J Entomol Zool Stud, 5*, 747–752.

Jha, S. K., & Kumar, M. (2017). Effect of weather parameters on incidence of whitefly, *Bemisia tabaci* (Gennadius) on tomato. *Journal of Entomology and Zoology Studies, 5*(6), 304–306.

Mahajan, R. (2001). Investigation on leaf curl virus of tomato (*Lycopersicon esculentum*) (Doctoral Dissertation, Sher-E-Kashmir University Of Agricultural Sciences And Technology Of Jammu).

Meena, L. K., & Bairwa, B. I. R. B. A. L. (2014). Influence of abiotic and biotic factores on the incidence of major insect pest of tomato. *The Ecoscan, 8*(3), 4.

Mehmood, M. A., Perveen, R., Chohan, S., Ishtiaq, M., Ahmad, M. M., Shaaban, M., Younas, A., Umer, H., Akram, N., Abid, M., & Sajid, M. (2018). Epidemiological studies of tomato leaf curl virus and whitefly population and their management using botanicals. *Pakistan Journal of Phytopathology, 30*(1), 27–36.

Nagamandla, R. S., Shantanu, J., & Nagulapally, S. L. (2017). Insect pests of tomato and their weather relations under open and cover cultivation. *International Journal of Current Microbiology and Applied Sciences, 6*(9), 368–375.

Naveed, K., Imran, M., Riaz, A., Azeem, M., & Tahir, M. I. (2015). Impact of environmental factors on tomato leaf curl virus and its management through plant extracts. *Int J Afr Asian Stud, 11*, 44–52.

Patra, B., Alam, S. F., & Samanta, A. (2016). Influence of Weather Factors on the Incidence of Whitefly, *Bemisia tabaci* Genn. on Tomato in Darjeeling Hills of West Bengal. *Journal of Agroecology and Natural Resource Management, 3*(3), 243–246.

Razvi, S. A., Azam, K. M., & Al-Raeesi, A. A. (1999). Monitoring of Sweet Potato Whitefly, *Bemisia tabaci* (Gennadius) with Yellow Sticky Traps. *Journal of Agricultural and Marine Sciences [JAMS], 4*(1), 11–16.

Sharma, D., Maqbool, A., Jamwal, V. V. S., Srivastava, K., & Sharma, A. (2017). Seasonal dynamics and management of whitefly (*Bemesia tabaci* Genn.) in tomato (*Solanum esculentum* Mill.). *Brazilian Archives of Biology and Technology*. https://doi.org/10.1590/1678-4324-2017160456

Subba, B., Pal, S., Mandal, T., & Ghosh, S. K. (2017). Population dynamics of whitefly (*Bemisia tabaci* Genn.) infesting tomato (*Lycopersicon esculentus* L.) and their sustainable management using biopesticides. *Journal of Entomology and Zoology Studies, 5*, 879–883.

Yasin, M. U., Arain, M. A., Zulfiqar, U., Tahir, M. A., Bilal, A., Ilyas, M., & Hayat, K. (2017). Tomato leaf curl virus disease (TLCVD) and its resistance management practices. *J. Glob. Innov. Agric. Soc. Sci, 5*(99), 104.

Publisher's Note